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Report of the NORC Social Change Project

Volume I

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CONTENTS

INTRODUCTION

This is one of two reports on the first two years work of the NORC "Social Change Project" (NSF Grant No. GS-38534).

The Social Change Project is closely tied to NORC's General Social Survey, an annual sampling of the U.S. adult population for the years 1972 through 1977 (NSF Grant No. SOC73-05504A02). By design, the majority of the questions in the General Social Survey are repeated each year and are of the baseline replication type where the item has been used in national surveys prior to 1972. This means that one can both follow short-run changes in the seventies and compare current patterns with the results in the prior baseline surveys. The aim of the Social Change project has been to collect as many of the baseline measures as possible and to analyze changes in selected content areas during the period from the early 1950s to the early 1970s.

As of July 1975, the project staff had obtained some 200 data sets for national surveys in which approximately 400 questions have been repeated since the late 1940s. Most of the surveys have been put in SPSS system-file form, and a computerized index has been developed to locate files with particular items and combinations of items.

Because the project is large, diffuse, and continuing, we have not attempted to produce a single, integrated report. Instead, we have collected various reports and working papers and organized them into two volumes:

Volume I: <u>Methodology</u>. A set of papers on statistical techniques useful for working with survey change data and methodological findings that have emerged from the analyses so far.

Volume II: <u>Substantive Results</u>. A collection of reports dealing in detail with specific areas of change such as Party Identification, Tolerance of Nonconformists, Subjective Social Class, and the like.

Both volumes, as well as individual papers (for the cost of duplication), can be obtained from the NORC Library, 6030 South Ellis Avenue, Chicago, Illinois 60637.

Although the papers have designated authors, the project required the coordinated effort of a large number of people. In addition to the project authors--James A. Davis, Principal Investigator; Rebecca G. Adams, Gregory Gaertner, Karen Newman Gaertner, Thomas Smith, Aaron Wade Smith, and D. Garth Taylor--major contributions were made by: John Fry, Programmer and Research Assistant; Patrick Bova and David Cook of NORC's Library; Susan Campbell, Paige Wickland, and Sylvia Piechocka, Editorial Department; Susan Rand, Mary Lawson, and Ellen Kaufman, Research Assistants; Toshi Takahashi, Mary Okazaki, and Irene Edwards of the NORC Steno Pool; Rita Hinckley, Administrative Assistant to the Director, NORC; and Edmund D. Meyers, Jr., Director of Computation Services.

We also wish to thank the Roper Public Opinion Research Center at Williams College and the Interuniversity Consortium for Political and Social Research at the University of Michigan for providing the many data sets.

James A. Davis

CONCEPTS AND PROCEDURES FOR CONSTRUCTING ODDS RATIO MODELS FOR CAUSALLY ORDERED, MULTIVARIATE CONTINGENCY TABLES

James A. Davis

February 1974

Models, models, models! Is it possible we need more models? We have econometric (simultaneous equation) models, but the survey data so dear to sociologists usually have qualitative categories or a few ordered classes where the interval scale assumptions of regression analysis require a leap of faith beyond the ability of many. What about Markov models? Fine in terms of measurement level but really only appropriate for panel data where the same measures are repeated on the same subjects.

Well, there are the new hierarchical and log linear models for contingency tables. Yes indeed. They are more like it and we will draw heavily on them. But there are a few problems. Hierarchical models, used alone, lack descriptive statistics to tell us the magnitude and sign of the effects they detect. Log linear models lead to natural descriptive statistics but they have two drawbacks: first, I have been unable to see how they are extended to the non-dichotomous case in a comfortable fashion, and second, there is the problem of causal order.

Sociologists have become sensitized to problems of causal order through the writings of Blalock, Duncan, and the new econometric school. From the causal point of view, existing contingency table approaches seem odd. Consider, for example, a cross-tabulation of father's and son's political party. Classical contingency table analysis proceeds by taking as <u>given</u> the distributions on the independent and dependent variables and assigning to "association" anything left. Causally, this is a bit queer since intuition says that the distribution of father's parties came first, then some sort of causal process took place, and finally there occurred the distribution on the dependent variable, son's party. (The paradox has been obscured because in the popular problem of fathers' and sons' occupations, the notion of a distribution of occupations determined by the economy to which sons are assigned makes sense. But the case of political preferences shows this to be a very special situation.)

Log linear models make a different assumption, that all effects are simultaneous. The one-variable effects for all items and the correlation (interaction) parameters are all simultaneous, as can be shown by the following hypothetical experiement: if you change a single-variable or higher effect parameter in a log linear model, you will almost always affect the marginal distributions of the items.

The issue may seem to be pure nit-picking, but it is not. Ultimately, the NORC social change project wishes to simulate and forecast changes in certain social variables in order to understand recent social trends. For example, we might be working with educational attainment, cohort, and some dependent attitude. It might be interesting to ask what would happen to the attitude distribution five years from now, when the nation's cohort composition will have changed a bit. To do so, we might adjust the cohort parameters in the model. Using classical contingency table models, we have to assume the final attitude distribution from the beginning; using log linear models, we might end up inadvertently producing counter-factual education distributions within cohorts. Thus we think it would be useful to have statistical models that:

a) are appropriate for dichotomies, qualitative polytomies, and variables with ordered classes,

b) follow the accepted logic for systems of variables with a causal order,

c) draw on the advantages of hierarchical and log linear model techniques,

d) express all empirical parameters in the useful common language of odds ratios, and

e) end up expressing each cell frequency in a cross-tabulation by means of an equation whose parameters can be manipulated for purposes of interpolation, extrapolation, and simulation.

Such a system is explained in this memorandum. The materials are organized around the steps involved in estimating such a model.

Step 1: State the causal order.

The analysis proceeds from left to right in a causal order, such as in Figure 1.

Figure 1

$$w \longrightarrow x \longrightarrow y \longrightarrow z$$

Such systems are familiar as "recursive systems," although the restrictions here do not allow more than one exogenous (source) variable. The approach can be extended easily to systems with loops or mutual relationships by using log linear effects within unorderable blocks of variables. This generalization is obvious when the within-block variables are dichotomies, but extension to polytomies needs some work. For this paper we will stick with the case of strict order.

Step 2: Define the comparisons for all variables.

Consider first the dichotomous variable, w, with category frequencies w_1 and w_2, and a total, N. First we arbitrarily choose one of the categories as our "base category" and call its frequency MU. Next we calculate the odds ratio, $w_2/MU = A$, calling it $\emptyset_{w_2/w_1}$. Some obvious equations:

$$w_1 + w_2 = N \tag{1}$$

$$w_1 = MU = \text{frequency of the base category} \tag{2}$$

$$\frac{w_2}{MU} = \emptyset_{w_2/w_1} = A \tag{3}$$

And some less obvious equations:

$$MU * A = w_2 \tag{4}$$

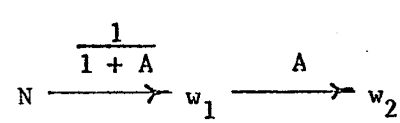
$$MU + MU * A = N \tag{5}$$

$$MU * (1 + A) = N \tag{6}$$

$$MU = \frac{N}{1 + A} \tag{7}$$

Equations (4) through (7) allow us to state a flow graph model (Stinchcombe, 1968; Heise, 1974; Huggins and Entwisle, 1968) giving the two cell frequencies of w as functions of the two independent empirical parameters, N and A. Thus:

Figure 2

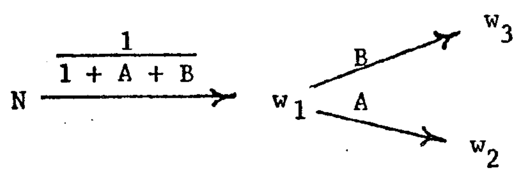


$A = \emptyset_{w_1/w_2}$

When we add a third category, w_3, there seem to be three different strategies: (a) constant base, (b) chain, and (c) cumulative.

In the constant base comparison strategy we merely add $\emptyset_{w_3/w_1} = B$ as a third parameter. It is easy to show that this produces the flow graph model in Figure 3.

Figure 3



$$A = \emptyset_{w_2/w_1}$$

$$B = \emptyset_{w_3/w_1}$$

The approach can be extended to handle any number of categories if we always compare the new category with MU and add the resulting odds ratio as an empirical parameter in the model.

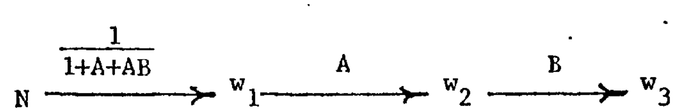
In the chain comparison strategy we compare the new category, w_3, with w_2, obtaining the following equations and flow graph:

$$\emptyset_{w_3/w_2} * \emptyset_{w_2/w_1} * MU = w_3 \qquad (8)$$

$$\emptyset_{w_2/w_1} * MU = w_2 \qquad (9)$$

$$\frac{N}{1 + \emptyset_{w_3/w_2} + \left(\emptyset_{w_3/w_2} * \emptyset_{w_2/w_1}\right)} = w_1 = MU \qquad (10)$$

Figure 4

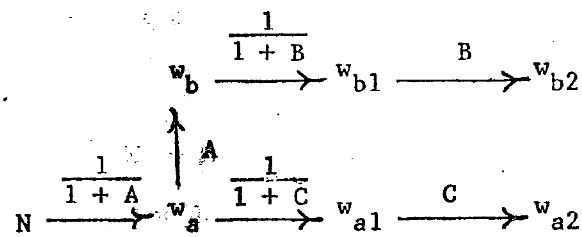


$$A = \emptyset_{w_2/w_1}$$

$$B = \emptyset_{w_3/w_2}$$

In the third strategy, cumulative, we make an initial dichotomy and then subsequent dichotomies within each. Consider, for example, an initial dichotomy, w_a versus w_b, with w_{a1} and w_{a2} included within the former, and w_{b1} and w_{b2} within the latter. Here is the flow graph, using w_a as MU for the initial dichotomy, and w_{b1} and w_{a1} as the subsequent base categories:

Figure 5



$A = w_b/w_a$

$B = w_{b2}/w_{b1}$

$C = w_{a2}/w_{a1}$

Statistically, the three strategies are equally attractive and each will reproduce the item distributions, given N and (C-1) odds ratios, where C is the number of categories. Intuitively, the following rules seem warranted:

1. All other things being equal, do not use very small cell frequencies for MU. It appears everywhere and when unreliable makes everything else less reliable.

2. The constant base strategy seems best for nominal data (unordered "qualitative" categories). For example, consider the following distribution for region of residence at age 16, cumulated for the 1972 and 1973 NORC General Social Surveys.

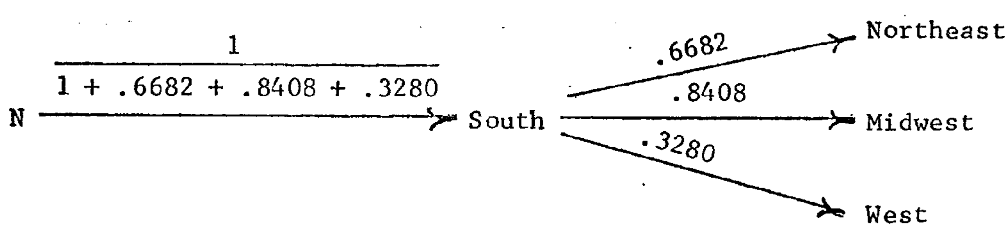
TABLE 1

REGION AT AGE 16, 1972-1973

Region	Frequency
Northeast	705
Midwest	887
West	346
South	1,055
	2,993
Non-U.S.	124
	3,117

It seems natural to pick South as a base and compare each other region with the frequency for South. This gives the following model:

Figure 6



Northeast/South = .6682
Midwest/South = .8408
West/South = .3280

3. The chain strategy seems best for ordinal data. The reason will become clearer when we turn to the addition of new variables. Table 2 and Figure 7 present data on educational attainment from the 1972 and 1973 NORC General Social Surveys which illustrate a chain.

TABLE 2

HIGHEST DEGREE RECEIVED, 1972-1973

Degree	Frequency	Ratio
Junior College or Higher	410	.2767
High School	1,482	1.2486
Less than High School	1,187	
	3,079	
No answer	38	
	3,117	

Figure 7

$$N \xrightarrow{\frac{1}{1 + 1.2486 + .2767 * 1.2486}} \text{Less than H.S.} \xrightarrow{1.2486} \text{H.S.} \xrightarrow{.2767} \text{College}$$

4. The cumulative strategy seems best when the categories have a branching structure. Size of place in the 1972-1973 NORC General Social Survey is a good example.

TABLE 3

SIZE OF PLACE, 1972-1973

Category	Frequency		Ratios	
Within SMSA	1.0084	1,552		
Suburb			581	.5984
Central City			971	
Outside SMSA		1,565		
Rural			451	.4048
Urban			1,114	
Total			3,117	

The primary distinction is between SMSA and non-SMSA. Within SMSA's we distinguish between Central City and Suburb; outside SMSA's, between Urban and Rural. Choosing SMSA as MU for the initial dichotomy, Central City as MU_1 within SMSA, Urban as MU_2 within non-SMSA, and using the ratios from Table 3, we obtain:

$$N * \frac{1}{1 + 1.0084} = \text{SMSA} = \text{MU} \tag{11}$$

$$1.0084 * \text{MU} = \text{Non-SMSA} \tag{12}$$

$$\text{MU} * \frac{1}{1 + .5984} = \text{Central City} = \text{MU}_1 \tag{13}$$

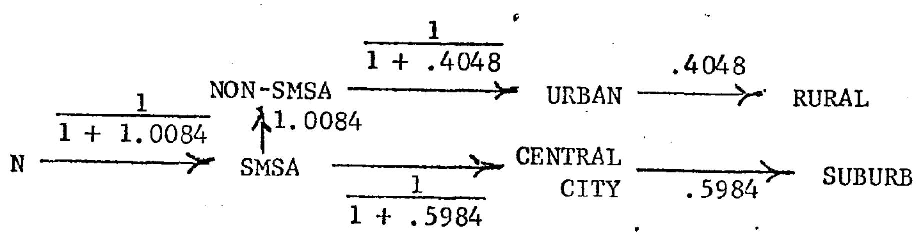
$$\text{MU}_1 * .5984 = \text{Suburb} \tag{14}$$

$$\text{MU} * 1.0084 * \frac{1}{1 + .4048} = \text{Urban} = \text{MU}_2 \tag{15}$$

$$\text{MU}_2 * .4048 = \text{Rural} \tag{16}$$

In flow graph form:

Figure 8



With more than three categories it is possible to combine strategies, but no new principles are involved.

In summary: For each variable a scheme of comparison is assigned, defining a base category and (C-1) odds ratios which determine the frequencies for all categories.

Step 3: Estimate the empirical parameters for the first variable.

Having assigned a causal order and chosen a scheme of comparisons for each variable, the next step is to estimate the C-1 empirical parameters for the initial variable, w. As shown in the previous examples, these estimates are given by calculating the various odds ratios.

Occasionally, the investigator may wish to test the "equiprobable hypothesis" that the category frequencies are identical. If so, each parameter would equal N/C, where N is the sample size and C is the total number of categories connected to each base. The familiar chi square test where the expected values are all set at N/C will do the trick here.[1]

Generally speaking, these parameters, while "empirical," are not terribly informative. They merely state concisely the relative category frequencies that could be obtained by inspection of the raw data.

There are some situations where these results are non-trivial:

First, one might wish to compare two sets of data in terms of their distributions for variable w, as, for example, comparing survey data with U.S. Census results. To do so, one would construct modeled data with parameters (odds ratios) from the standard (in this case, the Census) and N from the test data. The modeled data would constitute expected values, the test data observed values, and the usual chi square test could be applied.

---

[1]If the variable has numerous categories, one may be tempted by the notion that it can be separated into subsets, within which category frequencies are equal [e.g., $(w_1 = w_3 = w_5) \neq (w_2 = w_4)$]. The proposition is not strictly fallacious, since rejection of the null hypothesis that all categories are equal does not imply acceptance of the counter hypothesis that they are all different. This is a classic problem in methodology (e.g., significant ANOVA for a set of means does not prove that any two of them are significantly different). However, we cannot urge such an approach because of its ex post facto "fishing" character. The exception would be where such hypotheses are stated on the basis of theory prior to any analysis.

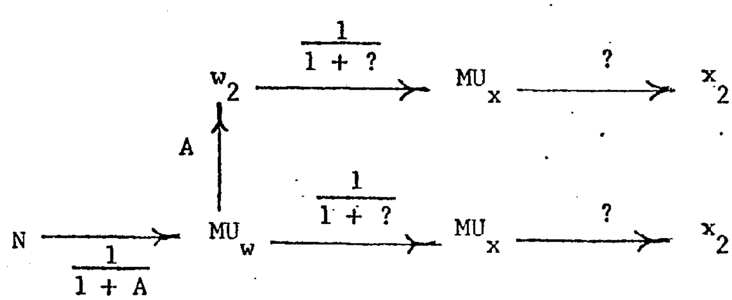
Second, in a multivariate analysis, one might want to use such a model to correct distributions on the initial variable for known biases. If, for example, the data are stratified disproportionately on w in a known fashion, the "true" model for w could be used to construct a better distribution.

Third, one might be interested in simulating or forecasting (projecting) hypothetical distributions for variable w. For example, one could construct the distribution for size of place under assumptions such as "The non-SMSA/SMSA ratio will decline to .8037, the Suburb/Central City ratio will increase to .7312, and the other parameter will remain unchanged." These three uses - detecting, correcting, and projecting - apply to each step in the model, but we will save further discussions until the final section.

Step 4: Estimate the empirical parameters for the second variable.

When a second variable, x, is added, the system looks like Figure 9, using the simplest case of two dichotomies:

Figure 9



We now must estimate the parameters for x denoted by "?" in Figure 9. In a way, nothing much has changed save this: the total in each of the two pairs of x's is no longer N but some expression in terms of the model.

For example, in Figure 9, the total for $(MU_x + x_2)$ within w_2 will be $(N)(\frac{1}{1 + A})(A)$ or $\frac{(N)(A)}{1 + (A)}$. What we do depends on whether w and x are independent.

To test the independence of the two variables we could make the standard chi square test, but since we will be using hierarchical modeling (Bishop, 1969; Goodman, 1970; Davis and Schooler, 1973) eventually, we might as well start here. We test the model (w) (x). If it fits, w and x are independent; if not, there is a "significant association."

When (w)(x) fits, we are persuaded that there are only chance differences between the conditional (on w) distributions for x. As far as we know, the parameter (indicated by "?" in Figure 9) or parameters (in more complex models) have identical values whatever the category of w. The marginal distribution for x gives the best estimate. We therefore calculate the w parameter(s) from the marginal (codebook) distribution for variable w.

When (w)(x) fails to fit, we are persuaded that the x parameters differ, depending on the category of w. If so, we should calculate as many <u>sets</u> of parameters as there are categories of w. We do not know that each condition is significantly different from all the others, but the discussion in footnote 1 applies again, as it will throughout the analysis.

The next part is simple, but important enough to develop through an example. To bring Figure 9 to life, we collapse region at age 16 to South versus non-South, and educational attainment to less than high school versus high school and beyond. The data necessary to analyze the system in Figure 9 are given in Table 4, a fourfold table cross-tabulating these items.

TABLE 4

REGION AT AGE 16 BY EDUCATIONAL ATTAINMENT IN 1972-1973

Region	Education		Total
	Less than High School	High School or More	
Other	612	1,311	1,923
South	519	515	1,034
			2,957
Not available . .			160
Total			3,117

Choosing South and less than high school as the bases, we proceed as follows:

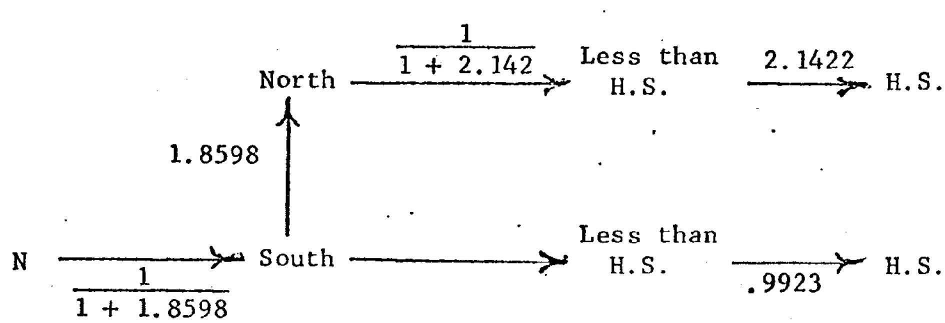
$$A = \frac{1,923}{1,034} = 1.8598 \qquad (17)$$

$$? \text{ (among } MU_w = \text{South)} = \frac{515}{519} = .9923 \qquad (18)$$

$$? \text{ (among } w_2 = \text{Other)} = \frac{1,311}{612} = 2.1422 \qquad (19)$$

We obtain:

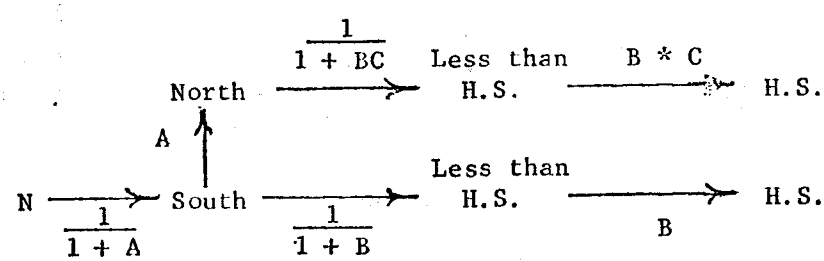
Figure 10



The model can be made more informative by the following trick: Call the odds ratio for x in the base category of w, "B." Here, B = .9923. Then divide the odds ratio in the other category (here, North) by B, calling the result "C." Here $\frac{2.143}{.9923} = 2.1588 = C$.

Clearly:

Figure 11



A = 1.8598

B = .9923

C = 2.1588

What did this do for us? It turns out that C, defined this way, is a familiar domestic animal, the "cross-product ratio" for the fourfold table. To convince the doubters:

$$\frac{1,311 * 519}{612 * 515} = \frac{680,409}{315,180} = 2.1588 = C. \qquad (20)$$

Which means that we can express the parameters in the model and reproduce the cells in the fourfold table given: (1) N, (2) the odds ratio for the prior variable, (3) the dependent variable odds ratio in the base category of the prior, and (4) the conventional measure of association for fourfold tables.

If one prefers a normed measure of association (Yule's Q):

$$\frac{C - 1}{C + 1} = \text{Yule's Q for w and x} \qquad (21)$$

$$\frac{2.1588 - 1}{2.1588 + 1} = +.3668 \qquad (22)$$

And:

$$C = \frac{Q + 1}{1 - Q} \quad (23)$$

$$C = \frac{.3668 + 1.000}{1.000 - .3668} = \frac{1.3668}{.6332} = 2.1589 \quad (24)$$

Equation (23) is useful for projection. For example, we might ask what the data would look like if Q_{wx} went up from + .3668 to + .4789, while A and B remained constant. To do so, we would find C using equation (23) and construct the new table. The new table will not necessarily have the same marginals for x. In this approach, marginals for prior variables are taken as fixed, but marginals for the dependent variables are not. Indeed the purpose of the projection might be to see what would happen to the x marginals if the association were to change.

The procedure is directly extended to polytomous systems since Step 2, defining the comparisons, makes it possible to express any cross-tabulation as a set of fourfold tables. We illustrate with region at age 16 by educational attainment (Figure 12).

Figure 12

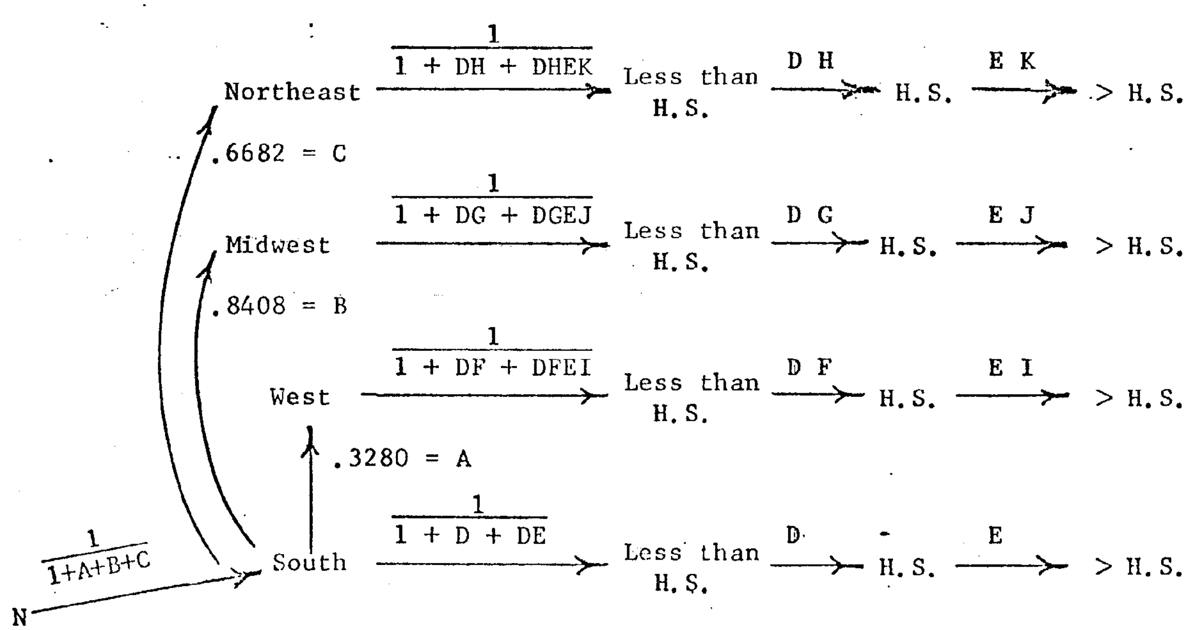


Table 5 gives the cross-tabulation frequencies.

TABLE 5

REGION AT AGE 16 BY EDUCATIONAL ATTAINMENT, 1972-1973

Region	Education			Total
	Less than High School	High School Graduate	Post High School Degree	
Northeast	213	370	118	701
Midwest	307	459	116	882
West.	92	186	62	340
South	519	422	93	1,034
				2,957
Not available .				160
Total.				3,117

NOTES: For the model (Region)(Degree), chi square = 111.44. For 6 d.f., $p < .001$.

The parameters in Figure 12 are estimated as follows:

1. A, B, and C are taken from Figure 5. This is an example of the "correcting" function. Because of NA (no answer) cases, the marginal distribution for region in Table 5 might differ from that in Table 1. If so, we believe that the Table 1 estimates are better and use them in the model.

2. D is the ratio of high school/less than high school in the South, 422/519 = .8131

3. E is the ratio of post high school/high school in the South, 93/422 = .2204

4. F through K are association odds ratios from the following fourfold tables:

$$F = \text{West/South v. H.S./less} = \frac{(186)(519)}{(92)(422)} = 2.4865$$

$$G = \text{Midwest/South v. H.S./less} = \frac{(459)(519)}{(307)(422)} = 1.8388$$

$$H = \text{Northeast/South v. H.S./less} = \frac{(370)(519)}{(213)(422)} = 2.1364$$

$$I = \text{West/South v. post/H.S.} = \frac{(62)(422)}{(186)\ (93)} = 1.5125$$

$$J = \text{Midwest/South v. post/H.S.} = \frac{(116)(422)}{(459)\ (93)} = 1.1468$$

$$K = \text{Northeast/South v. post/H.S.} = \frac{(118)(422)}{(370)\ (93)} = 1.4471$$

The procedure is easily adapted to any other comparison system, e.g., cumulative by constant base.

Step 5: Inspect the parameters estimated in Step 4.

Coefficients F....K in Figure 12 are not merely pasted onto the model. Standing alone, they describe the association between variables w and x. Since the analyst is (or should be) interested in findings as well as intellectual Tinker Toys, it is useful to inspect the coefficients. They should be (a) normed to Q, following equation (19), and (b) arranged in a matrix in which the rows are the w comparisons and the columns are the x comparisons. For the data in Table 5, the results are as follows:

TABLE 6

NORMED VALUES FOR COEFFICIENTS F THROUGH K IN FIGURE 11

Region Comparison	Education Comparison: High Graduate v. Less		Education Comparison: Post High v. High Graduate	
Northeast/South	(H)	+ .319	(K)	+ .183
Midwest/South	(G)	+ .295	(J)	+ .068
West/South	(F)	+ .426	(I)	+ .204

Table 6 suggests these conclusions:

1. Since all signs are positive, educational attainment is lower in the South compared to any other region and for both educational comparisons.

2. Since the left-hand coefficients are larger than those on the right, the southern educational deficit is stronger in terms of high school completion than in terms of college degrees.

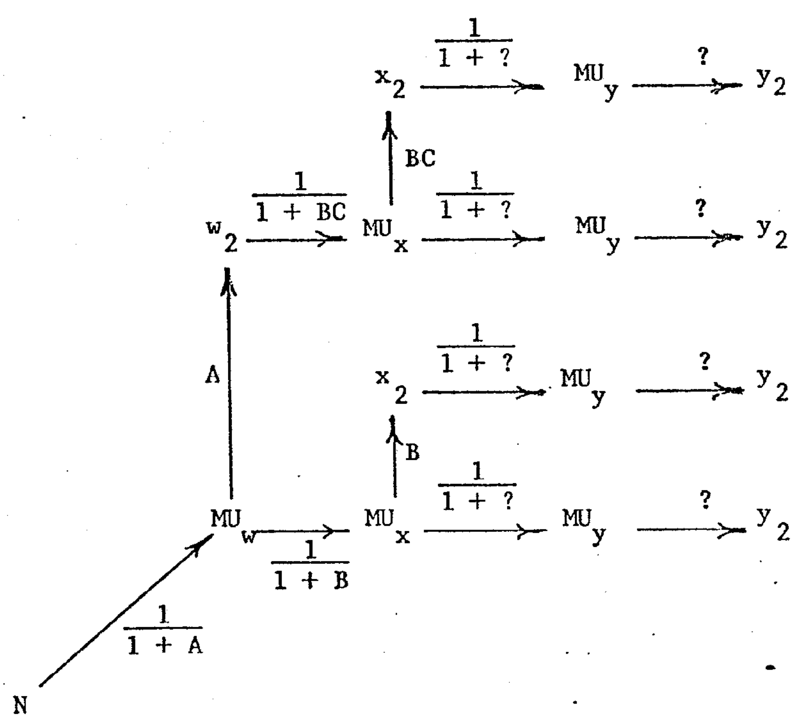
3. Since both coefficients for West are the highest in their columns, it is the "best educated" region for either comparison.

When w and x are ordinal variables treated by the chain comparison method, and the coefficient matrix is laid out with the comparisons in order, the following property holds: when all coefficients have the same sign, the table is isotropic (Davis, 1971, p. 76). Strictly speaking, this implies that any collapse of the table will have the same direction of association (sign). More loosely, it means that the association is consistent: higher (lower) values of w are associated with higher (lower) values of x, regardless of the categories chosen.

Step 6: Estimate the parameters for the third variable.

When a third variable, y, is added, the flow graph for the simplest system, three dichotomies, looks like this:

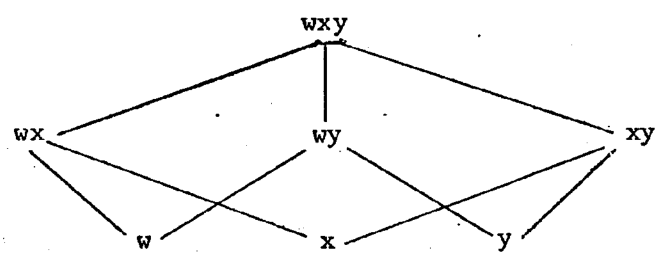
Figure 13



Our first task is to estimate the "?" parameter in four single-variable tables with totals fixed by prior parameters in the model. What is to be done depends again on the pattern of independence and association for y.

We now consider the hierarchical effects that may exist in a three-variable table. The diagram in Figure 14 lists them. In this figure, solid lines connect the various hierarchical inclusions.

Figure 14.--Hierarchical Effects for Variables w, x, and y



We are interested only in effects involving y. The possible y effects in Figure 14 turn out to be: (y w x), (y w), (y x), and (y).

There is no unambiguous algorithm for finding the necessary and sufficient effects in hierarchical modeling, but the following steps seem practical:

1) Test the significance of each effect involving y. Here we merely list the tests; later we give a more general rule.

TABLE 7

y Effect	Effects Allowed in Test Model
(y w x)	(y w) (y x) (w x)
(y w)	(y x) (w x)
(y x)	(y w) (w x)
(y)	(w x)

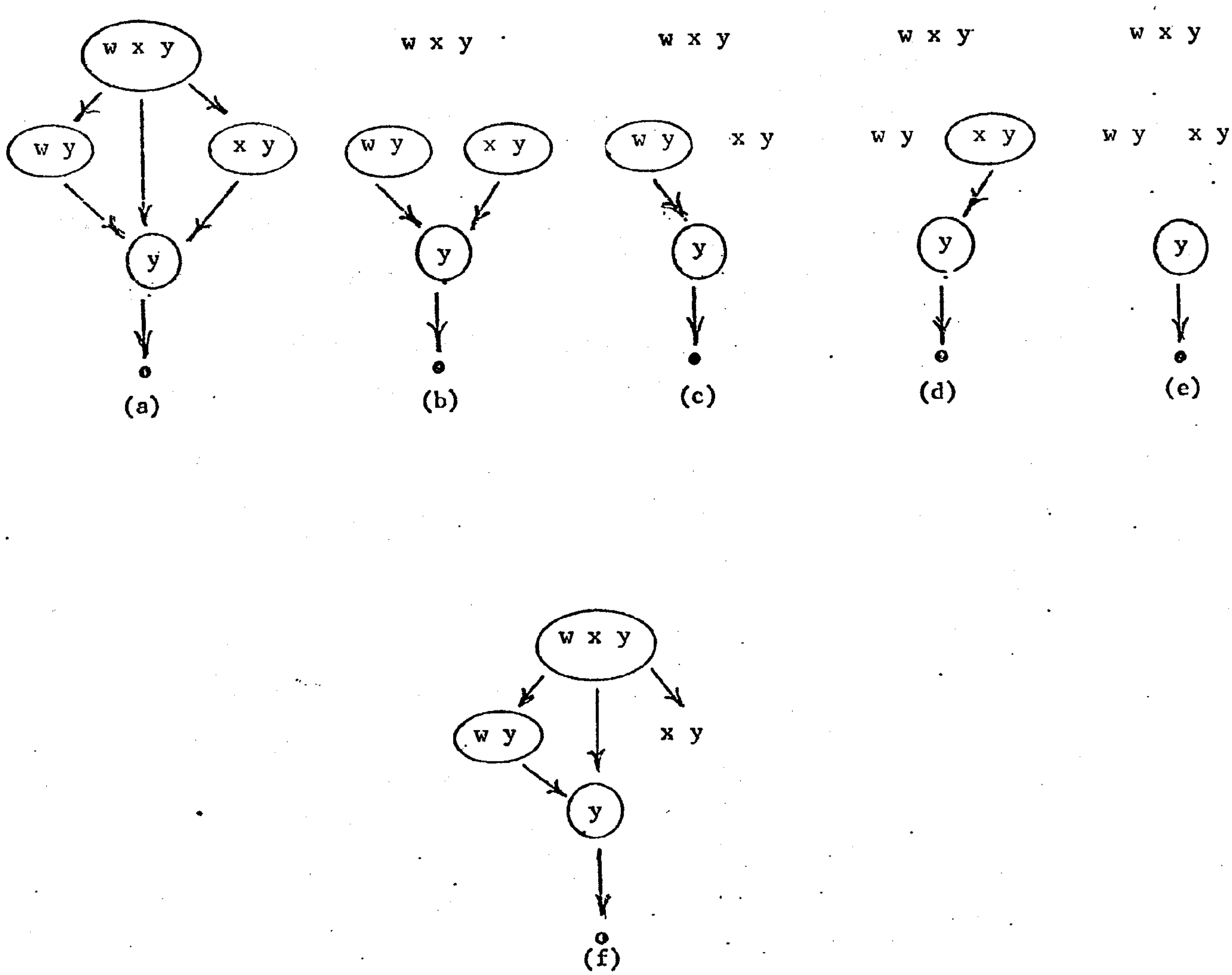
2) Redraw the lattice of hierarchical effects, deleting effects that do not involve y, the new variable, and leaving out the vertical lines.

3) Draw a circle around each significant effect.

4) Draw an arrow from each circled effect to the lower-order effects it subsumes.

The result is an "effect lattice." Figure 15 gives some illustrative effect lattices. Effect lattices may be consistent or inconsistent. In an inconsistent lattice, e.g. example (f) in Figure 15, one or more arrows run into a non-circled effect. All others are consistent.

Figure 15



Considering consistent effect lattices--(a) through (c) in Figure 15--the rule is this:

5) Recognize as significant all effects that are "sources," i.e. that have an arrow running out but none running in. In Figure 15, this gives:

(w x y) in example (a)

(w y) and (x y) in example (b)

(w y) in example (c)

(x y) in example (d)

(y) in example (e)

Inconsistent effect lattices appear because data do not always meet the following logical requirement: the significance of higher-order effects implies the significance of lower-order effects they include, while the insignificance of a lower-order effect implies the insignificance of higher-order effects including it. Consider, as a hypothetical example, (f) in Figure 15. If (xy) is insignificant, the implication is that the odds ratio for y is identical for every category of x. If (wxy) is significant, the implication is that the odds ratio for y differs across certain w-x combinations. These two implications are contradictory.

Inconsistent lattices seem to turn up when (1) effects are of borderline significance and (2) there is a big disparity between the degrees of freedom for the two inconsistent effects. As far as I know, there is no general rule for resolving such contradictions, that is, for telling us whether to treat example (f) in Figure 15 as if it were the same as example (a) or example (c). Indeed there seem to be competing principles. On the one hand, we will always improve the fit of our model by choosing to include the higher-order effect [here, opting for (a)]. On the other hand, parsimony and the difficulties in interpreting higher-order affects suggest the opposite rule--accept an effect only if all its included effects are significant. I prefer the rule of parsimony, but the next memo in this series shows that I don't always apply the rule.

At the end of step (5), you will have a list of y effects that must be plugged into the model and inspected for substance. If none of the y effects are significant, the "equiprobable hypothesis" holds, i.e., the category frequencies for y are essentially identical across y and over the categories of w and x. Each "?" parameter is then estimated to be 1.00 because all other frequencies will equal MU.

If (y) is significant but none of the others are, there is a single "?" value, estimated from the codebook marginals for y.

If (wy) or (xy) but not (wxy) is significant, we have two-variable partial associations; for example, a partial association between y and w, controlling for x. There will be two estimates of each partial parameter, one from each condition of the control variable. To combine them into a pooled estimate, it seems natural to extend the notion of a partial Q (Davis, 1971, pp. 84-85) to a partial odds ratio. For concreteness, consider the following example (Table 8).

TABLE 8

REGION AT AGE 16 BY EDUCATION BY SIZE OF PLACE, 1972-1973

w	x	y		Total
Region at 16	Education	Size of Place Non-SMSA	SMSA	
North	High school or more	742 = A	760 = B	1,502
	Less than high school	184 = C	237 = D	421
South	High school or more	261 = E	254 = F	515
	Less than high school	325 = G	194 = H	519
				2,957
		Not Available		160
		Total		3,117

The partial odds ratio for xy, controlling w =

$$\frac{(B*C) + (F*G)}{(A*D) + (E*H)}.$$

The partial odds ratio for wy, controlling x =

$$\frac{(B*E) + (D*G)}{(A*F) + (C*H)}.$$

More generally, if we have a set of ratios (numerator and denominator values) that purport to be estimates of the same true ratio, each may be viewed as the true ratio times some weight for sample size plus some random error term. Assuming that the error terms sum to zero, it is easy to show that the sum of the numerators divided by the sum of the denominators equals the true ratio (because the weights, appearing in both numerator and denominator, cancel out).

To plug these coefficients into all-dichotomous models like Figure 13, we may think of four "?" parameter values as a fourfold table, as in Table 9.

TABLE 9

VALUE OF y ODDS RATIO

w	x:	MU_x	x_2
	w_2	D*F	D*E*F
	MU_w	D	D*E

D = Odds ratio for y in the "MU-MU" cell

E = Partial odds ratio for xy

F = Partial odds ratio for wy

In Figure 13, the "?" odds ratios from top to bottom would be: D*E*F, D*F, D*E, and D.

Here too, a bit of "correcting" is present. It is unlikely that each conditional odds ratio will be exactly equal to the partial. Therefore, the model will not fit the data exactly. But we are undaunted since (a) there can be only chance differences between the cell and the model, by the logic of selection of effects, and (b) if anything, the pooled estimate is better than the conditional cell estimate, particularly if the conditional has a very small total of cases.

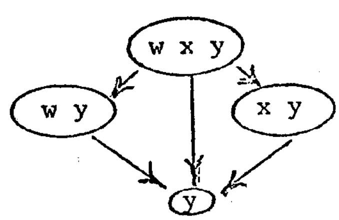
Finally, we consider the case where wxy is significant. Table 10 and Figure 16 show this to be the case for the data presented in Table 8.

TABLE 10

y EFFECTS IN TABLE 8

Effect	Model Tested			Chi Square	d.f.	Probability
(w x y)	(w x)	(w y)	(x y)	18.2706	1	.0001
(w y)	(w x)		(x y)	33.7469	2	.0001
(x y)	(w x)	(w y)		19.2825	2	.0002
(y)	(w x)			40.0486	1	.0001

Figure 16



There seem to be three distinct strategies for stating parameters in the presence of a three-variable interaction: (1) typological, (2) specification, and (3) special cell.

In the typological approach, we introduce a different coefficient for each non-MU-MU cell in Table 9. Thus:

TABLE 11

TYPOLOGICAL COEFFICIENTS

w	x:	MU_x	x_2
	w_2	D*F	D*G
	MU_w	D	D*E

D = Odds ratio for y in the MU-MU cell.

E = y odds ratio in the $MU_w x_2$ cell divided by D.

F = y odds ratio in the $MU_x w_2$ cell divided by D.

G = y odds ratio in the $w_2 x_2$ cell divided by D.

This approach is called "typological" because it amounts to collapsing w and x into a new nominal variable handled in the baseline comparison manner. If so, w and x may be viewed as a typology rather than as two distinct variables.

In the specification approach, we view one of the variables as a condition that affects (specifies) the size of the partial association between the other variable and y. Thus we can look at the partial associations between w and y for the two conditions of x, or look at the partial associations between x and y in the two conditions of w. Table 12 shows the latter.

TABLE 12

COEFFICIENTS FOR SPECIFICATION APPROACH
WITH w AS THE SPECIFIER

w	x: MU_x	x: x_2
w_2	F	F*G
MU_w	D	D*E

D = Odds ratio for y in the MU-MU cell

E = same as Table 11

F = Odds ratio for y in the w_2MU_x cell

G = y odds ratio in the w_2x_2 cell divided by F

(Incidentally, G/E will be the famous three-variable interaction odds ratio, B*C*E*H/A*D*F*G, in terms of the cell lettering of Table 8.)

In the special cell approach, we assume that there are partial associations for wy and xy and, in addition, that one (any one) of the four cells has an especially high or low level on y. To use this approach, one:

a) arbitrarily picks the "special cell," say w_2x_2;

b) calculates the three-variable interaction odds ratio as defined a few lines above, calling the result "G"; and

c) divides the special cell by G if it is MU-MU or w_2x_2, multiplies it by G if it is w_2MU_x or MU_wx_2.

This done, we have removed the interaction effect and proceed to calculate the partial odds ratios as in Table 9. The final coefficients are given in Table 13.

TABLE 13

COEFFICIENTS FOR SPECIAL CELL APPROACH WITH w_2x_2 AS THE SPECIAL CELL

		x: MU_x	x: x_2
w	w_2	D*F	D*E*F*G
	MU_w	D	D*E

Each of the strategies will fit the data and give four coefficients, D,E,F, and G. Their differences lie only in the substantive assumptions the modeler chooses to make regarding the underlying causal processes.

Extension to polytomies is direct, although the work can become intricate when there are many categories. Rather than spelling out the many possibilities, we suggest the reader examine Memo II in this series, where several concrete examples appear.

Further Steps: Additional Variables

Any number of sequential, dependent variables can be added to models such as those we have been working with, as long as the cases hold out. Rather than working through concrete examples, we will merely list a number of methodological tips and rules that may be helpful when working with large systems.

1. Estimating effects. A general magical[2] formula for testing the significance of a particular effect in a multivariate data set goes like this:

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[2]The result is not pure magic. It is what results when one applies these rules: (a) Eliminate the test effect. (b) Eliminate anything that includes the test effect. (c) Allow the effects included in the test effect. (d) Allow everything not covered in (a), (b), and (c).

(a) With V number of variables, write out a list of all possible V-1 effects. There will be V number of such effects. For example, if V equals 5, with variables A,B,C,D,E, the V-1 effects are: ABCD, ABCE, ABDE, ACDE, BCDE.

(b) Choose the effect to be tested, e.g. CDE.

(c) Eliminate any V-1 effect that is or includes the test effect, e.g. ACDE, BCDE.

(d) The remaining effects constitute the test model, e.g. (ABCE)(ABDE).

2. <u>Effect lattices</u>. Standard lattices for four and five variables are presented for reference (Figures 17 and 18). In each case, we assume the "new variable" being added to the system is "A." In the case of five variables, effects not including A are dropped for simplicity.

Figure 17.--Four Variables

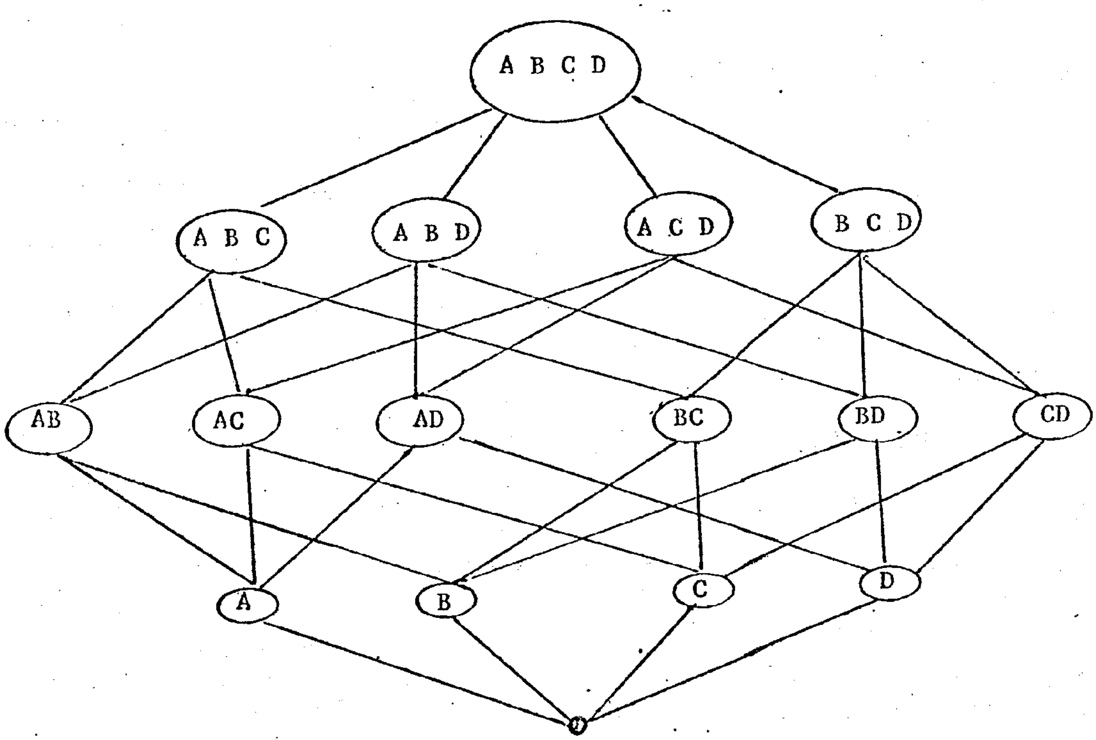
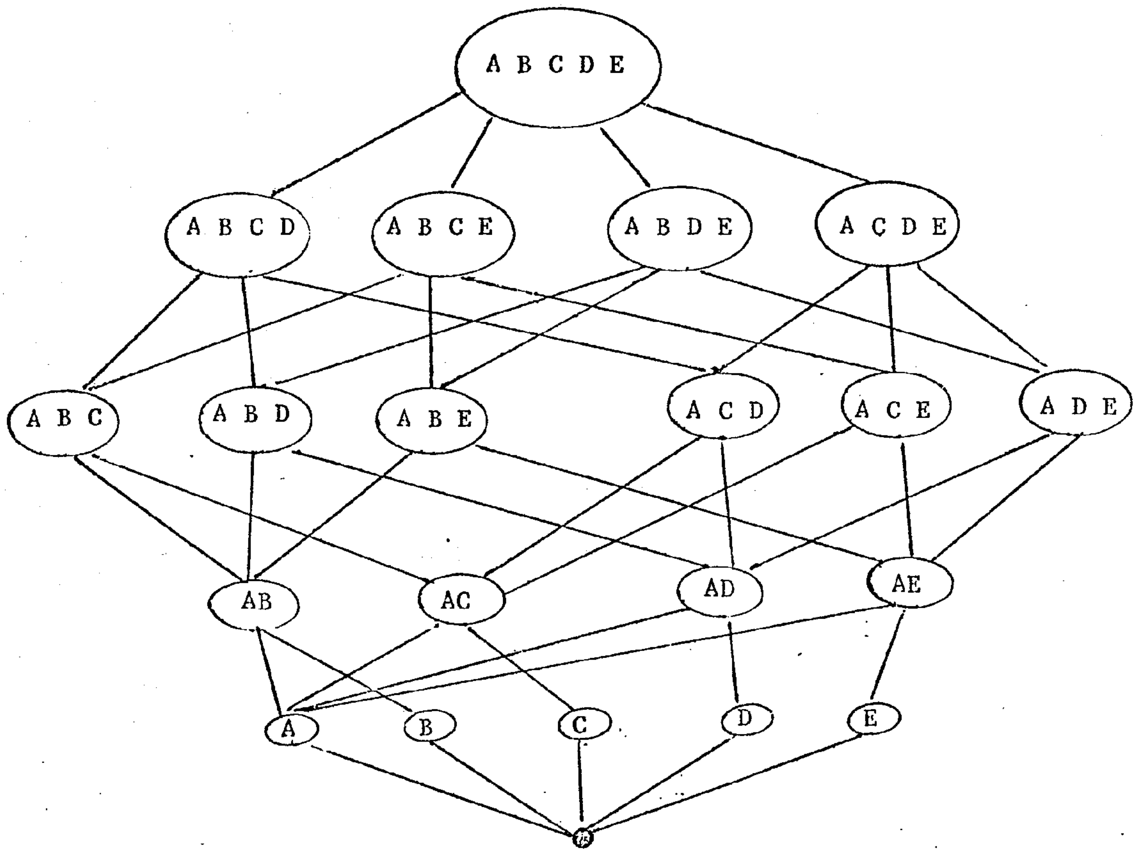


Figure 18.--Five Variables



3. Partials. It is necessary to calculate partials whenever the highest (V) level interaction is not significant and whenever one or more of the remaining effects is recognized. For example, with variables A-B-C-D-E and effects ABE, ACE, and AD, we would calculate partial values for the two three-variable effects as well as for the familiar two-variable partial. To calculate a partial odds ratio:

(a) Locate the variables not in the effect. Within each cell formed by the cross-tabulation of these variables, lay out a cross-tabulation involving the variables in the effect (e.g. AxBxE).

(b) Calculate the numerator within each condition and sum them.

(c) Calculate the denominator within each condition and sum them.

(d) Divide (b) by (c).

Single-variable effects, e.g. (D), are estimated when the data suggest that the only variation in D is the same skew across the other cells of the data. Therefore, single-variable effects are estimated from the marginals, and the notion of a partial does not apply.

4. Norming. Any effect odds ratio may be normed using equation (21). The result may be interpreted as the degree of association (Q) between any one of the items and the magnitude of the effect defined by the others. (For example, for wxy, a Q of + .21 means that there is a Q of + .21 between any one variable and the partial association for the other two.)

Conclusion

We shall not discuss the advantages, disadvantages, applications, and limitations of this set of procedures here because they are better seen in concrete applications. The NORC Social Change Project has completed data analysis on several data sets using these procedures. A report on cohort, sex, region, education, and time for data from 1952 to 1972 is nearing completion. The project also plans to report on trends in party identification from 1952 to 1972 and tolerance of nonconformists for 1954-1973 using these techniques. These companion reports should make clear how the techniques can be used and their utility.

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D SYSTEMS: ANALYZING CONTINGENCY TABLES WITH LINEAR FLOW GRAPHS

James A. Davis

Spring 1975

This paper is a revised version of one presented at the 1974 American Sociological Association meetings in Montreal, Canada ("Linear Flow Graphs as a Mathematical Model for Analyzing Contingency Tables"). The current version appears in Sociological Methodology, 1976. I am indebted to the students at the 1974 British Social Science Research Council Summer School (at the University of Reading, England) for their diplomatic but firm insistence that these ideas would be a lot more clear if written down. I am also indebted to Martin Frankel, Stephen Fienberg, and Leo Goodman for advice on the statistical problems, as well as to John Fry, D. Garth Taylor, and Gregory Gaertner for their assistance. David Heise spent hours helping me get things straight, for which I am extremely grateful.

Flow Graphs as a Theoretical Tool

In his seminal book, Constructing Social Theories, Arthur L. Stinchcombe introduces the sociological theorist to the remarkable quantitative technique, "linear flow graphs" (Stinchcombe, 1968, pp. 130-148).[1] Flow graphs enable one to translate a set of linear equations into a diagram and then apply simple rules to find interesting mathematical results.

Equations may be represented as a graph by applying three conventions: (1) Variables become points (sometimes called nodes or vertices). (2) Coefficients are associated with one-way arrows running into the variable whose value is given by the equation. (3) Constants are associated with the origin of unlabeled one-way arrows running into the variable. (By convention, an unlabeled arrow has the value of 1.0.)

Following these conventions, any linear system can be drawn as a graph. Since distance has no meaning ("linear graphs" and the familiar "Cartesian graphs" of elementary algebra have little in common save the unfortunate, but long established, common word), a particular graph may be drawn in many different ways. Usually, one aims for a version that makes clear any ordering among the variables and minimizes arrow crossings.

Given a linear graph, the analyst is usually interested in one or both of two activities: (1) finding the "graph transmittance" from one variable to another; or (2) decomposing inferred change for a dependent variable. (Both of these will be explained and illustrated later.) These activities can be carried out using algebra, because graphs have no

[1]For a readable and more extensive treatment of linear graphs, see Huggins and Entwisle, 1968. For a similar approach to theory construction, see Mullins, 1971.

unique mathematical properties; they merely translate equations into a visual language. The advantage of graphs is simplicity. A class of sociology students can master the principles of graph manipulation on the basis of a one hour lecture--it has not been my experience that they can learn algebra so fast.

Stinchcombe illustrates how linear graphs can be used as a marvelous tool for theorizing, but he does not tell us how to test these theories with conventional research data. Since a linear flow graph looks like a path diagram and regression results appear in the form of linear equations, path analysis is an obvious candidate. Indeed, David Heise develops the major principles of path analysis from flow graphs in a most interesting new book (Heise, in press). Nevertheless, many, perhaps most, sociological data come in the form of nominal scales (unorderable categories) or ordinal classes (e.g., major census occupational groups or Agree-Disagree groupings). Such measures can be forced into regression routines and numbers will emerge, but many of us would feel more comfortable if we could apply flow graph analysis without going beyond the statistics for contingency tables. It is the purpose of this paper to show how graph theory can be used as a mathematical model for analyzing and interpreting contingency table data.

The scheme can be applied to nominal and ordinal category data (but not fully ranked scales), extended to as many variables as the case bases will tolerate, used for cross-section and over-time designs, and modified to allow analysis of systems of partially ordered variables. As with classical path analysis, there are serious identification problems in a system where loop effects must be estimated. In models with "instrumental variables" (Heise, in press) there is no theoretical obstacle to estimating certain loops by econometric techniques, but I have never tried to do so and am not prepared to discuss the problem here.

The paper is organized as follows:

1. Strictly Ordered Dichotomous Variables With No Interactions
2. Strictly Ordered Polytomous Variables With No Interactions
3. Estimating the Parameters
4. Block Recursive Models for Partially Ordered or Interaction-Ridden Systems
5. Comparisons with Other Techniques
6. Conclusions.

1. Strictly Ordered Dichotomous Variables With No Interactions

We start with the most rudimentary bivariate data, the fourfold table. The data are pooled from the 1972, 1973, and 1974 NORC General Social Surveys. The GSS is an annual sampling of continental U. S. adults (18 and older) living in non-institutional quarters.[2] The sample is a multistage area probability sample to the block or segment level. At the block level, quota sampling is used with quotas based on age, sex, and employment status. The sample sizes for 1972, 1973, and 1974 are 1613, 1504, and 1484, respectively, giving a total of 4601.

The two items in our example are Region at Age 16 and Attitude toward Racial Intermarriage. The prior item is the respondent's reported region of residence at age 16 ("In what state or foreign country were you living when you were 16 years old?"). The small number of foreign born have been excluded and the remainder dichotomized as SOUTH (Census regions: South Atlantic, East South Central, and West South Central) versus NON-SOUTH.

The dependent item is a precoded question on attitude toward racial intermarriage ("Do you think there should be laws against marriages between Negroes and whites?"). Respondents are divided into those answering "No" (TOLERANT) and those answering "Yes" or "Don't know" (LESS TOLERANT). Blacks (totaling 617 in the three surveys) were not asked the question and are excluded from the tabulations. Table 1 gives the crosstabulation.

The figures show a familiar pattern. Among WHITES, those who grew up in the NON-SOUTH are more tolerant on racial matters. The difference

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[2]The project is funded by the National Science Foundation. Pilot funds for 1972 were awarded by the Russell Sage Foundation. The data are placed in the public domain immediately on completion of the data tapes. For information, write The Roper Public Opinion Research Center, Williams College, Williamstown, Massachusetts.

TABLE 1

REGION AT AGE 16 AND ATTITUDE TO RACIAL INTERMARRIAGE, U.S. WHITES, 1972-3-4 (DICHOTOMIZED)

Region at Age 16	A. Frequencies		
	Intermarriage		Total
	LESS TOLERANT	TOLERANT	
NON-SOUTH	858	1,842	2,700
SOUTH	597	489	1,086
Total	1,455	2,331	3,786
		No Answers	198
		Blacks	617
			4,601

Region at Age 16	B. Proportions
	Proportion TOLERANT
NON-SOUTH	.682 (2,700)
SOUTH	.450 (1,086)
d	+.232
Total	.616 (3,786)

is statistically significant (as will be explained later) and d, the difference in proportions, is +.232.

To express these data as a flow graph, we first show that they can be treated as a set of equations. It is well known that when the categories in fourfold tables are assigned the arbitrary values of 0 and 1 (here, 0 for SOUTH, 1 for NON-SOUTH; 0 for LESS TOLERANT, 1 for TOLERANT), there are a number of analogies to linear equations. Specifically:

1) The marginal proportion in the "1" category of the prior variable (here the proportion NON-SOUTH or 2700/3786 = .713) equals its mean (2699 * 1 + 1085 * 0/3786 = .713).

2) The marginal proportion in the "1" category of the dependent variable (here the proportion TOLERANT = 2331/3786 = .6157) equals its mean.

3) The difference in proportions, d, (here +.232) equals the "slope" or coefficient for the linear relationship between the two variables.

4) The proportion in the "1" category on the dependent variable among those in the "0" category on the prior variable is equivalent to the intercept in the linear plot or constant in the linear equation (here 489/1086 = .450).

Using these analogies, we can express the data in Table 1 in two equations:

$$\text{NON-SOUTH} = .713 \quad (1)$$

$$\text{TOLERANT} = (+.232 * .713) + .450 = .6154 \quad (2)$$

Equations (1) and (2), like any equations, can be represented as a flow graph by applying the following conventions: (1) The "source" node is the "1" category for the prior variable. (A source node is one with no in-coming arrows.) (2) The "sink" node is the "1" category for the dependent variable. (A sink node is one with no out-going arrows.) (3) The coefficient for the arrow from source to sink equals d. (4) The "constant" or "intercept" becomes a dummy node with an arrow running into the sink. (In general, we will call such "0" categories "bases" or "base categories.") Figure 1 illustrates.

The analogy extends to systems with any number of ordered variables. For example, let us introduce Educational Attainment (High School Graduate or more = HIGH SCHOOL PLUS, other = LESS THAN HIGH) as an intervening variable between Region at 16 and Attitude toward Intermarriage. To justify the order, we argue that in most cases the final level of schooling is settled one way or another after the age of 16 but well before the interviewer assesses current attitudes. Other analysts might, of course, specify the model differently. Table 2 gives the figures required to incorporate Education in the model.

Table 2, Part A shows that persons raised in the NON-SOUTH are more likely to become HIGH SCHOOL PLUS, d = +.116. Table 2, Part B shows that both Region and Education are related to Tolerance. In both SOUTH and NON-SOUTH there is an educational difference of +.326; in both LESS THAN HIGH and HIGH SCHOOL PLUS there is a regional difference of +.194.

The notion of a conditional difference in proportions is extremely important because, once we get beyond two variables, every d coefficient appears in two or more control conditions. The key principle is this: <u>If the conditional d's are the same, d will have the same algebraic properties as coefficients in linear equations (partial slopes in linear plots).</u>

In Table 2 the conditional d's are identical (suspiciously so to

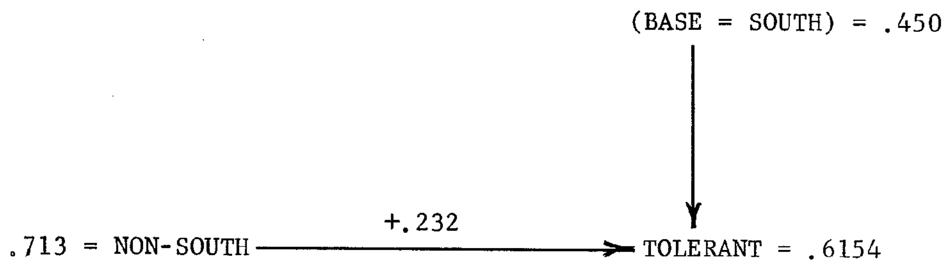


Fig. 1.--Linear Flow Graph for Data in Table 1

TABLE 2

REGION AT AGE 16, EDUCATIONAL ATTAINMENT, AND ATTITUDE TO RACIAL INTERMARRIAGE, U.S. WHITES, 1972-3-4 (DICHOTOMIZED)

Region at Age 16	A. Region and Education: Proportion HIGH SCHOOL PLUS
NON-SOUTH	.690 (2,700)
SOUTH	.574 (1,086)
d	+.116
Total	.657 (3,786)[a]

Region at Age 16	B. Region, Education, and Tolerance[a] (Proportion TOLERANT): Education: LESS THAN HIGH SCHOOL	Education: HIGH SCHOOL PLUS	Conditional d
NON-SOUTH	.457 (837)	.783 (1,863)	+.326
SOUTH	.263 (463)	.589 (623)	+.326
Conditional d	+.194	+.194	All cases .615 (3,786)

[a]For exclusions, No Answers, and Totals, see Table 1.

the eye of the experienced data analyst, who is advised to wait until we get to Section 3 for an explanation). We can therefore write the following equation for Tolerance as a 0-1 system:

Tolerance = (+.326 * Education) + (.194 * Region) + .263 (3)

(The .263 constant is the mean on Tolerance for those scoring zero on both Region and Education--that is, those in the combination SOUTH and LESS THAN HIGH SCHOOL.)

Remembering that category proportions are the same as variable means when one works with dichotomies, we get equation (4).

Proportion TOLERANT = (.326 * Proportion HIGH SCHOOL PLUS)
+ (+.194 * Proportion NON-SOUTH) + (Constant = Proportion
TOLERANT among SOUTH and LESS THAN HIGH SCHOOL (4)

The relationship between Region and Education can be graphed a la Figure 1. The parameters necessary to add the sink variable follow from Equation (4). Therefore, we can graph the three-variable system in Figure 2.

More generally, to graph a categorical system with ordered variables and identical conditional d's:

1) Pick a base (zero) category for each variable.
2) Enter the non-base categories of the source variable as source nodes.
3) Enter the marginal proportions for the source categories as source values.
4) Enter all the non-base categories for the other variables as nodes.
5) Draw a one-way arrow from each prior node to each later node.
6) Assign the relevant d or conditional d as the arrow coefficient.
7) Add dummy node constants for each non-source node, their values being the proportion in that category for cases in the all-base combination of prior variables.

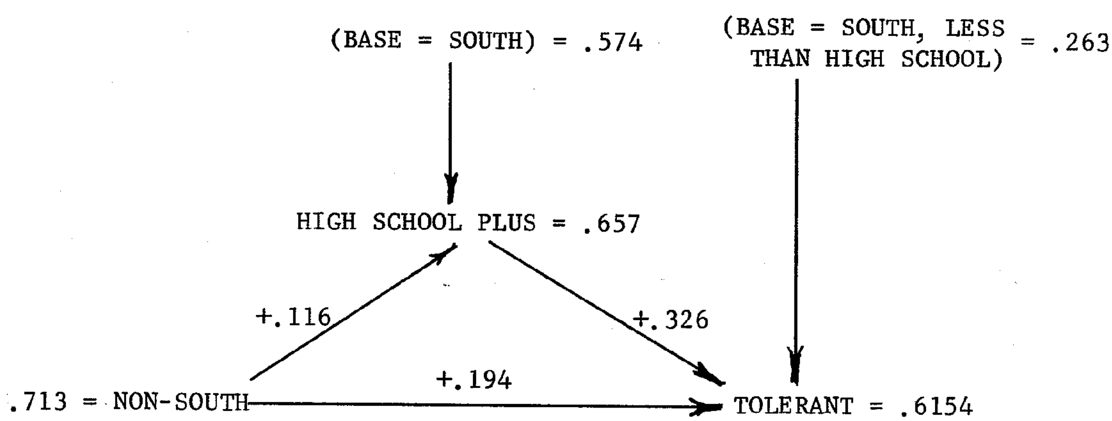


Fig. 2.--Linear Flow Graph for Data in Table 2

What good is Figure 2?

First, it gives a bird's eye view of the system that is not easily obtained from a set of equations. We see at a glance that both Region and Education are associated with Tolerance and also that Region and Education are related.

We can also calculate "transmittances" from prior to later variables. To do so: (1) Find all distinct paths from the prior to the later node. (2) Find the value of each path by multiplying the values of its coefficients. (3) Sum to obtain the transmittance. For example, there are two paths from NON-SOUTH to TOLERANT in Figure 2, a direct one with a value of +.194, and a two-step, indirect path, +.116 * +.326 = +.0378, giving a total transmittance of .194 + .0378 = .2318. Turning back to Figure 1, we see that the transmittance equals the zero-order difference (within errors of rounding). The source-sink transmittance decomposes a zero-order percentage difference into path components, in much the same way that classical path analysis decomposes a zero-order product moment correlation. Strictly speaking, the analogy is to decomposition of a regression coefficient, not a product moment correlation. The logical interrelations among d-systems, regression, and correlation are discussed in Section 5.

For a source and sink, the transmittance must be identical to the zero-order difference (assuming conditional d's are identical). For an intervening variable, this will not, in general, be true. For example, consider LESS THAN HIGH SCHOOL and TOLERANCE, with a single direct path of -.326. If we rework the data in Table 2, we find the zero order d for Education and Tolerance to be -.346. The difference, .346 - .326 = .020, is the "spurious" component in the zero-order correlation. One may always find the spurious component by subtracting the transmittance from the zero-order difference, but it does not emerge from path multiplications of the sort used in classical path analysis.

To repeat: In ordered systems with a single exogenous variable, when conditional d's are identical, the source-sink transmittance is identical to the zero-order difference in proportions; the transmittance between an intervening variable and a later one is the sum of the non-spurious relationships, the spurious component being obtainable by subtracting the transmittance from the zero order.

Transmittance decomposition allows one to look for "explanations," "suppressor variables," "reinforcers," "spurious correlations," and similar ideal types beloved by survey analysts working in the Lazarsfeld tradition. Transmittances lead directly to the useful notion of "reduced form equations" that define the values of dependent variables in terms of the values of system inputs. As Heise puts it (Heise, in press):

> The reduced form expressions obtained from graph analysis constitute input-output equations for a system. Given a particular configuration of values among the input variables at a given time, the ultimate consequences for all dependent variables can be calculated.... The use of graphs and reduced form expressions provides two benefits over more informal approaches to prediction. First, a change in an input can be traced readily to all its consequences, even when multiple and convoluted pathways are involved. Second, changes in a dependent variable can be anticipated in terms of all the system inputs, thereby avoiding oversimplifications and errors of judgment.... Flowgraphs and the reduced form expressions obtained from them, can guide policy decisions by indicating which source variables can be changed to achieve a desired effect, by suggesting how much manipulation is necessary to obtain the desired change, and by revealing what additional effects a manipulation will have besides the desired one.

Reduced form equations can be static descriptions of the system at a particular time or change equations that allow one to infer increases or decreases in the levels of the variables. To write a reduced form change equation one: (1) uses Δ (amount of change) instead of variable means and constants; (2) uses the transmittances as coefficients; and (3) assumes the coefficients in the original graph remain constant.

For example, here is the reduced form equation for TOLERANT in the system in Figure 2:

$$\Delta_{\text{TOLERANT}} = (+.232 * \Delta_{\text{NON-SOUTH}}) + (+.326 * \Delta'_{\text{HIGH SCHOOL PLUS}}) + (\Delta'_{\text{TOLERANT}}) \qquad (5)$$

Equation (5) may be read as follows: Assuming the arrow coefficients stay the same between Time_1 and Time_2, the shift in marginals for proportion TOLERANT will equal (a) the transmittance for NON-SOUTH times the marginal change in the proportion NON-SOUTH, plus (b) the transmittance for HIGH SCHOOL PLUS times the change in proportion HIGH SCHOOL PLUS net of Region, plus (c) residual change in TOLERANT net of Region and Education.

Note that the Δ symbols for HIGH SCHOOL PLUS and TOLERANT have primes. This is a reminder that change measures for non-source variables are now the raw differences, but change net of prior variables. (If we did not "remove" Region's contribution to change in Education it would be counted twice because this effect also appears in the transmittance for Education.) In the next section, we will explain how to estimate $\Delta^{1'}$ parameters.

Equation (5) can be graphed, as shown in Figure 3.

To estimate the parameters (arrow coefficients) and Δ' values (changes in node numbers) we need data from two points in time. Alas, the parameters in Figure 2 do not change enough over 1972, 1973, 1974 to give

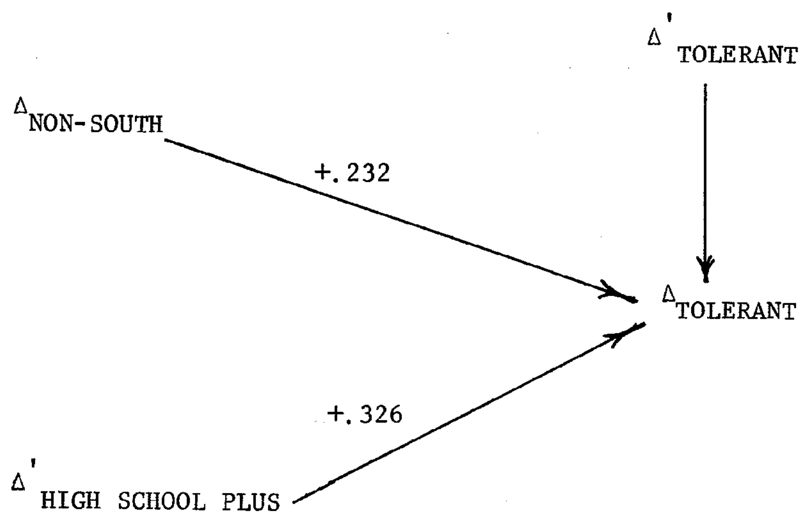


Fig. 3.--Graph for Equation 5

a good example, but the steps required will be discussed later.

Even without change data, reduced form graphs can be used for conjectures about the future (i.e., simulation), as mentioned by Heise. For example, let's assume that "in the next generation" the proportion growing up in the NON-SOUTH declines .050; the proportion graduating from High School increases .120; and no other variables affect changes in Tolerance, i.e., $\Delta'_{TOLERANT} = .000$. If so, the net change in TOLERANT will be (-.05 * + .232) + (.120 * .326) = +.027. We "project" a .027 increase in TOLERANCE under these assumptions. Clearly, there is no way to turn equations into crystal balls, but the technique does allow the analyst to make reasoned inferences instead of wild guesses.

2. Strictly Ordered Polytomous Variables With No Interactions

Dichotomous variables have the advantage of simplicity and universality--any variable can be dichotomized. Their disadvantage is loss of information. When we divided Region as SOUTH v. NON-SOUTH, we lumped NORTHEAST, CENTRAL, and WEST together. Consequently, we do not know that each of these is more Tolerant than SOUTH. In Table 3, we break out the three NON-SOUTH regions.

In each comparison with SOUTH, the other region is more Tolerant, the differences being +.172 for CENTRAL, +.250 for NORTHEAST, and +.299 for WEST. Since each is an independent comparison (we can not infer anything about the d for CENTRAL v. SOUTH from the d for NORTHEAST v. SOUTH), each of the three can be used as a node in a flow graph. Figure 4 illustrates.

Figure 4 obeys all flow graph rules. In particular:

$$\text{TOLERANT} = (.333 * +.172) + (.251 * +.250) + (.128 * +.299) + .439 = .597 \qquad (6)$$

(The figures for the constant and sink values differ trivially from those in Figure 1 for reasons to be explained in the next section.)

The process can be extended to non-sink variables. Table 4 and Figure 5 illustrate.

We trichotomized Education and chose HIGH SCHOOL as the base. Following the convention of classical path analysis, coefficients that are not significant have been deleted from the diagram. (We use the convention of solid lines for positive values, dashed lines for negative values. This is very helpful in keeping transmittance signs straight.)

The major "findings" in Figure 5 are as follows: (1) All three comparison regions have lower proportions LESS THAN HIGH than SOUTH. (2) Those raised in the NORTHEAST are more likely to report MORE THAN HIGH

TABLE 3

REGION AT AGE 16 AND TOLERANCE

Region at Age 16	Proportion TOLERANT	d v. SOUTH	N	Proportion
SOUTH	.439	--	1,086	.287
CENTRAL	.611	+.172	1,262	.333
NORTHEAST	.689	+.250	952	.251
WEST	.738	+.299	486	.128
Total . . .	.598		3,786	.999

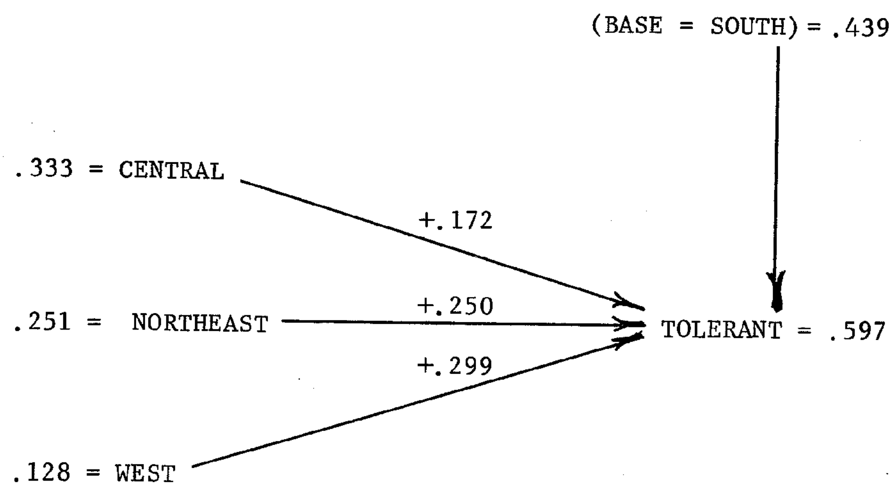


Fig. 4.--Linear Flow Graph for Data in Table 3

TABLE 4

REGION AT AGE 16, EDUCATIONAL ATTAINMENT, AND ATTITUDE TO RACIAL INTERMARRIAGE, U.S. WHITES, 1972-3-4

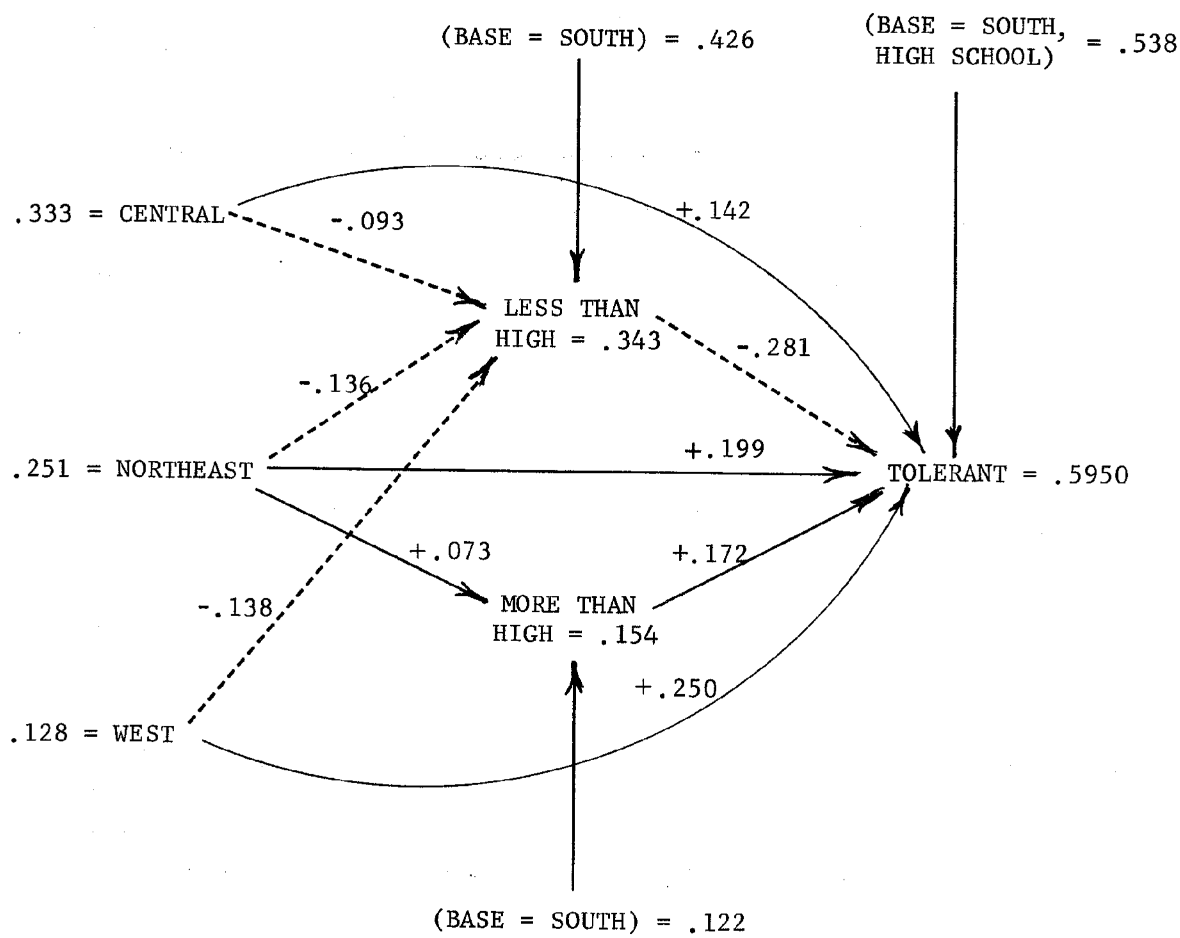
A. Region at 16 and Educational Attainment[a]

Region at Age 16	Education: LESS THAN HIGH SCHOOL	HIGH SCHOOL	MORE THAN HIGH SCHOOL	Total	N	Versus SOUTH: LESS THAN HIGH SCHOOL	Versus SOUTH: MORE THAN HIGH SCHOOL
SOUTH	.426	.452	.122	1.000	(1,086)	--	--
CENTRAL	.334	.524	.143	1.001	(1,262)	-.092	+.021
NORTHEAST . . .	.290	.516	.194	1.000	(952)	-.136	+.072
WEST	.288	.533	.179	1.000	(486)	-.138	+.057
Total . . .	.343	.502	.154	.999	(3,786)		

B. Region at 16, Education, and Tolerance[a] (Proportion TOLERANT)

Region at Age 16	Education: LESS THAN HIGH SCHOOL	HIGH SCHOOL	MORE THAN HIGH SCHOOL	Versus HIGH SCHOOL: LESS THAN HIGH SCHOOL	Versus HIGH SCHOOL: MORE THAN HIGH SCHOOL
SOUTH	.257 (463)	.538 (491)	.710 (132)	-.281	+.172
CENTRAL	.399 (421)	.680 (661)	.852 (180)	-.281	+.172
NORTHEAST . . .	.456 (276)	.737 (491)	.909 (185)	-.281	+.172
WEST	.507 (140)	.788 (259)	.960 (87)	-.281	+.172
Versus SOUTH					
CENTRAL . .	+.142	+.142	+.142		
NORTHEAST .	+.199	+.199	+.199	Proportion TOLERANT	
WEST . . .	+.250	+.250	+.250	All Cases	.598 (3,786)

[a]For exclusions, No Answers, and Totals, see Table 1.



Arrows deleted:

CENTRAL to MORE THAH HIGH = +.021
WEST to MORE THAN HIGH = +.057

Fig. 5.--Linear Flow Graph for Data in Table 4

than are Southerners, but the other two regions don't differ significantly from the SOUTH on higher education. (Significance tests will be explained in the next section.) (3) Net of Education, each of the comparison regions is more TOLERANT (+.142 for CENTRAL, +.199 for NORTHEAST, +.250 for WEST). (4) Net of Region, LESS THAN HIGH respondents are less TOLERANT than HIGH SCHOOL (-.281); MORE THAN HIGH are more TOLERANT than HIGH SCHOOL (+.172).

Transmittances can be calculated for Figure 5 as in any other graph. As an example, let us look at NORTHEAST to TOLERANT. The figures are:

Direct		+.199
Via Education		
MORE THAN HIGH	+.073 * +.172	+.0126
LESS THAN HIGH	-.136 * -.281	+.0382
		+.2498

The total transmittance, +.2498, is the zero-order d for the fourfold table NORTHEAST v. SOUTH by TOLERANT v. LESS TOLERANT. The decomposition tells us that Education contributes +.0508 to the total, but +.199 remains as a direct effect.

Similarly, comparing the -.281 for LESS THAN HIGH to TOLERANT with the zero-order difference, .301 (calculated from the figures in Table 4, Part B), we see that .020 of the total is spurious--produced by the lower proportions LESS THAN HIGH in the more Tolerant NON-SOUTH regions.

Figure 6 gives the reduced form expressions in a change graph.

The transmittances for CENTRAL and WEST differ slightly from those in Figure 4 because we chose to ignore their small, insignificant coefficients to MORE THAN HIGH.

The ability to treat polytomies allows the procedure to avoid the

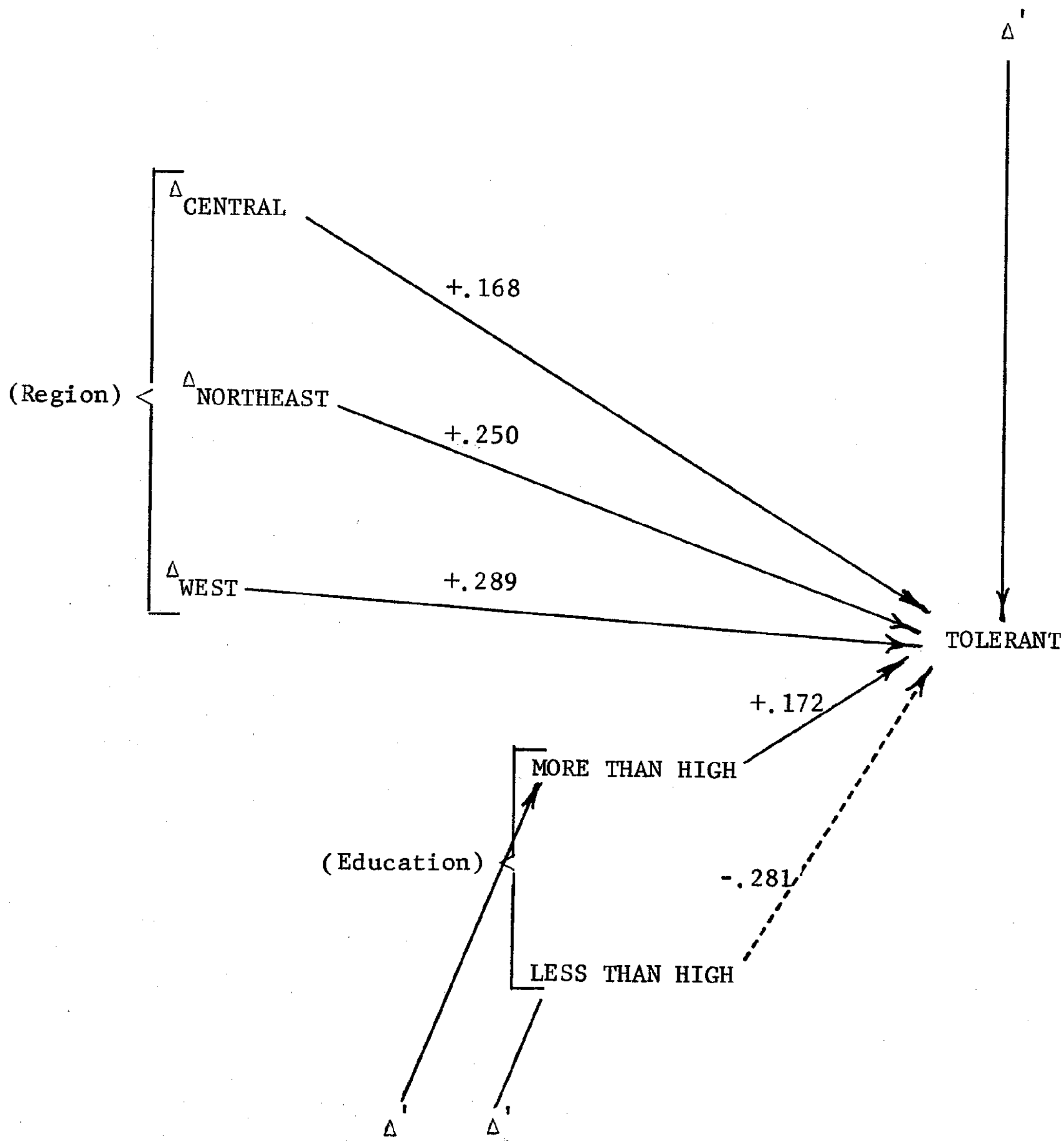


Fig. 6.--Reduced Form Graph for System in Figure 5

"toy" flavor of systems that can only handle dichotomies. The choice of base, however, adds an arbitrary character to the endeavor. With dichotomies, if one reverses bases (i.e., using NON-SOUTH instead of SOUTH as the base in Figure 1), the only effect is a reversal of sign for all coefficients and a change in the constant terms--which are generally not given a substantive interpretation. Changing bases for polytomies usually changes all of the coefficients, although each specification is mathematically correct.

Choice of base has less impact on reduced form equations. We can hypothesize changes in base or non-base categories at will, provided that the $Time_2$ marginals add up correctly. For example, if we were to assume that the proportion in the base category HIGH SCHOOL will increase .100 net of region, and the proportion LESS THAN HIGH decrease .13, we would get the change in MORE THAN HIGH by subtraction, +.10 - .13 + .03 = .00, and infer the resulting change in TOLERANCE (.03 * +.172) + (-.13 * -.281) = +.042.

Although the choice of base is arbitrary, three practical rules exist:

1) Choose bases with large case frequencies. Since the base category appears in each fourfold table, it should be as reliable as possible.

2) Choose bases that are substantively distinctive. SOUTH is a good example. It is clear from Figure 5 that the "big difference" is the lower Tolerance in the South. The other regions are relatively similar.

3) In contrast to specifying order, there is nothing wrong with trying various bases and presenting the specification that gives the clearest results.

3. Estimating the Parameters

We now show how standard statistics can be used to estimate: (1) source proportions, (2) zero order d's, (3) partial d's, (4) Δ, and (5) Δ'.

(1) Source proportions. For the non-base categories of the source variable, we must estimate the marginal proportions. The raw data proportions are generally satisfactory and every introductory statistical text gives their sampling variance, capital letters designating universe values.

$$V_P = \frac{(P)\ (1-P)}{N} \qquad (7)$$

Since P is seldom known, we customarily use the sample value of the proportion, p.

$$v_p = \frac{(p)(1-p)}{N} \qquad (8)$$

Some investigators shade a bit toward .5 (Blalock, 1972, p. 212), but this seldom has any practical effect on the estimate. Confidence intervals for p can be found using $\sigma_p = \sqrt{v}$

(2) Zero-order d's. Coefficients for the source and second variable are differences in proportions for zero-order fourfold tables. The sample results are the maximum likelihood estimator. Calling the two categories, i and j, the classic result is:

$$v_d = v_i + v_j \qquad (9)$$

(3) Conditional d coefficients. Coefficients for the third and subsequent variables can be estimated using results in Goodman (1963, p. 97). Since these useful tests are not well known, we will explain them by working through an example.

Consider a difference in proportions, d, estimated within k mutually exclusive conditions of a control variable. Let us, as an example, estimate the coefficient from MORE THAN HIGH SCHOOL to TOLERANT in Figure 5, which has a value of +.172. In the raw data we have four fourfold tables giving the proportion TOLERANT for MORE THAN HIGH and for HIGH SCHOOL in each of the regions (including the base category). Table 5 gives the figures.

Row 1 gives the proportions. In the SOUTH, the 132 MORE THAN HIGH cases had .781 TOLERANT, in comparison with .538 for 491 HIGH SCHOOL cases.

Row 2 gives the four conditional d's.

Rows 3 and 4 give the sampling variances for each proportion (e.g., .00051 is the variance for $p = .781$ and $N = 132$).

Row 5 gives the variance for each conditional d, v_k, using equation (9).

Row 6 changes each conditional variance to its reciprocal so that its "weight" will be inverse to the variance.

In Row 7 we calculate w_k, the weight associated with each condition. The weight is a percentage, obtained by dividing each entry in Row 6 by the Row 6 sum.

Row 8 gives the estimate of d, the common percentage difference. Goodman tells us that the weighted sum of the conditional d's is the maximum-likelihood estimator of d in the absence of interactions.

Row 9 allows us to test for interactions--significant differences in values among the conditional d's. We subtract d from each d_k, square the difference, and divide by v_k. Goodman tells us that the sum (here 4.788) is distributed as chi square with K-1 degrees of freedom. For d.f. = 3, $.20 > p > .10$. Thus, we conclude that there is no significant interaction effect and that we are therefore justified in estimating d.

TABLE 5

ESTIMATING MORE-THAN-HIGH-TO-TOLERANT IN FIGURE 5

Steps	Control Category of Region = k for Steps 2-11				
	SOUTH	CENTRAL	NORTHEAST	WEST	Total
(1) Proportion TOLERANT:					
MORE THAN HIGH SCHOOL	.781 (132)	.839 (180)	.924 (185)	.954 (87)	
HIGH SCHOOL .	.538 (491)	.711 (661)	.743 (491)	.791 (259)	
(2) d_k	+.243	+.128	+.181	+.163	
(3) v_i	.00051	.00075	.00038	.00050	
(4) v_j	.00130	.00031	.00039	.00064	
(5) v_k	.00181	.00106	.00077	.00114	
(6) $1/v_k$	552.486	942.631	1300.555	877.193	3672.865
(7) w_k	.1504	.2566	.3541	.2388	.9999
(8) $w_k * d_k$	.0366	.0328	.0641	.0389	.1724 = d
(9) $(d_k - d)^2/v_k$.	2.754	1.860	.096	.078	4.788
(10) d_k^2/v_k	32.624	15.457	42.547	23.306	113.934
(11) $v_k * w_k^2$	.00004	.00007	.00010	.00007	.00027 = v

Row 10 gives Goodman's test for the significance of d. One squares each d_k, divides by v_k, and sums. The total (here 113.934) is distributed as chi square with K degrees of freedom. Our sample result is significant at the .001 level.

Row 11 allows us to estimate the variance of d. In the absence of interactions, the variance of d is the weighted average of the v_k's where the weights are the squares of the w_k's in Row 7 (Martin Frankel, personal communication). The square root for our example value of .00027 is .0164. Multiplying by 2, we get .0328 as .95 confidence intervals for our d.

All of these formulas assume simple random samples, whereas almost all real data come from multistage samples with cluster effects that make variances higher than the textbook formulas. A standard rule of thumb is that multistage variances are twice as large as simple random sample formulas suggest (Moser and Kalton, 1972, p. 202). Our personal rule is to multiply all variances by 2, and all standard deviations by 1.5 (a rough approximation of 1.414, the square root of 2). In the case of Rows 6 and 9, we can simply divide the final chi square by 2 since v_k appears in each denominator. The adjusted .95 confidence intervals for d become .0328 * 1.5 = .0492. While the calculations in Table 5 might appear complicated, they are easily programmed and not hard to do by hand.[3]

The previously suspicious reader will now see how the "perfect" data in the examples were produced. We started with the raw figures

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[3]John Fry of NORC has written an interactive program, "CATFIT," that estimates all required parameters, calculates transmittances, makes the chi square tests, calculates confidence intervals, produces modeled cell frequencies, allows one to shift base categories, and "reblocks" the data. Copies can be obtained by writing to NORC, 6030 South Ellis Avenue, Chicago, IL 60637.

(those in Table 5 being a portion), estimated all parameters and constants (finding all interactions to be non-significant), and constructed the data for the examples. (Given the values for a model, it is always possible to construct a complete modeled crosstabulation table.) Table 6 gives the raw and modeled data for our example.

The fit is quite good. (Note that the value of .538 for SOUTH and HIGH SCHOOL is identical in both tables--because the value in the "base-base" combination of prior variables is taken as the starting point for the analysis.) The reader should remember that the arguments regarding graph analysis of the system apply exactly only in terms of the modeled data. Even when there are no significant interactions, the d's and transmittances for variables beyond the first two will not be exactly the same as the raw data. Whether the level of discrepancy is tolerable is a matter of judgment. With small samples, data with no significant interactions can be "bouncy"; with large samples, models can fit quite well despite interactions that are statistically significant.

(4) Source Δ's. With data where the same measures are taken at two times (though not necessarily on the same subjects), changes in source marginals can be estimated by analyzing a two-variable contingency table in which the rows are categories of the source variable and the columns represent the two times. Confidence intervals for d are a convenient test.

(5) Δ' Coefficients. These can easily be estimated with over-time data, following this methodological rule: in contingency tables, "net of" means "within." Again, an example may be helpful.

Table 7 gives the proportion TOLERANT within the 12 Region by Education groups for the years 1972, 1973, and 1974 separately. Differences from year to year within these categories estimate change in Tolerance,

TABLE 6

RAW AND MODELED DATA FOR REGION AT 16, EDUCATION, AND ATTITUDE TO INTERMARRIAGE

Region at Age 16	Education		
	LESS THAN HIGH SCHOOL	HIGH SCHOOL	MORE THAN HIGH SCHOOL
	A. Raw Data (Proportion TOLERANT)		
SOUTH	.251 (463)	.538 (491)	.780 (132)
CENTRAL	.394 (421)	.711 (661)	.839 (180)
NORTHEAST	.482 (276)	.743 (491)	.924 (185)
WEST	.586 (140)	.792 (259)	.954 (87)
	B. Modeled with Parameters (as in Figure 5) Estimate from Raw Data (Proportion TOLERANT)		
SOUTH	.257	.538	.710
CENTRAL	.399	.680	.852
NORTHEAST	.456	.737	.909
WEST	.507	.788	.960

TABLE 7

ATTITUDES TOWARD INTERMARRIAGE BY REGION AT AGE 16
AND EDUCATION, 1972, 1973, AND 1974

A. Data (Proportion TOLERANT)

Region at Age 16	Education	1972	1973	1974	Δ_k' 73-72	Δ_k' 74-72
SOUTH	MORE THAN HIGH	.704 (27)	.729 (48)	.860 (57)	+.025	+.156
	HIGH SCHOOL	.438 (137)	.584 (178)	.568 (176)	+.146	+.130
	LESS THAN HIGH	.258 (155)	.222 (162)	.274 (146)	-.036	+.016
CENTRAL	MORE THAN HIGH	.783 (60)	.873 (55)	.862 (65)	+.090	+.079
	HIGH SCHOOL	.699 (219)	.701 (211)	.732 (231)	+.002	+.033
	LESS THAN HIGH	.374 (155)	.389 (131)	.422 (135)	+.015	+.048
NORTHEAST . . .	MORE THAN HIGH	.893 (56)	.949 (59)	.929 (70)	+.056	+.036
	HIGH SCHOOL	.740 (196)	.729 (155)	.764 (240)	-.011	+.024
	LESS THAN HIGH	.504 (113)	.488 (84)	.443 (79)	-.016	-.061
WEST.	MORE THAN HIGH	.966 (29)	.903 (31)	1.000 (27)	-.063	+.034
	HIGH SCHOOL	.714 (91)	.839 (87)	.827 (81)	+.125	+.113
	LESS THAN HIGH	.578 (45)	.556 (45)	.620 (50)	-.022	+.042

B. Tests for Δ_k'

Tests	1973 - 1972	1974 - 1972
Interaction		
Chi Square	13.4	8.1
D. F.	11	11
Probability	.265	.704
Significance of d		
d	+ .025	+ .044
Chi Square	15.6	15.4
D. F.	12	12
Probability	.210	.217

net of the prior variables (i.e., Δ' for TOLERANT). Applying the same procedures as in Table 5 with 1972 as the base, we find (in Table 7B) no significant interactions and Δ' estimates of +.025 and +.044. These positive trends, however, are not statistically significant. (Since the simple random sample figures are not significant, there is no reason to adjust for multistage sampling.) Consequently, we estimate Δ' to be .00 in both cases. More generally, to estimate Δ' one examines the d between Time and the variable in question, controlling for prior variables in the model. In the absence of interactions, the estimated d is the estimate of Δ'.

Significant interactions imply that some of the coefficients in the system have changed (if two categories show different increases, the difference between them changes over time) and the reduced form models discussed above are not applicable. For a discussion of how to handle data with changing coefficients see Davis, 1975.

When Δ' is zero, all change in the dependent variable is accounted for by changes, if any, in the prior items. For our example, while Δ' for TOLERANCE is estimated to be zero, other analyses show no significant changes in the prior variables. That is, the systems in 1972, 1973, and 1974 are not significantly different--which is why we were justified in pooling the data.

In these elementary examples, we ignored the interesting problem of lagged effects, implicitly assuming the lags to be zero or the follow-up period to be long enough for the system to return to equilibrium. For a discussion of alternative assumptions and their implications, see Heise (in press).

4. Block Recursive Models for Partially Ordered or Interaction-Ridden Systems

So far we have considered variables with a strict causal order. We stopped with a three-variable chain, but the approach can easily be extended to chains of any length, the upper limit being reached when the cell sizes become so small as to threaten the d estimations. To my knowledge, this problem has not been explored.

For the practical research worker, strict order can be a fairly stiff restriction; it is possible, however, to apply the scheme to a set of variables that is "block recursive" (Blalock, 1969, pp. 71-74). In a block recursive model, the variables are divided into groups (blocks) where (a) causal directions are ignored or even unknown within blocks, but (b) the various blocks form a strict causal order. The classic example is the most common research design of all, a set of source variables and a single dependent variable, the implicit model for the perennial question, "What sort of things are correlated with ____?"

To illustrate, we can respecify the model for the data in Table 2 and Figure 2, assuming, perhaps, that certain qualms had arisen regarding the order for Region at 16 and Education. (After all, some kids drop out of school at age 14). To do so:

1) View Region by Education as a single variable with four categories: SOUTH-LESS-THAN-HIGH, NON-SOUTH-LESS-THAN-HIGH, SOUTH-HIGH-SCHOOL-PLUS, and NON-SOUTH-HIGH-SCHOOL-PLUS.
2) Arbitrarily choose one of the items as a base (e.g., SOUTH-LESS-THAN-HIGH).
3) Estimate the Region and Education coefficients as before. (Note that in estimating coefficients to a third variable the order for the first two is irrelevant. We can enter the data

with either Region or Education as the source.)

4. Enter as coefficients the appropriate sums. That is, the coefficient for a combination in a block is the sum of the coefficients for its categories in an ordered model.

5) Percentage the block categories to get source values.

Alternatively, one might merely collapse the data (e.g., from a 2 x 2 x 2 table to a 4 x 2) and analyze it as explained in the previous sections. We will call this method "typological" for reasons to be explained when we consider data with interactions. With totally interaction-free data, the same coefficients will emerge. However, the non-typological approach in Steps (3) and (4) has two advantages: (1) one gets more reliable estimates for small categories of the source variable since the coefficients are based on pooled data, and (2) one gets numbers for interpretation associated with each pre-collapsed non-base category. Figure 7 illustrates.

Such graphs can be interpreted in the same way as any previous models. The prices paid are total loss of information about causal relations among variables within a block and a cluttered diagram when the block variables are polytomies.

Blocks can be formed for intervening or sink variables. They are particularly helpful when the problem is to see whether a collection of intervening variables explains a source-sink correlation. Generally speaking, it is difficult to interpret coefficients running <u>into</u> a block. For example, what would it mean if we found a +.158 arrow from, say, Race to SOUTH-HIGH-SCHOOL-PLUS? Thus, the following advice: (1) Avoid sink blocks except when the combinations "make sense" as a typology (e.g., LIBERAL-DEMOCRATS, CONSERVATIVE-DEMOCRATS, LIBERAL-REPUBLICANS, CONSERVATIVE-REPUBLICANS); (2) use intervening variables as a block only when

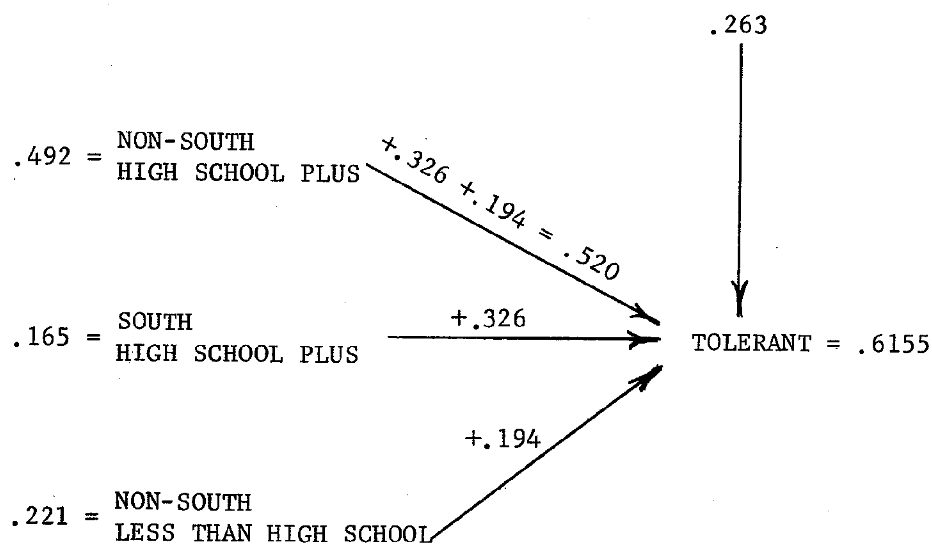

Fig. 7.--Block Model for Data in Table 2 and Figure 2

the major interest is interpreting a source-sink relationship.

Block models are useful in handling data with strong interactions. Consider, for example Race, Mother's Education, Father's Education, and Respondent's Education. To specify the model we chose Race as the source, assuming, in effect, that respondent's race is a measure of parental race; placed Mother's and Father's Education as an intervening block since there seems to be no plausible ordering for these two variables; and placed Respondent's Education as the sink. See Figure 8.

Table 8A gives the raw data, pooling cases over the General Social Surveys of 1972, 1973, and 1974, and dichotomizing all three Education measures as HIGH SCHOOL PLUS v. LESS THAN HIGH.

Table 8B gives the estimates for the arrows running from prior variables into Respondent's Education. For Race (with WHITE as base), there is a coefficient of -.127 and no significant interaction. In each parental education group, NON-WHITES are roughly .127 lower in HIGH SCHOOL PLUS. For Father and Mother, however, there are significant interactions.

To interpret the interactions, let us examine the proportions in Table 8C. Among WHITES, the pattern is clear. Compared to the .546 in the low-low corner, the addition of one HIGH SCHOOL PLUS parent of either sex adds about +.29 to Education, but a second HIGH SCHOOL PLUS parent adds only an additional +.10. The effect of one parent is not independent of the level of Education for the other parent.

Among NON-WHITES, the interaction effect has the same sign (the conditional d is smaller when the other parent is HIGH SCHOOL +) but the magnitude is not so strong. Since, however, the Race effect did not show a significant interaction, and since changing four cases in the Father = LESS THAN HIGH, Mother = HIGH SCHOOL + cell would give exactly the same

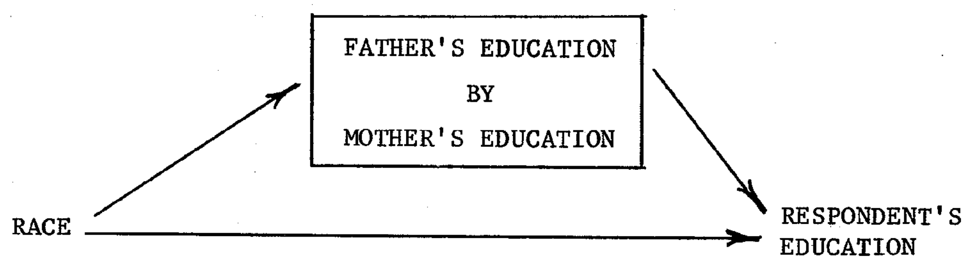

Fig. 8.--Block Model for Race, Parental Education, and Education

TABLE 8

RACE, MOTHER'S AND FATHER'S EDUCATIONS, AND EDUCATIONAL ATTAINMENT, 1972-3-4

A. Raw Data

Race	Education of: Father	Mother	Respondent: LESS THAN HIGH	HIGH SCHOOL +	
WHITE	HIGH SCHOOL +	HIGH SCHOOL +	53	715	
	HIGH SCHOOL +	LESS THAN HIGH	37	183	
	LESS THAN HIGH	HIGH SCHOOL +	59	317	
	LESS THAN HIGH	LESS THAN HIGH	674	812	
					2850
NON-WHITE	HIGH SCHOOL +	HIGH SCHOOL +	9	36	
	HIGH SCHOOL +	LESS THAN HIGH	5	13	
	LESS THAN HIGH	HIGH SCHOOL +	12	16	
	LESS THAN HIGH	LESS THAN HIGH	143	111	
					345
					3195
				No Answer	1406
				Total	4601

B. Coefficients for Respondent's Education

Prior	Interaction: d	Chi Square[a]	D.F.	P	Significance: Chi Square[a]	D.F.	P
NON-WHITE	-.127	1.3	3	>.05	12.2	4	<.05
FATHER.	-.162	16.6	3	<.05			
MOTHER.	-.209	16.6	3	<.05			

C. Proportion of Respondent's Who are HIGH SCHOOL +

Race	Father	Mother: LESS THAN HIGH	HIGH SCHOOL +	d_k
WHITE	HIGH SCHOOL +	.832 (220)	.931 (768)	+.099
	LESS THAN HIGH	.546 (1,486)	.843 (376)	+.297
	d_k	+.286	+.088	
NON-WHITE	HIGH SCHOOL +	.722 (18)	.800 (45)	+.078
	LESS THAN HIGH	.437 (254)	.571 (28)	+.134
	d_k	+.285	+.229	

Table 8.--Continued

TABLE 8--Continued

D. Coefficients for Respondent's Education With Parental Education Treated as a Typology

Prior	Interaction				Significance		
	d	Chi Square[a]	D.F.	P	Chi Square[a]	D.F.	P
NON-WHITE	-.127	1.3	3	>.05	12.2	4	<.05
FATHER + MOTHER - .	-.098	0.0	1	>.05	7.05	2	<.05
FATHER - MOTHER + .	-.093	0.8	1	>.05	11.0	2	<.05
FATHER - MOTHER - .	-.383	0.05	1	>.05	309.8	2	<.05

E. Coefficients for Parental Education with Parental Education Treated as a Typology

Source to	Father	Mother	d	2 sigma[b]	Constant
NON-WHITE	+	-	- .025	.039	.052
NON-WHITE	-	+	- .051	.048	.081
NON-WHITE	-	-	+ .215	.078	.736

[a]Value divided by 2 to correct for multistage sampling.

[b]Sigmas have been multiplied by 1.5 to correct for multistage sampling.

d_k's as we have for the WHITES, we will not make anything of the discrepancy.[4]

With such interaction-ridden data we cannot use Rule (4) above (summing coefficients) to obtain the arrow values, since the whole point is that they have been shown to be non-additive. Therefore, we re-run the data, treating parental Education as a four-category nominal variable, with HIGH SCHOOL +, HIGH SCHOOL + as the base (so all nodes in Figure 9 show categories that lower Educational Attainment). Parts D and E of Table 8 give the results, and Figure 9 the final flow graph.

The story in Figure 9 is as follows: (1) Among WHITES whose mothers and fathers are both HIGH SCHOOL +, .800 are HIGH SCHOOL +; (2) if one parent is less than HIGH SCHOOL +, the proportion drops about .09; (3) if neither parent is HIGH SCHOOL +, the proportion drops .38; (4) regardless of parental Education, the proportion among NON-WHITES is less by -.127; (5) NON-WHITES are considerably more likely to have neither parent HIGH SCHOOL + and a bit less likely to have one parent HIGH SCHOOL + (both coefficients of borderline significance).

Examining the transmittance from NON-WHITE to HIGH SCHOOL +, we get:

Net of Parental Education			-.127
Via Parental Education			
-.025 * -.098 =	+.002450		
-.051 * -.093	+.004743		
+.215 * -.383	-.082345		
	-.075151		-.075
		Total	-.202

[4]The reader should remember that we have not 'shown the effects to be the same' within the two races. Rather, with the small number of blacks available even in the pooled samples, our design is unable to detect any racial difference in the interaction. Problems of Type I and Type II errors are no greater or less in this approach than in any other.

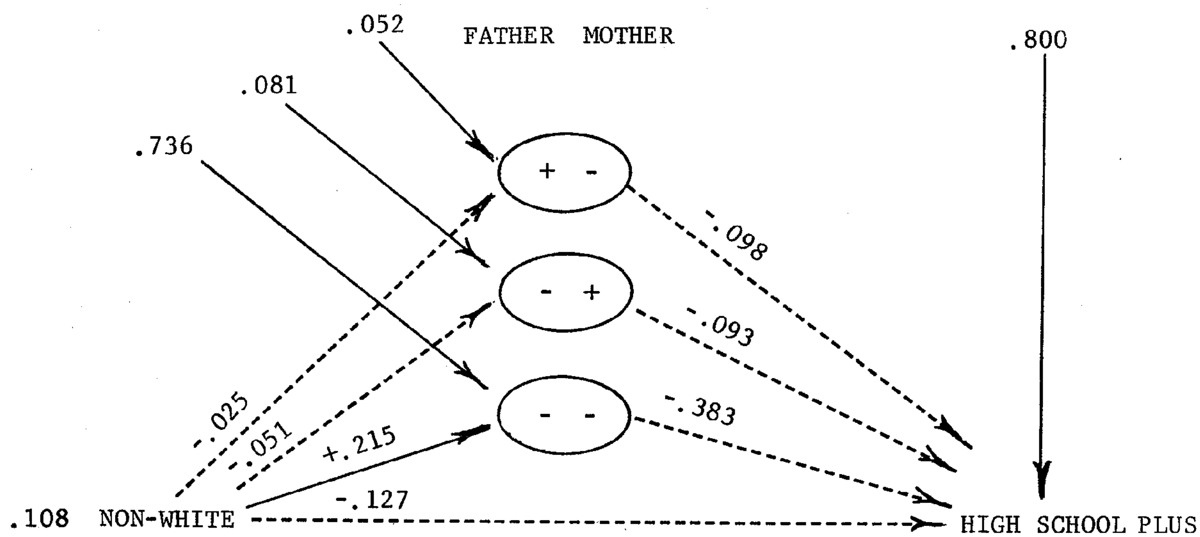

Fig. 9.--Block Model (With Interactions) for Data in Table 8

The zero-order d for Race and Education, -.202, is decomposed into -.075 via parental Education and -.127 direct. Lower parental education contributes to, but does not explain, the lower Educational Attainment of NON-WHITES.

Block models with "typological" coefficients (as opposed to additive coefficients) add considerably to the generality of the system. Data can be flow graphed whatever the level of measurement, and whether or not interactions are present, provided only that it is plausible to distinguish between a source block and a sink variable or typology. The price to be paid is the spinning out of the block categories so their case bases dwindle and coefficients become unreliable. (Note, however, that the significance of an interaction implies rejection of the null hypothesis that all typological coefficients are zero.) With large samples, small interaction effects can be statistically significant. If the absolute discrepancies are "tolerable" (whatever that may mean in the context of a particular research problem) the analyst may prefer to use an additive model.

5. Comparisons With Other Techniques

One hesitates to break the beautiful silence of Professor Duncan's (1974) proposed decade of Methodological ZPG (Zero Publication Growth) with still another contraption for multivariate analysis. Before doing so, common decency requires comparison of the proposed techniques with those lucky enough to have been developed before 1975. We shall consider in turn: (1) regression, (2) correlation, (3) path analysis, and (4) odds ratio techniques.

(1) Regression. The system proposed here is closely related to ordinary least squares regression. In fact, with data totally devoid of interaction, the two procedures give identical results. If one were to feed a matrix of zero-order d's from interaction-free data into a regression program (using .000 as inter-category d's for categories in the same polytomous variable), the raw regression coefficients would be exactly the same as the coefficients in our models. But real data--unlike Tables 2 and 4--are never totally devoid of interactions, even when interaction effects are insignificant. What then is the practical difference? To see it, let handle the data in Table 2 by regression. Figure 10 gives the necessary data.

We wish to solve for the two betas, $b_{zx.y}$ and $b_{zy.x}$. Assuming flow graph principles, and remembering that order among prior variables is irrelevant when estimating coefficients into a sink, we can write two equations:

$$(1) * b_{zx.y} + .116 * b_{zy.x} = .232 \quad (10)$$

$$.101 * b_{zx.y} + (1) * b_{zy.x} = .346 \quad (11)$$

Equation (10) is the transmittance for $b_{zx.y}$; Equation (11) is the transmittance for Y with the X-Y order reversed.

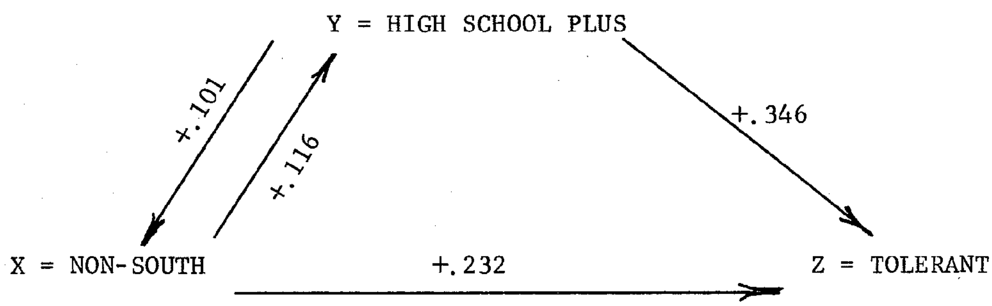

Fig. 10.--Diagram of <u>Zero-Order</u> D's for Data in Table 2

Given two such equations and an algebra textbook, we can find a solution by applying "Cramer's rule," a classic algorithim using determinants. Using Cramer's rule, we get:

$$b_{zx.y} = \frac{.232 - (.346 * .116)}{1 - (.101)*(.116)} = .1941 \qquad (12)$$

$$b_{zy.x} = \frac{.346 - (.232 * .101)}{1 - (.101)*(.116)} = .3264 \qquad (13)$$

Our two calculated betas are .1941 and .3264. We notice two things. First, they are identical to the results in Table 2, save for rounding; and second, equations (12) and (13) are the standard textbook formulas for betas in the three-variable problem. In other words, regression analysis takes all of the zero-order coefficients at face value and uses flow graph principles to solve for partial coefficients, assuming no interactions; while the system proposed here takes the empirical partial d's at face value and solves for the zero-order correlations (beyond the second variable), assuming no interactions. Clearly, the two approaches are closely related, but equally clearly, they will not give the same results on the same real data.

If one wishes to carry out flow graph analysis of the system, with a small number of variables, it is hard to choose between the approaches. One could test for interactions using the approach presented here[5] and then calculate the coefficients with a regression routine, or one could simply follow the procedures given here. Unless the data have substantial interactions, virtually the same numbers will emerge. Putting it another way, there are two separate issues here--the estimation procedures and the

---

[5]If some of the variables are truly interval-level scales, it would be necessary to make arbitrary groupings to test for interactions.

method of graphing categorical data. The choice of estimators probably turns on one's interest in interactions and, possibly, on advanced questions of efficiency and robustness beyond the scope of this paper.

Let us now consider how to graph categorical data. How else might we do it?

Dummy variables (Suits, 1957; Miller and Erickson, 1974) are a possibility. In dummy variable analysis, one dichotomizes prior variables the way we dichotomize dependent variables and drops one to avoid redundancy. Thus, to handle Figure 4 by dummy variables, we would examine d's in three fourfold tables involving TOLERANCE: (1) CENTRAL v. NON-CENTRAL, (2) NORTHEAST v. NON-NORTHEAST, and (3) WEST v. NON-WEST. The three d's can be fed into a regression routine and slope-like numbers will emerge. Unfortunately, the operation inevitably creates negative correlations among the three dummy variables (Cohen, 1968, p. 429). Such correlations are spectacularly counterintuitive and make it impossible to handle source values by flow graph techniques, which require single sources or sources with zero interrelations. In sum, dummy variables can be useful when one wishes to add a qualitative variable or two to a bucket of interval variables in a regression meat grinder. Dummy variables seem to be less useful than d systems when one takes a theory-oriented approach in which qualitative data are analyzed with enumerative data statistics following a causal model.

Multiple Classification Analysis (MCA) (Andrews, Morgan, and Sonquist, 1967) is a somewhat more attractive possibility. MCA is similar to the proposed system except that (a) it uses all categories; (b) it uses the mean (marginal proportion) of the dependent category as the base; and (c) it takes the regression approach of assuming non-interaction. To illustrate, Figure 11 shows how MCA would handle Figure 1.

Figure 11 is amenable to flow graph operations and avoids the arbitrary choice of base, but I have been unable to find a way to extend it to a third variable in such a fashion that flow graph rules apply. This hardly shows the feat to be impossible, but I am persuaded that the problem is not trivial. MCA also suffers from redundancy problems. The simplest is the addition of nodes and arrows that convey no further information (compare Figure 11 and Figure 1). Second, there are technical problems in estimating significance when the parameters are not independent--that is, we have more parameters than degrees of freedom. Third, there are problems in interpretation when the base is not independent of the categories. The classic example is provided by MCA analyses involving Race and SES. They generally show non-whites to have below average SES, while whites are near average (because the white population is so much larger it virtually determines the average). How one group can be below average when nobody is above average is difficult to understand.

Dubbing the approach developed here "d systems" after its central statistic, d systems do not do badly when compared with dummy variables and MCA. Dummy variables are plainly inappropriate for flow graphs, and MCA has not yet been generalized to systems beyond a source block and a dependent variable.

(2) Correlation. If regression is viewed as the analysis of linear trends, correlation can be seen as the analysis of case variation around the trend lines. Such analyses have no analogy among the ideas suggested here since categorical data simply do not have such individual variation. One defines the cases in each cell of the crosstabulation as homogeneous on the variables in the analysis. One may, of course, see

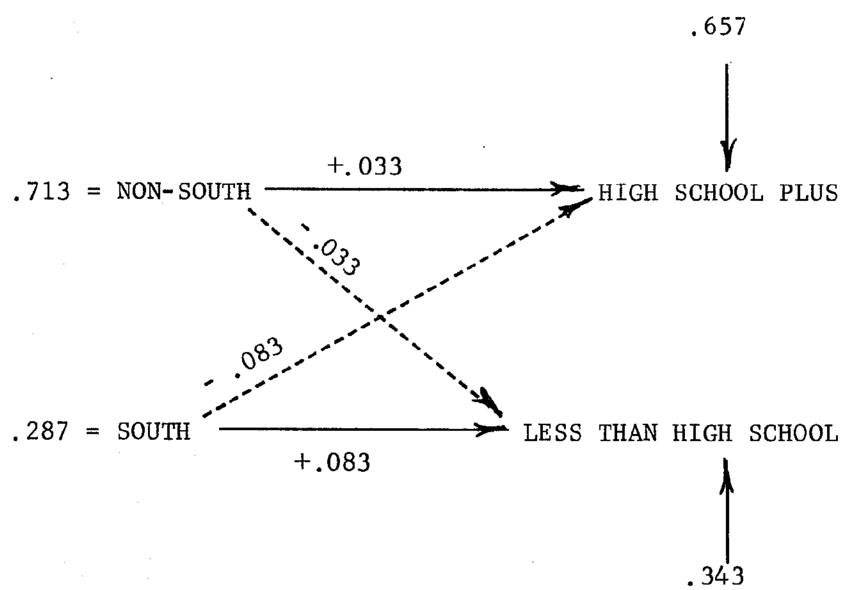

Fig. 11.--"MCA" Version of System in Figure 1

what happens when categories are collapsed or broken out, but with a particular crosstabulation the concept of "residual variation" simply doesn't make sense. Consequently, there is (so far) no analogy to r or R in d systems, and no worries about homoscedasticity.

(3) Path analysis. The distinction between correlation and regression helps clarify the relationships between d systems and classical path analysis. Clearly there are similarities. Indeed, with interval-level variables one can use path diagrams to analyze changes in means using exactly the same flow graph principles as discussed above--provided that there is only one exogenous variable and the system is perfectly ordered, or, if partially ordered, that the ambiguous variables have zero coefficients (i.e., Simon-Blalock models). But, the usual apparatus for analyzing path diagrams (curved double-headed arrows, running backwards and forwards along paths, finding residuals from R, etc.) is correlational--that is, it decomposes case variability. (The coincidence that r equals the zero-order beta for standardized variables unfortunately tends to blur this distinction.)

Flow graphs define the values of variables; path diagrams define the values of variances and covariances. The two kinds of analytic systems have a number of correspondences because of properties of linear systems, but they are really two different modes of analysis concerned with different quantities and involving partially different rules.

(4) Odds ratio techniques. In the last few years, social scientists have become quite enthusiastic about a new set of techniques for contingency table analysis involving "odds ratios." D systems are much influenced by these ideas. In particular, the notion of testing for interactions and estimating parameters from modeled, interaction-free data

(when interactions are not significant) is taken directly from "hierarchical modeling" (Goodman, 1970). In a sense, Goodman's 1963 proposals allow one to do for "percentage tables" what his 1970 results allow one to do with odds.

But there are at least two differences. The obvious one is that d's (differences in proportions) are not odds ratios but a different way to express comparative frequencies. There are important relationships between the two (Goodman, 1975--Chapter 10 in this volume) but they do not generally give the same numbers for the same data. Some would argue that proportions and d's are more "natural," others favor odds. The choice seems to be one of taste.

The second difference involves "path diagrams." In a recent paper, Goodman (1973) draws path-like diagrams whose coefficients are parameters in odds ratio models. He says such a diagram "summarizes some of the information obtained" but does not consider whether flow graph-like manipulations give results analogous to transmittances and variable values. There is some reason to be cautious about the possibility. Davis and Schooler (1974) show that for multivariate odds ratios and Q's (Q is an odds ratio normed to remain within limits of +1.00 and -1.00) path principles apply nicely with three variables; in four-variable systems, however, odd structures emerge in the transmittance that simply do not make intuitive sense in terms of traditional path or flow diagram interpretation.

In sum, d systems are closely related to regression, differing mainly in the strategy of estimation; somewhat akin to dummy variable and MCA approaches, neither of which seems more promising for flow graphing; totally distinct from correlational approaches and thus less like classical path analysis than one might think; and parallel to odds ratio approaches in handling interactions, but with certain advantages in structural reasoning.

6. Conclusions

It is unlikely, after all this discussion, that the author will conclude that his proposed system is a snare and a delusion. Nevertheless, he is prepared to admit that it is not without drawbacks.

First, the system is cumbersome and case base problems arise with systems of more than half a dozen variables. Fans of vacuum cleaner techniques such as stepwise regression will not like this technique. I happen to think sociologists should focus on careful analysis of small systems, but this is surely a personal opinion, not a methodological rule.

Second, the arbitrary choice of base is aesthetically displeasing, but I am persuaded there is no other way to beat the redundancy problem and the technique seems inherent in categorical approaches to linear systems (Cohen, 1968; Fennessey, 1968).

Third, as in any categorical system, there is always the nagging fear that things might come out differently (partial d's in particular) if the variables are "cut" or "collapsed" differently.

Fourth, as in contemporary regression, assumptions about variable order are very important. One can make iffy assumptions about homoscedasticity and the like without coming to much detectable harm, but different numbers will emerge when the same data are specified with different variable orders. Those who are dubious about causal orders in cross-sectional, non-experimental data will not clasp this technique to their bosoms.

Fifth, with ordered categories, life is a lot simpler if one merely slaps numbers on the variables and feeds the data into a canned regression routine, such operations being especially easy on the con-science if one doesn't bother to examine zero-order plots of the data.

In compensation, I think the system has some definite merits.

On the technical side, it allows one to handle survey data in the framework of linear systems without making queasy level-of-measurement assumptions; it gets at interactions directly, instead of through non-intuitive product terms in equations; and it uses the old shoe concept of the "percentage difference."

Substantively, and this is the main idea behind the whole thing, the system allows the survey analyst to bring causal and dynamic thinking into his familiar "percentage tables" with a scheme that is rigorous and rich in the possibility of inferences. If survey research doesn't need this scheme, it surely needs another that does the same thing better.

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A NOTE ON QUESTION WORDING EFFECTS

Karen Newman Gaertner

May 1975

One of the difficulties encountered in the analysis of attitude changes over time is inconsistency in the data to be compared; more specifically, there are any number of ways to ask a question on opinion surveys, and relatively little consistency over time and across research organizations in question wordings used. The purpose of this paper is to review one question wording difference found in the National Opinion Research Center's (NORC) analysis of social change, noting the apparent impact this wording difference has on the marginal distribution of responses, the impact it has on correlations with demographic variables, and the different conclusions a researcher might come to using the different question wordings. It should be understood that our analysis will be both simple and narrow, and that generalizations must therefore be made with caution.

The item to be examined is that measuring the attitudes of whites toward residential integration, for which there are nine data points with three question forms. The first form, which we shall call the "double option" form, is:

> Which of these statements would you agree with: White people have a right to keep black people out of their neighborhoods if they want to; black people have a right to live wherever they can afford to, just like anybody else.

This form appears in five studies: the Michigan Election studies of 1964, 1968, and 1970, and two National Opinion Research Center studies in 1965 (SRS 868) and 1966 (SRS 889A).[1]

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[1]Even here we have had to make some assumptions about trivial variations in question wording. The 1964 Election study ended the question with "just like white people," and the two NORC studies exclude the last phrase entirely and show a slight difference in the opening phrase, "Now which of these two statements do you agree with more?" The question was also asked in the 1972 Election study, but the data were restricted and thus not available for analysis at this writing.

The second form of the question is:

> White people have a right to keep Negroes out of their neighborhoods if they want to, and Negroes should respect that right. (Respondent is asked to agree or disagree.)

We will call this the "single option" form. Three data points are of this type, all from the National Opinion Research Center: one study done in 1968 (SRS 4050), one from 1970 (SRS 4100), and the General Social Survey from 1972.

The last question is also of the "single option" type, but is "inverted" in that the respondent was asked to agree or disagree with an integrationist rather than segregationist statement. It appears in the 1966 Michigan Election study and reads:

> In talking with people, they sometimes tell us things that I'd like your opinion about. Some people say that Negroes should be allowed to live in any part of town they want to. How do you feel? Should Negroes be allowed to live in any part of town they want to, or not?

Our analysis of these items will include only non-black respondents, since blacks were not asked this question on many of the studies.[2] We have also excluded from analysis all persons responding "it depends," "don't know," or "no answer," dichotomizing the substantive responses into "segregationist" and "integrationist." Table 1 gives the marginal proportions for these data and the proportion "segregationist" is graphed in Figure 1. The solid line extending from 1964 to 1970 represents double option versions of the question, the dashed line represents the single option version, and the solitary point in 1966 is the "inverted single" from the Michigan study of that year.

The obvious immediate conclusion is that question wording makes a difference. Indeed, it makes a difference of about 25 per cent, comparing the two lines given. If asked the double option version of the question, the respondent is considerably less likely to respond in a segregationist manner.

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[2]Blacks were asked the question on the Michigan Election Studies but not on the NORC/SRS studies; that is, they were not asked on five of eleven studies.

TABLE 1

MARGINALS[a]

	Data								
Survey	ELEC64	SRS868	SRS889A	ELEC66	SRS4050	ELEC68	SRS4100	ELEC70	GSS72
Date	11/64	10/65	6/66	12/66	3/68	11/68	4/70	12/70	3/72
Per cent segregationist	35.1 (1,232)	29.8 (1,212)	34.8 (1,308)	43.5 (933)	55.9 (1,226)	27.2 (1,302)	46.6 (1,162)	23.5 (659)	40.1 (1,253)

[a]The sample sizes of the 1964, 1968, and 1970 Election Studies are probably smaller than most given in the literature from the same data sets. This is because we reweighted these studies to allow for the bias introduced by weighting.

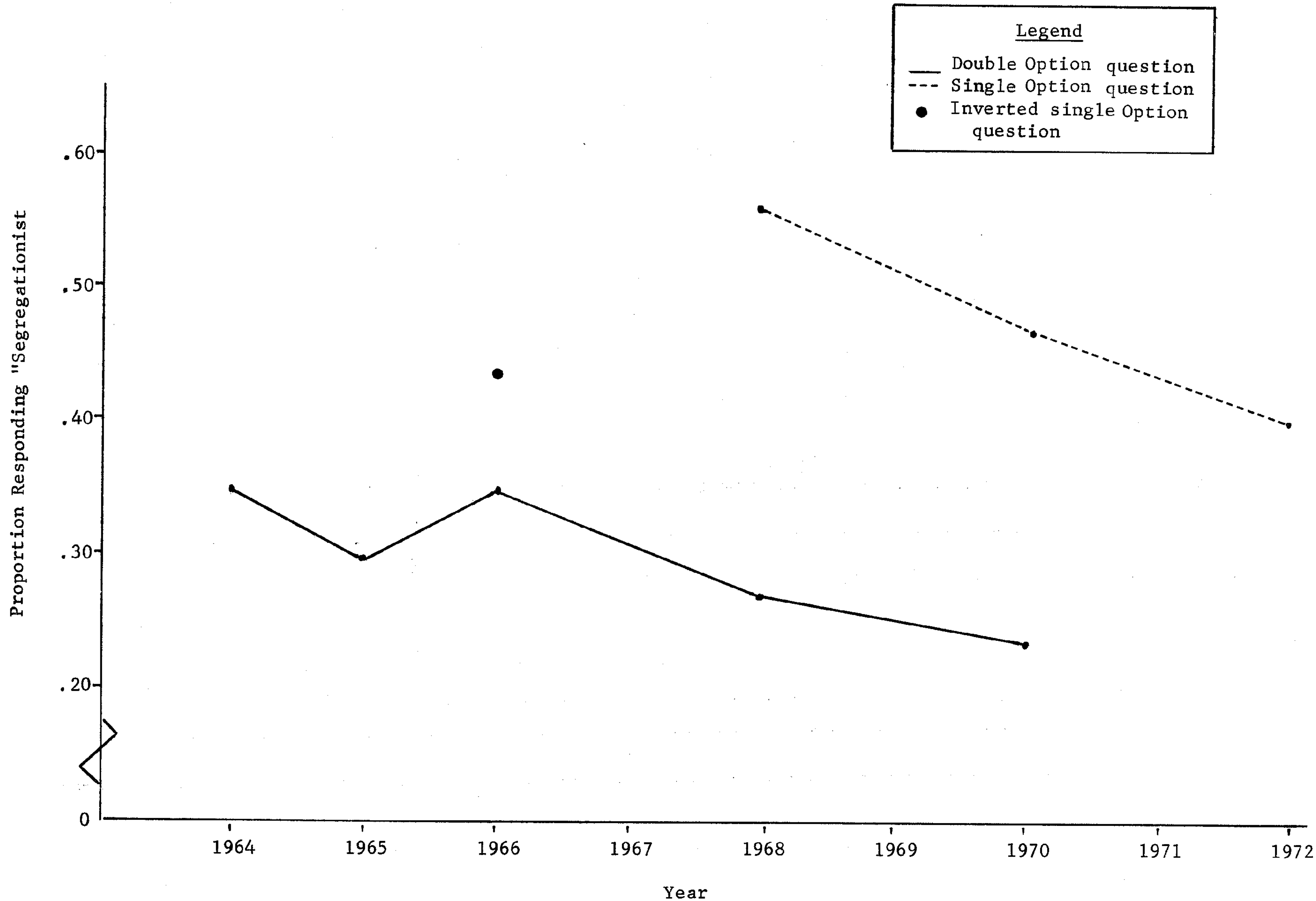

Fig. 1--Attitude toward residential integration by year

Though our data are incomplete, we would also suggest that we have found a yea-saying effect in view of the inverted single option data point (1966). In this case, the respondent had to disagree with the statement given to be coded a segregationist, whereas in the other single option questions (dashed line) the respondent had to agree with the statement given to be coded a segregationist. The single 1966 point is clearly lower than the line created by the other single option data points would indicate, by 15 to 20 per cent. It should also be noted, however, that the inverted single option response marginals are still almost 10 per cent above those obtained from the double option version. Without more data of the inverted single option type, further speculation would be foolish. Let us simply say that marginal responses on these items lead us to believe that (1) the double option version yields fewer intolerant or segregationist responses than either single option version, and (2) there appears to be a tendency for respondents to be biased toward agreement with the statement given.

Of perhaps greater interest is a comparison of the two main question types in years in which they were both asked; that is, a comparison of the single and double option versions in 1968 and 1970 to determine whether differences in question wording produce significant differences in the marginal distributions on this attitude item and in correlations between the item and other variables. The procedure for this was quite simple. Seven different four-variable models were set up. Three of the four variables used were the same in all models: year (1968, 1970), wording (double, single), and the attitude item (integration, segregation). The fourth variable differed in each model, but was always a background or demographic variable.[3] The technique used

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[3]The background items are region (non-South, South), education (less than high school, high school, college), family income (less than $4,000, $4,000-$9,999, $10,000 and more), occupation (blue collar, white collar), birth cohort (pre-1907, 1907-1923, 1924-1939, post-1939), religion (Protestant, non-Protestant), and sex (male, female). The birth cohorts are also referred to as old, middle, young, and new, respectively.

was linear flow graph analysis with percentage differences.[4] The general form of the model is given in Figure 2.

This type of analysis allows examination not only of the effect of question wording on marginals (path f), but also of sample size differences (path a and residuals h and i), sampling frame differences (path b), changes in the distribution of background variables (path c), change in attitude toward residential integration (path d), and differences in attitude among subgroups in the population (path e). But, although this information is of some interest, our primary target is the identification of differences caused by question wording, and examination of the ways in which observed differences might be incorrectly attributed to this cause. Toward accomplishing this end we were able to pool a number of effects across all seven models, yielding the constant effects shown in Figure 3.[5] Each parameter is net of all prior and intervening variables, and all are more than three times their standard error. (The data from which these pooled effects were obtained, as well as all the data for subsequent analysis, are shown in Tables 2 through 8.) En route to the substantive part of the analysis, we will move through the model (as shown in Figure 3) and briefly explain the meaning of some of these parameters.

The year residual (.418) indicates simply that 41.8 per cent of all the respondents were sampled in 1970. The question wording residual tells us that, among the 1968 respondents, 48.4 per cent were sampled by NORC (the single option question). The path between year and question wording indicates that the 1970 NORC survey was 15.4 per cent larger than the 1968 NORC study. Thus, with these three parameters we have obtained information concerning sample sizes--hardly a central concern, but illustrative of the use of this method.

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[4] See Davis (in press) and Taylor (1975) for a more complete discussion of the general methodology and the specific application used herein.

[5] The occupation model parameters were excluded from estimation of the time residual, the question wording residual, and the time-to-question wording path because of sample size variation resulting from differences in the number of respondents asked the question.

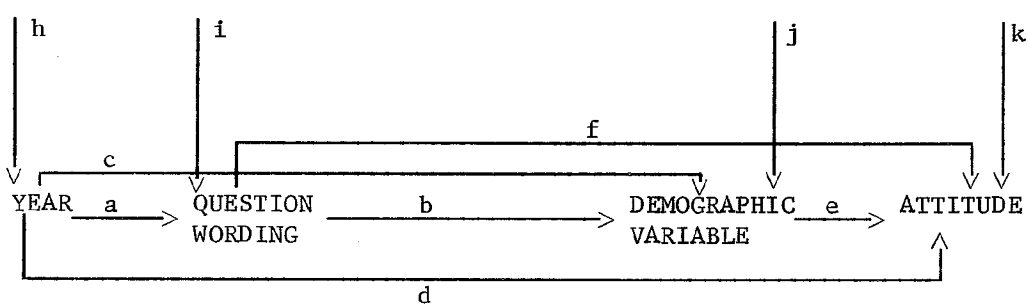


Fig. 2--General Flow Model Used to Determine Question Wording Effects

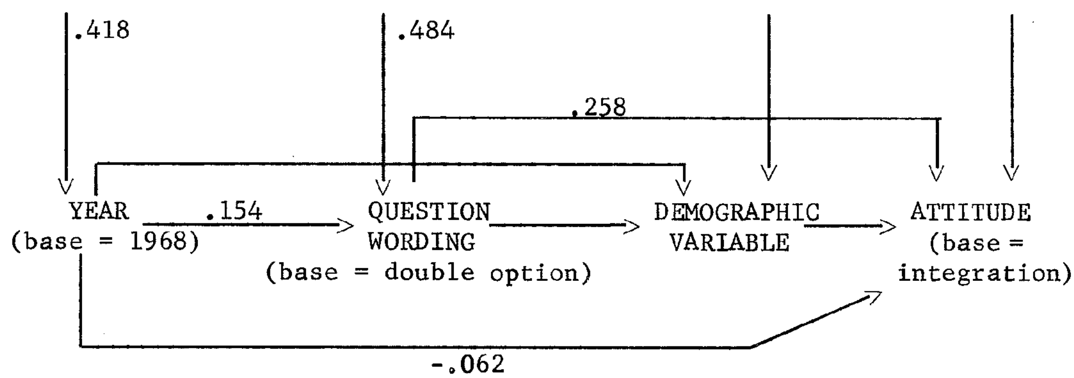


Fig. 3--Constant Parameters for All Models

TABLE 2

REGION EFFECTS

Data				
Survey	ELEC68	SRS4050	ELEC70	SRS4100
Date	11/68	3/68	12/70	4/70
Per Cent Segregationist:				
North	19.2 (940)	48.0 (891)	15.2 (466)	36.7 (831)
South	47.7 (362)	76.7 (335)	43.3 (193)	71.3 (331)

Statistical Analysis

Base Categories:

Year	=	1968
Wording	=	Double Option
Region	=	Non-South
Integration Attitude	=	Integrationist

Path	Hypothesis	Model	x^2	df	p	Decision
a (Year to Wording)	1) No difference	d=0	103.9	1	<.05	Reject
	2) Constant difference	d=dp	0	0	>.05	Accept
b (Wording to Region)	1) No difference	d=0	.2	2	>.05	Accept
c (Year to Region)	1) No difference	d=0	.9	2	>.05	Accept
d (Year to Attitude)	1) No difference	d=0	30.1	4	<.05	Reject
	2) Constant difference	d=dp	5.9	3	>.05	Accept
e (Region to Attitude	1) No difference	d=0	381.3	4	<.05	Reject
	2) Constant difference	d=dp	3.0	3	>.05	Accept
f (Wording to Attitude)	1) No difference	d=0	377.9	4	<.05	Reject
	2) Constant difference	d=dp	6.3	3	>.05	Accept

(Continued)

TABLE 2--Continued

Final Models

Paths	a	d = .153	σ = .015
	b	d = 0	
	c	d = 0	
	d	d = -.067	σ = .014
	e	d = .302	σ = .016
	f	d = .263	σ = .014
Residuals	h (Year)	r = .419	σ = .007
	i (Wording)	r = .485	σ = .010
	j (Region)	r = .278	σ = .012
	k (Attitude)	r = .193	σ = .013

TABLE 3

EDUCATION EFFECTS

Data

Survey	ELEC68	SRS4050	ELEC70	SRS4100
Date	11/68	3/68	12/70	4/70
Per Cent Segregationist:				
Less than High School	38.1 (482)	64.3 (541)	32.9 (234)	58.8 (486)
High School	21.5 (431)	55.3 (376)	25.9 (241)	43.0 (374)
College	19.6 (387)	41.4 (307)	8.2 (182)	31.1 (299)

Statistical Analysis

Base Categories:

Year	= 1968
Wording	= Double Option
Education	= Less than High School
Integration Attitude	= Integrationist

Path	Hypothesis	Model	x^2	df	p	Decision
a (Year to Wording)	1) No difference	d=0	103.9	1	<.05	Reject
	2) Constant difference	d=dp	0	0	>.05	Accept
b_1 (Wording to High School Graduate)	1) No difference	d=0	5.3	1	>.05	Accept
b_2 (Wording to College)	1) No difference	d=0	7.8	2	*	
	2) Constant difference	d=dp	1.0	1	>.05	Accept
	Reduction from constant parameter		6.8	1	*borderline	
c_1 (Year to High School Graduate)	1) No difference	d=0	3.0	2	>.05	Accept

Table 3--Continued

Path	Hypothesis	Model	x^2	df	p	Decision
c_2 (Year to College)	1) No difference	d=0	1.1	2	>.05	Accept
d (Year to Attitude)	1) No difference	d=0	41.2	6	<.05	Reject
	2) Constant difference	d=dp	16.8	5	*	
	Reduction from constant parameter		24.4	1	<.05	Significant
e_1 (High School to Attitude)	1) No difference	d=0	63.0	4	<.05	Reject
	2) Constant difference	d=dp	5.8	3	>.05	Accept
e_2 (College to Attitude)	1) No difference	d=0	189.8	4	<.05	Reject
	2) Constant difference	d=dp	4.3	3	>.05	Accept
f (Wording to Attitude)	1) No difference	d=0	335.1	6	<.05	Reject
	2) Constant difference	d=dp	13.3	5	*	
	Reduction from constant parameter		321.8	1	<.05	Significant

Final Models

Paths	a		d = .153	σ = .015
	b_1		d = 0	
	b_2		d = -.036	σ = .014
	c_1		d = 0	
	c_2		d = 0	
	d		d = -.068	σ = .014
	e_1		d = -.128	σ = .017
	e_2		d = -.230	σ = .017
	f		d = .250	σ = .014
Residuals	h	(Year)	r = .418	σ = .007
	i	(Wording)	r = .485	σ = .010
	j_1	(High School Graduate)	r = .332	σ = .013
	j_2	(College)	r = .298	σ = .013
	k	(Attitude)	r = .382	σ = .022

* $p < .05$ without correction for non-random sample and $p > .05$ after correction.

TABLE 4

INCOME EFFECTS

Data				
Survey	ELEC68	SRS4050	ELEC70	SRS4100
Date	11/68	3/68	12/70	4/70
Per Cent Segregationist:				
<$4,000	35.6 (257)	59.9 (289)	31.8 (118)	53.8 (253)
$4,000 - $10,000 .	28.8 (579)	57.3 (572)	24.8 (238)	47.1 (444)
>$10,000	18.9 (436)	47.4 (291)	17.6 (273)	39.2 (383)

Statistical Analysis

Base Categories:

Year	= 1968
Wording	= Double Option
Income	= <$4,000
Integration Attitude	= Integrationist

Path	Hypothesis	Model	x^2	df	p	Decision
a (Year to Wording)	1) No difference	d=0	102.8	1	<.05	Reject
	2) Constant difference	d=dp	0	0	>.05	Accept
b_1 (Wording to $4,000-$10,000)	1) No difference	d=0	5.9	2	=.05	Accept
b_2 (Wording to >$10,000)	1) No difference	d=0	34.3	2	<.05	Reject
	2) Constant difference	d=dp	.1	1	>.05	Accept
c_1 (Year to $4,000-$10,000)	1) No difference	d=0	26.9	2	<.05	Reject
	2) Constant difference	d=dp	.1	1	>.05	Accept
c_2 (Year to >$10,000)	1) No difference	d=0	42.4	2	<.05	Reject
	2) Constant difference	d=dp	.1	1	>.05	Accept

(Continued)

TABLE 4--Continued

Path	Hypothesis	Model	x^2	df	p	Decision
d (Year to Attitude)	1) No difference	d=0	19.1	6	*	
	2) Constant difference	d=dp	5.2	5	>.05	Accept
	Reduction from constant parameter		13.9	1	<.05	Significant
e_1 ($4,000-$10,000 to Attitude)	1) No difference	d=0	9.4	4	>.05	Accept
e_2 (>$10,000 to Attitude)	1) No difference	d=0	54.6	4	<.05	Reject
	2) Constant difference	d=dp	.7	3	>.05	Accept
f (Wording to Attitude)	1) No difference	d=0	299.0	6	<.05	Reject
	2) Constant difference	d=dp	4.7	5	>.05	Accept

Final Models

Paths	a		d = .157	σ = .015
	b_1		d = 0	
	b_2		d = -.086	σ = .015
	c_1		d = -.082	σ = .016
	c_2		d = .098	σ = .015
	d		d = -.055	σ = .015
	e_1		d = 0	
	e_2		d = -.149	σ = .020
	f		d = .252	σ = .015
Residuals	h	(Year)	r = .414	σ = .008
	i	(Wording)	r = .475	σ = .010
	j_1	($4,000 - $10,000)	r = .455	σ = .014
	j_2	(>$10,000)	r = .343	σ = .013
	k	(Attitude)	r = .358	σ = .030

TABLE 5

OCCUPATION EFFECTS

Data

Survey	ELEC68	SRS4050	ELEC70	SRS4100
Date	11/68	3/68	12/70	4/70
Per Cent Segregationist:				
Blue Collar	30.4 (432)	62.3 (324)	30.5 (217)	50.6 (433)
White Collar	23.2 (462)	47.1 (297)	19.6 (240)	39.9 (318)

Statistical Analysis

Base Categories:

Year	= 1968
Wording	= Double Option
Occupation	= Blue Collar
Integration Attitude	= Integrationist

Path	Hypothesis	Model	x^2	df	p	Decision
a (Year to Wording)	1) No difference	d=0	126.6	1	<.05	Reject
	2) Constant difference	d=dp	0	0	>.05	Accept
b (Wording to Occupation)	1) No difference	d=0	14.1	2	<.05	Reject
	2) Constant difference	d=dp	2.6	1	>.05	Accept
c (Year to Occupation	1) No difference	d=0	4.2	2	>.05	Accept
d (Year to Attitude)	1) No difference	d=0	15.1	4	*	
	2) Constant difference	d=dp	5.7	3	>.05	Accept
	Reduction from constant parameter		9.4	1	<.05	Significant

(Continued)

TABLE 5--Continued

Path	Hypothesis	Model	x^2	df	p	Decision
e (Occuption to Attitude)	1) No difference	d=0	36.4	4	<.05	Reject
	2) Constant difference	d=dp	2.7	3	>.05	Accept
f (Wording to Attitude)	1) No difference	d=0	187.0	4	<.05	Reject
	2) Constant difference	d=dp	7.1	3	>.05	Accept

Final Models

Paths	a	d = .212	σ = .019
	b	d = -.066	σ = .020
	c	d = 0	
	d	d = -.056	σ = .018
	e	d = -.103	σ = .018
	f	d = .245	σ = .018
Residuals	h (Year)	r = .444	σ = .010
	i (Wording)	r = .410	σ = .013
	j (Occupation)	r = .517	σ = .017
	k (Attitude)	r = .303	σ = .022

TABLE 6

COHORT EFFECTS

Data				
Survey	ELEC68	SRS4050	ELEC70	SRS4100
Date	11/68	3/68	12/70	4/70
Per Cent Segregationist:				
New (Post 1939) . . .	21.8 (225)	49.7 (193)	13.9 (177)	32.2 (276)
Young (1924-1939) . .	22.5 (412)	51.9 (405)	20.8 (190)	44.7 (291)
Middle (1907-1923). .	27.3 (396)	60.1 (348)	30.2 (184)	53.4 (313)
Old (Pre 1907) . . .	38.4 (265)	61.1 (275)	35.7 (105)	55.4 (276)

Statistical Analysis

Base Categories:

Year	=	1968
Wording	=	Double Option
Cohort	=	Middle
Integration Attitude	=	Integrationist

Path	Hypothesis	Model	x^2	df	p	Decision
a (Year to Wording)	1) No difference	d=0	103.6	1	<.05	Reject
	2) Constant difference	d=dp	0	0	>.05	Accept
b_1 (Wording to new)	1) No difference	d=0	3.2	2	>.05	Accept
b2 (Wording to young)	1) No difference	d=0	3.6	2	>.05	Accept
b_3 (Wording to old)	1) No difference	d=0	18.8	2	<.05	Reject
	2) Constant difference	d=dp	5.3	1	*	
	Reduction from constant parameter		13.5	1	<.05	Significant

Table 6--Continued

Path	Hypothesis	Model	x^2	df	p	Decision
c_1 (Year to new)	1) No difference	d=0	47.1	2	<.05	Reject
	2) Constant difference	d=dp	.4	1	>.05	Accept
c_2 (Year to young)	1) No difference	d=0	20.2	2	<.05	Reject
	2) Constant difference	d=dp	3.3	1	>.05	Accept
c_3 (Year to old)	1) No difference	d=0	6.5	2	*	
	2) Constant difference	d=dp	5.3	1	*	
	Reduction from constant parameter		1.2	1	>.05	Not Significant
d (Year to Attitude)	1) No difference	d=0	29.1	8	*	
	2) Constant difference	d=dp	12.4	7	>.05	Accept
	Reduction from constant parameter		16.7	1	<.05	Significant
e_1 (New to Attitude)	1) No difference	d=0	49.5	4	<.05	Reject
	2) Constant difference	d=dp	9.4	3	*	
	Reduction from constant parameter		40.1	1	<.05	Significant
e_2 (Young to Attitude)	1) No difference	d=0	16.5	4	*	
	2) Constant difference	d=dp	1.1	3	>.05	Accept
	Reduction from constant parameter		15.4	1	<.05	Significant
e_3 (Old to Attitude)	1) No difference	d=0	9.5	4	*	
	2) Constant difference	d=dp	4.5	3	>.05	Accept
	Reduction from constant parameter		5.0	1	*	Borderline
f (Wording to Attitude)	1) No difference	d=0	342.5	8	<.05	Reject
	2) Constant difference	d=dp	10.8	7	>.05	Accept

Table 6--Continued

		Final Models		
Paths	a		d = .153	σ = .015
	b_1		d = 0	
	b_2		d = 0	
	b_3		d = .046	σ = .012
	c_1		d = .087	σ = .013
	c_2		d = -.058	σ = .014
	c_3		d = 0	
	d		d = -.059	σ = .014
	e_1		d = -.127	σ = .020
	e_2		d = -.072	σ = .018
	e_3		d = .047	σ = .021
	f		d = .258	σ = .014
Residuals	h	(Year)	r = .418	σ = .007
	i	(Wording)	r = .485	σ = .010
	j_1	(New Cohort)	r = .173	σ = .011
	j_2	(Young Cohort)	r = .317	σ = .013
	j_3	(Old Cohort)	r = .204	σ = .011
	k	(Attitude)	r = .273	σ = .022

TABLE 7

RELIGION EFFECTS

Data

Survey	ELEC68	SRS4050	ELEC70	SRS4100
Date	11/68	3/68	12/70	4/70
Per Cent Segregationist:				
Protestant	32.0 (878)	60.3 (829)	26.6 (439)	51.3 (723)
Non-Protestant	33.1 (411)	46.7 (396)	18.5 (205)	38.7 (439)

Statistical Analysis

Base Categories:
Year = 1968
Wording = Double Option
Religion = Protestant
Integration Attitude = Integrationist

Path	Hypothesis	Model	x^2	df	p	Decision
a (Year to Wording)	1) No difference	d=0	107.7	1	<.05	Reject
	2) Constant difference	d=dp	0	0	>.05	Accept
b (Wording to Religion)	1) No difference	d=0	6.6	2	*	
	2) Constant difference	d=p	3.4	1	>.05	Accept
	Reduction from constant parameter		3.2	1	>.05	Not significant
c (Year to religion)	1) No difference	d=0	7.8	2	*	
	2) Constant difference	d=dp	3.4	1	>.05	Accept
	Reduction from constant parameter		4.4	1	*	Borderline
d (Year to attitude)	1) No difference	d=0	22.4	4	<.05	Reject
	2) Constant difference	d=dp	4.6	3	>.05	Accept

(Continued)

TABLE 7--Continued

Path	Hypothesis	Model	x^2	df	p	Decision
e (Religion to attitude)	1) No difference	d=0	83.5	4	<.05	Reject
	2) Constant difference	d=dp	1.3	3	>.05	Accept
f (Wording to Attitude)	1) No difference	d=0	355.4	4	<.05	Reject
	2) Constant difference	d=dp	3.5	3	>.05	Accept

Final Models

Paths	a		d = .156	σ = .015
	b	d = 0 or	d = .026	σ = .015
	c	d = 0 or	d = .031	σ = .015
	d		d = -.061	σ = .014
	e		d = -.131	σ = .014
	f		d = .266	σ = .014
Residual	h (Year)		r = .418	σ = .008
	i (Wording)		r = .487	σ = .010
	j (Religion)		r = .319	σ = .013
	k (Attitude)		r = .320	σ = .016

TABLE 8

SEX EFFECTS

Data				
Survey	ELEC68	SRS4050	ELEC70	SRS4100
Date	11/68	3/68	12/70	4/70
Per Cent Segregationist:				
Male	25.2 (595)	52.2 (598)	23.4 (293)	43.0 (577)
Female	28.8 (507)	56.5 (628)	23.5 (366)	50.1 (585)

Statistical Analysis

Base Categories:

Year	=	1968
Wording	=	Double Option
Sex	=	Male
Integration Attitude	=	Integrationist

Path	Hypothesis	Model	x^2	df	p	Decision
a (Year to Wording)	1) No difference	d=0	103.9	1	<.05	Reject
	2) Constant difference	d=dp	0	0	>.05	Accept
b (Wording to sex)	1) No difference	d=0	7.0	2	*	
	2) Constant difference	d=dp	.5	1	>.05	Accept
	Reduction from linear parameter		6.5	1	*	Borderline
c (Year to sex)	1) No difference	d=0	.5	2	>.05	Accept
d (Year to Attitude)	1) No difference	d=0	26.8	4	<.05	Reject
	2) Constant difference	d=dp	6.6	3	>.05	Accept

(Continued)

TABLE 8--Continued

Path	Hypothesis	Model	x^2	df	p	Decision
e (Sex to Attitude)	1) No difference	d=0	8.3	4	>.05	Accept
f (Wording to Attitude)	1) No difference	d=0	348.7	4	<.05	Reject
	2) Constant difference	d=dp	6.7	3	>.05	Accept

Final Models

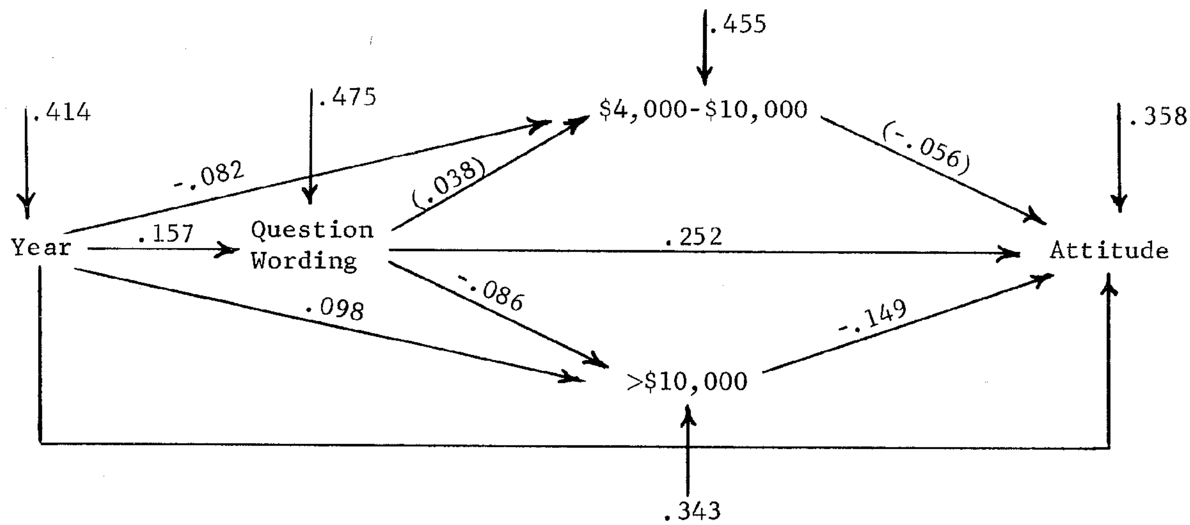
Paths	a		d = .153	σ = .015
	b	d = 0 or	d = -.039	σ = .015
	c		d = 0	
	d		d = -.065	σ = .014
	e		d = 0	
	f		d = .265	σ = .014
Residuals	h (Year)		r = .419	σ = .007
	i (Wording)		r = .485	σ = .010
	j (Sex)		r = .543	σ = .014
	k (Attitude)		r = .252	σ = .018

Of more interest are the year-to-attitude and question wording-to-attitude paths. The former indicates that segregationist responses decreased by 6.2 per cent between 1968 and 1970, net of question wording differences and demographic differences. In other words, both question types produced the same overall change in response to the attitude item, as did all categories of intervening demographic variables. The single exception to this is found when education is the demographic variable in the model (see Table 3). In this case, all but one of the combinations of education categories and question wording categories show the decrease in segregationist responses. The exception here occurs in the Election studies (double option question), where persons with a high school education show an increase in segregationist response of 4.5 per cent, rather than the expected decrease. This is the only significant exception to the overall finding that segregationist responses have decreased regardless of question wording and demographic classification. Put another way, our analysis strongly suggests that question wording does not affect the relationship between time and the attitude item under consideration.

The last constant parameter is that showing the relationship between question wording and the attitude item. Our results suggest that the single option version yields 25.8 per cent more segregationist responses, net of year and demographic characteristics. Again, the single possible exception to this overall trend involved education, as might be expected. Looking at Table 3, we see that among the high school graduates, the difference in segregationist responses between the 1968 Election study and the 1968 NORC study is 33.8 per cent, rather than the predicted 25.8 per cent; for the two 1970 studies the same difference is only 17.0 per cent. This is quite consistent with the earlier finding that high school graduates in the Election studies became more segregationist rather than less, as the overall analysis would suggest. (Another way of looking at this is that in 1968 the high school graduates were more integrationist than expected, whereas in 1970 they were more segregationist.) This interaction is the only one found in this analysis, and of only marginal significance, so we are inclined to pay it little heed. Our overall conclusion is that the single option version of the question produces more segregationist responses by about 26 per cent, regardless of year and demographic characteristics of respondents. Thus far, then, our analysis suggests that question wording affects marginals, but not correlations, with time.

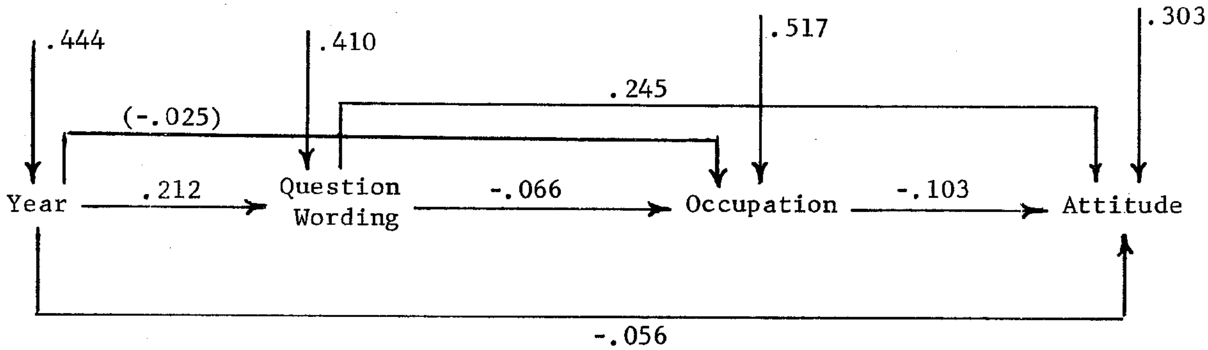
The next step in the analysis is to determine whether the samples under consideration are different from each other and whether these differences could have any effect on the observed question wording effect. The coefficients for path b provide the answer to this question (see Tables 2 through 8, data for path b). After the correction for multistage sampling, we find two differences in sample composition between the NORC studies (single option question) and the Election studies (double option question): (1) the NORC samples have significantly fewer persons with a family income of more than $10,000 a year (see Table 4); and (2) the same bias holds for occupation--the NORC samples have fewer white collar persons (see Table 5). This bias could account for some of the observed difference in marginal distribution because, as we will see in a moment, the very people that NORC tends to undersample are those more likely to give an integrationist response on this item; that is, high income, white collar persons tend to be less segregationist than lower income, blue collar persons. Thus, that NORC undersamples these people, relative to Michigan, could produce a bias toward more segregationist responses, thereby increasing differences between the two sets of studies.

The extent of the effect of this bias on the attitude marginals can be determined by examining the path from question wording to the attitude item through the intervening demographic variable. Figures 4 and 5 show the path coefficients for income and occupation, respectively. The effect of a bias on income or occupation in one set of studies is determined by multiplying the appropriate path coefficients and residual, in this case, paths b and e and residual i. If there is more than one path, the multiplication is carried out for all paths and the products are summed. That is, the transmittance from question wording through the demographic variable to the attitude is given by i*b*e. In the case of income, this is (.475 * -.086 * -.149) + (.475 * .038 * -.056) = .006 - .001 = .005. In other words, the path through the high income



Note: Coefficients in parentheses are not significant at .05 level.

Fig. 4--Path Coefficients for Income as Demographic Variable



Note: Coefficients in parentheses are not significant at .05 level.

Fig. 5--Path Coefficients for Occupation as Demographic Variable

category yields a .6 per cent increase in the segregationist attitude marginals while the path through the other income category yields a decrease of .1 per cent, leaving a net increase in the attitude marginals of .5 per cent that can be attributed to biases in samples. With respect to occupation (Figure 5), the effect of the bias is reached through the same process: .410 * -.066 * -.103 = .003. Thus, the bias caused by different occupational distributions is an even smaller .3 per cent. Given these results, it seems safe to say that the differences found in samples could not possibly account for the difference in marginals.[6]

Finally, we turn to the correlations between background items and attitude toward residential integration (path e). Here, the question is whether or not question type interacts with these correlations. The data for this question are presented in Tables 2 through 8, in the path e section. Let us briefly summarize the findings.

As is quite often the case in survey research, we found no sex differences in attitudes toward residential integration, but all other background variables are correlated with the attitude item. In a nutshell, the segregationists seem to be southern, older, less educated, poorer, blue collar Protestants. But, interestingly enough, with only one exception these correlations do not vary across question wording, with the exception occurring in the case of cohort. As has been noted, the general result is that younger cohorts tend to be more integrationist, but we found a marginally significant interaction in the comparison between the new cohort and the middle cohort. When the correction for multistage sampling was applied, however, even this interaction became

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[6]There are several marginally significant biases in samples found in the data. NORC is slightly more likely to sample persons in the old cohort (path b_3, Table 6), and older people are also more segregationist. The effect of this bias is a .1 per cent change in the marginals in favor of the segregationists. The other possible biases are in the wrong direction. NORC tends to oversample non-Protestants, but persons in this group tend to be integrationists (Table 7). The marginal change attributable to this difference is -.2 per cent, a decrease in the number of segregationists. Similarly, NORC tends to sample more men than does Michigan, yet because there is an insignificant correlation between sex and the attitude item, this bias accounts for less than .1 per cent of a marginal shift away from the segregationists (see Table 8).

insignificant. Nevertheless, because this is a central finding, we will explore the exception briefly. Table 9 shows the conditional effect parameters for the relationship between cohort and attitude toward residential integration. The numbers shown are simply the differences between the middle cohort and each of the others in proportion responding segregationist, for each possible combination of year and question wording.

Note that we found no interactions with year and/or question wording when the young and old cohorts were compared to the middle cohort: the conditional parameters were close enough in value to the pooled parameter that we are able to accept the pooled parameter as adequately describing the data. In the case of the new cohort comparison, however, the conditional parameters differ considerably from the pooled parameter. More specifically, the 1968 Election study shows too small a difference (-.055), whereas the 1970 NORC study shows too large a difference (-.211). As a result, we cannot pin the interaction to either year or question wording because the two deviant conditions have nothing in common. Had they both occurred in Election studies, we might have been able to conclude that question wording specifies the relationship between the cohort category and the attitude item. As this is not the case, we must conclude that question wording has no effect on the relationship between these background variables and the attitude item.

The marginal proportions presented in Table 6 support this result. Although the overall trend is for persons to become less segregationist over time (6.2 per cent), the middle cohort in the Election studies became more segregationist by about 2.9 per cent. In the NORC studies, this cohort behaved as it should, decreasing in segregationist sentiment by 6.7 per cent over the two-year period. Among the new cohort in the NORC studies, the decrease in segregationist responses is too large (17.5 per cent), but this is not true of the new cohort in the Election studies. If we compare the two question types within year, the same cohorts seem to contribute to variations from the general findings. The difference between the two questions in

TABLE 9

CONDITIONAL EFFECT PARAMETERS FOR RELATIONSHIP BETWEEN COHORT AND ATTITUDE TOWARD RESIDENTIAL INTEGRATION

		YEAR				
		1968		1970		Pooled
	QUESTION WORDING	Double	Single	Double	Single	Effect
COHORT	New	-.055	-.103	-.158	-.211	-.127
	Young	-.047	-.082	-.094	-.087	-.072
	Old	.112	.010	.025	.021	.047

1968 within the middle cohort is 32.8 per cent, while the overall result is 25.8 per cent. Similarly, the comparison in 1970 within the new cohort is too small, 18.1 per cent. Thus, the interaction, which was only marginal to begin with, cannot be pinned to year or question wording, but must be attributed to different cohort deviations in both of these areas.

What are the implications of our results? First, and quite clearly, differences in question wording seem to affect the marginal distribution of responses to the question and these effects are invariant over the time span studied and across subgroups of the population studied. Second, and perhaps more important, question type, at least in this case, does not seem to affect correlations between demographic variables and the attitude, nor does it affect correlations with time. Thus, if one's analysis is concerned with the graphing of marginal proportions, question wording can have a great deal of influence on the kinds of conclusions drawn. One only has to use a little imagination with Figure 1 to see that an analyst could derive very different conclusions regarding trends in race relations, depending on the mix of question wordings used. Indeed, it was a suspicious bump in this trend line that led to this analysis in the first place.

The analysis presented here leads us to the tentative conclusion that question differences are not nearly as potent in multivariate analysis as they are in univariate analyses. If this is the case, it would be a boon to those involved with the study of social change; the task is difficult enough without the problem of wording differences adding to the confusion. If these results can be generalized, and if researchers do more than plot marginal proportions over time, it would appear that the question wording problem is not as severe as might have been suspected.

We have also presented a very tentative but plausible finding that suggests yea-saying may account for 15 to 20 per cent of the observed 26 per cent difference between the two forms. It is indeed unfortunate that we do not have more data on this point, but these effects have been noted elsewhere (Wells, 1961).

The finding that is most difficult to explain is the apparent ability of the double option form of the question to produce a skew in the marginals that more than compensates for the tendency of respondents to agree with a given statement. Looking at Figure 1, we could present the argument that in 1968 about 45 per cent of the respondents were hard-core integrationists: even when the question was asked in segregationist terms, these people held fast to their beliefs. If the question were asked from the integrationist point of view, we could expect 15 to 20 per cent more integrationist responses--from those who were perhaps less certain about their beliefs and would tend to agree with whatever the interviewer said. Finally, when both alternatives were given and the respondent had more information concerning the implication of his or her response, another 5 to 10 per cent was added to the ranks of integrationists.

We have, of course, only the data at hand to support this possibility, and the data are tentative, at best. More research, with a variety of questions and subject areas, is needed for a complete understanding of the meaning of questions to respondents and the effect that various question forms have on responses.

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THE USE OF AIPO SURVEYS: TO WEIGHT OR NOT TO WEIGHT

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Thanks to Martin R. Frankel for technical assistance.

The purpose of this memo is quite simple: to describe the use made by the Social Change Project at the National Opinion Research Center (NORC) of the data weighting procedures available with surveys from the American Institute of Public Opinion (AIPO - Gallup). It is hoped that this description will help others use these surveys in the future. We will be dealing with two groups of AIPO studies--those done between 1960 and mid-1967 and those done after mid-1967. To the best of our knowledge, studies dated before 1960 have no predetermined weights, and thus the question of weighting must be left entirely to the individual investigator.[1]

The "mission" of the Social Change Project was to retrieve all previous usages of items found in the NORC General Social Survey (NORC 4139, 4164, and 4187). The search for previous usages led us to AIPO surveys, and, indeed, the vast majority of our data files are AIPO studies. We approached these studies in a very naive manner, assuming there was nothing unusual about any of them. Unfortunately, this assumption was wrong, and quite costly to boot. We did then arrive at a way of working with the studies. It should be understood, however, that the methods we will describe come entirely from our experience and perspective; we did not handle every AIPO study done since 1960, so there may be exceptions to our procedures, dictated by an exceptional data set or a different research question. Still, we were unable to find any conclusive documentation concerning the use of these studies, and are attempting to at least partially fill that void.

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[1]Paul Perry, of the Gallup organization, told us that some pre-1960 studies had been post-stratified on education ("balanced") within categories of sex and region, but was unable to be more specific. Additionally, there is apparently no way to recover the "unbalanced" or raw data from these studies, nor is it known exactly which studies were balanced. The question of "unweighting" these studies must therefore be ignored.

Using an AIPO study necessarily involves dealing with the Roper Public Opinion Research Center. The Roper Center is the archiving agency for all AIPO studies, and rents data sets to investigators. All documentation that exists for a particular study is also disseminated by the Roper Center. With respect to weights, this documentation is not complete. The front of a codebook from Roper contains a standard explanation of weighting which simply tells the user what the basis for weighting was, not specifically how the file was or could have been weighted. Upon request, the Roper Center will send the user a list of studies that have been weighted, indicating whether or not the weights are punched for the years 1960 through mid-1967. Table 1 is an exact reproduction of this list. (Note the title. These are not the only surveys using these weights. These are the surveys where card duplication was used to weight the files.) Roper will also send a flow chart of sorts that indicates how the weights were applied. This flow chart is at least misleading, if not incorrect. It implies that the weights are additive when they are actually multiplicative. The meaning of this will become clear in a minute. At any rate, the documentation provided by the Roper Center, which certainly derives from AIPO documentation, is not adequate if one is concerned about the proper use of weighted studies.

AIPO uses two weights, one which is supposed to correct for unequal probabilities of persons falling into the sample, and one which restratifies the sample on a criterion population characteristic. The first weight, known as "Times-at-Home" (T-A-H), assigns weights to respondents, according to their probability of being at home when the interviewer knocks on the door. Quite simply, the respondent is asked how many times he or she was at home during the last k days between certain hours. A weight is assigned to that respondent which is inversely related to the number of times the person was home. In other words, a person who was home every day during the specified period would receive a small weight, while someone who was only home once during the period would receive a larger weight.[2] The final weights are

[2]For a more complete discussion of this weighting procedure, see Politz and Simmons (1949), or Kish (1965).

TABLE 1

SURVEYS CONTAINING TIMES-AT-HOME AND EDUCATIONAL WEIGHTS

AIPO	T-A-H	ED
636	79	80
637	not punched	
638	not punched	
639	not punched	
640	not punched	
641	79	80
642	79	80
643	79	80
644	79	80
645	79	80
646	77	78
647	79	80
648	79	80
649	79	80
650	79	80
651	not punched	
652	79	80
653	79	80
654	79	80
655	80	41
656	79	80
657	79	80
658	79	80
659	79	80
660	79	80
661	79	80
662	79	80
663	79	80
664	79	80
665	79	80
666	79	80
667	79	80
668	79	80
669	79	80
670	79	80
671	79	80
672	79	80
673	49	58
674	79	80
675	79	80
676	79	80
677	79	80
678	79	80
679	79	80
680	79	80
681	79	80
682	79	80
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696	79	80
697	79	80
698	79	80
699	79	80
701	79	80
702	79	80
704	79	80
705	79	80
706	41	60
708	79	80
709	79	80
710	79	80
711	52	68
712	79	80
713	79	80
714	79	80
715	79	80
716	79	80
717	79	80
718	79	80
719	79	80
720	79	80
721	80	36
722	80	59
723	79	80
724	79	80
725	79	80
726	80	57
727	79	80
728	79	80
729	79	80
730	79	80
731	79	80
732	79	80
733	79	80
734	79	80
735	79	80
736	79	80
737	79	80
738	80	67
739	79	80
740	79	80
741	79	80
742	79	80
743	79	80
744	79	80

always integers and usually range in value from one to five. Unfortunately, the research that has been done on the "Times-at-Home" weight indicates that it does not do what it is supposed to do. Thus, its utility is dubious at best.

The second weight is a post-stratification procedure based on educational attainment within categories of sex and region. In general, AIPO attempts to weight the sample such that the education marginals in the study "look like" education marginals from Current Population Surveys done by the Census. The practical effect of this weight is to increase the number of "less-educated" respondents relative to others in the sample. Again, these weights are always integers and usually range in value from one to five.

In studies done between 1960 and 1967, these weights appear as two separate variables. In later studies, the two weights are combined, appearing as one variable in the data, and it is apparently impossible for the researcher to separate the two.

Now that we have opened the can, we may proceed to sort out the worms. The easiest studies to deal with are from the second period, mid-1967 and later. When the user receives the data, he or she should notice that the sample size is characteristically about 1500. This represents the actual number of interviews conducted. Thus, using the unweighted file is the "default option;" that is, as long as the researcher uses the data as received, the file will be unweighted or raw. One may also wish to weight the file, in which case three options are available. The first option is simply to multiply each case by the weight associated with that case, resulting in a sample size of about 3000. The weight variable is usually found near the end of the file, is typically unlabelled, and usually has values of one through four.[3] This single-weight variable is a combination of the times at home weight

[3] A few studies in the 1970s have two weights. One is based on an incomplete sample. For example, if AIPO had a publication deadline, they may have had to compute weights and report results before all of the cases were received and coded. The second weight, typically called "trend factor," is based on the entire sample. It is "more correct" and thus should be the weight used by the researcher. For all practical purposes, however, there are no differences between the two weights.

and the education weight previously described. Many computer programs used for data analysis will do this for the researcher, given the proper instructions. For users of SPSS (Statistical Package for the Social Sciences), one simply saves the weight as a variable, then weights the file by that variable. The drawback of this option is that it artificially inflates the sample size, thus making significance testing difficult, if not impossible. If the researcher is interested in anything more sophisticated than marginal percentages, our advice is not to use this option.

The second option is to decimalize the weights so that the resulting weighted sample size is the same as the unweighted sample size. This procedure is also quite easy. One simply multiplies each weight by the raw N divided by the weighted N. For example, if the raw N was 1493 and the weighted N was 3115, old weights of 1, 2, 3, and 4 would become new weights of .479, 959, 1.438, and 1.917 (see Table 2). Using this procedure preserves the relative case weights and results in a sample size equal to the raw N. For the non-purist this method is probably adequate. It still has a drawback, however, because variances will be underestimated in a weighted sample. By weighting a sample, one attempts to increase the relative proportion of certain types of persons in the sample to make up for undersampling of these types. In this case, for example, we find that those who are less likely to be at home get weighted to "make up" for those missed because they were not at home. By weighting these persons, one creates, for example, three John Does instead of one, with responses to every item identical to the original one. But common sense tells us that the uninterviewed persons John Doe is supposed to be representing will not be exactly like John Doe in every respect. Thus, weighting a file artifically decreases the variability of responses. The correction for this bias leads us to the third option.

The final correction factor involves reducing the sample size again by a factor of 1/ (1 + relative variance), where the relative variance is equal to the variance of a variable divided by its mean. If the weights have a small relative variance, this correction will reduce the sample size less than if the relative variance of the weight

TABLE 2

EXAMPLE OF DECIMALIZING INTEGER WEIGHTS

OLD WEIGHT	*	(RAW N/WEIGHTED N)	=	NEW WEIGHT
1	*	1493/3115	=	.479
2	*	1493/3115	=	.959
3	*	1493/3115	=	1.438
4	*	1493/3115	=	1.917

is large. If the variance of the weight is calculated from the decimalized weight (option 2), its mean will be 1, thus simplifying the formula for the relative variance. Table 3 gives the complete calculation with a hypothetical variance of .365. The resulting sample size would be 1493/1.365 or 1094.

By correctly weighting the file the researcher "loses" cases proportional to the size of the weight variance. At about this point, the investigator obviously has to make a decision regarding the trade-off between number of cases and whatever precision is gained by weighting the file. AIPO studies are supposed to be "representative cross sections" of the universe sampled, so it is not a sin to use the unweighted data.

Before we move along to the discussion of weighting procedures for the earlier studies (1960 - mid-1967), we can summarize the weighting procedure just described as a 5-step process.[4]

1. Determine the raw and weighted sample sizes.
2. Decimalize the weight by multiplying it by the ratio of the raw N to the weighted N.
3. Calculate the variance of the decimalized weight.
4. Correct the weight for the bias introduced in weighting the sample by multiplying the decimalized weight by 1/(1+ relative variance of weight).
5. Weight the file by the results from step 4.

As mentioned earlier, the Social Change Project has had the opportunity to use many AIPO studies, but not, by any means, all of them. Table 4 shows the AIPO studies done since mid-1967 that we have seen, and for which the procedure described should be appropriate.

The set of studies falling between 1960 and mid-1967 presents one with a somewhat more challenging problem because they are pre-weighted. The file one receives from the Roper Center has a sample size of about 3000 rather than 1500. Moreover, the two weights are discrete; they have not been combined. The reason for this switch is simple. Until mid-1967, AIPO used a counter-sorter for their data analysis and duplicated cards to achieve a weighted file. During 1967, they gained access

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[4]For users of SPSS, the Appendix to this paper shows the SPSS control cards necessary to accomplish this task.

TABLE 3

EXAMPLE OF FULLY CORRECTED INTEGER WEIGHTS

ORIGINAL WEIGHT	*	RAW N / WEIGHTED N	*	1 / 1+ WEIGHT VAR.	=	CORRECTED WEIGHT
1	*	1493/3115	*	1/(1+.365)	=	.351
2	*	1493/3115	*	1/(1+.365)	=	.703
3	*	1493/3115	*	1/(1+.365)	=	1.053
4	*	1493/3115	*	1/(1+.365)	=	1.404

TABLE 5

EXAMPLE OF AIPO WEIGHT VALUES AND LABELS

TIMES AT HOME			EDUCATION		
N	Punch	Label	N	Punch	Label
1000	0	Original Cards	1543	0	Original Cards
391	1	Original Cards	801	1	Original Cards
27	2	Original Cards	7	2	Original Cards
91	3	Original Cards	814	3	Duplicated Cards
25	4	Original Cards			
1631	5	Duplicated Cards			

The second option is to reweight the file in a way that the relative case weights are preserved but the sample size is equal to the actual number of interviews conducted. This is where things start getting messy, so we will use an example to illustrate each step in the process. Before wading through this, however, the reader should keep in mind that our goal is the same as it was for the studies already discussed: we want to decimalize the weight, but before that is possible we have to "create" a single-weight variable. The first step is to crosstabulate the two weight variables. We have done this for AIPO 649 and the results are shown in Table 6.

Remembering that the last category of each variable represents the duplicated cards, the reader should note that all of the education duplicates (category 3) are also times-at-home duplicates (category 5), as advertised. Given the "knowledge" that the category values equal the number of times a case was duplicated, it should be true that the number of times-at-home duplicates is equal to the number of cases in each category multiplied by the weight. That is, looking at the first row in Table 6, it should be true that 570 = (607*0) + (265*1) + (20*2) + (61*3) + (20*4). Well, almost. It turns out, in this case, that the weights multiplied by the appropriate frequencies equal 568. The same multiplication-addition sequence for the second row is equal to 249 rather than 245. And for the third row the sum is actually 1 instead of 2. These kinds of discrepancies exist in virtually all of the studies of this era that we used. We can only attribute this to human error in one or more of the steps in the process that converts questionnaires to data sets.

The next step in the reweighting process is to create one weight out of the two given. This is accomplished by deleting the duplicate cases, adding 1 to each category value of each weight, and multiplying the two weights together. When the file is to be weighted, the idea is to weight the raw data; thus, we delete the duplicate cases. The actual number of times a case appears in the weighted file is the number of times it was duplicated plus one. That is, the cases with a weight value of 0 were not duplicated. They appear in the file only

TABLE 6

CROSSTABULATION OF EDUCATION WEIGHT AND TIMES-AT-HOME WEIGHT

EDUCATION WEIGHT	TIMES-AT-HOME WEIGHT 0	1	2	3	4	5	TOTAL
0	607	265	20	61	20	570	1543
1	389	125	7	30	5	245	801
2	4	1	0	0	0	2	7
3	0	0	0	0	0	814	814
TOTAL	1000	391	27	91	25	1631	3165

once, and therefore have a weight of 1. Similarly, cases with a weight value of 3 actually appear in the file four times. Thus, we add 1 to the value of the weight. The justification for multiplying the two weights rather than adding them is simple--that is the way AIPO did it. For example, a case that has a value of 3 for times-at-home and a value of 2 for education will end up with a single weight of 12 ((3+1)*(2+1)). The case was duplicated three times, yielding four identical cases, and each of those four was duplicated twice, yielding eight "new" cases. Add these eight to the four already attained, and you end up with 12 copies of the same case, or a case weight of 12. Table 7 shows the new weights for each cell of the original table.

The next step is to determine the true weighted N. Because of errors made in the duplicating process, the user should always calculate the weighted N given in the file. In our example, the calculated sample size is 3169. This number is achieved by multiplying each non-duplicate cell frequency by its new weight and summing. This is obviously not the same as the weighted N given in the file (3165), but do not despair. We are essentially unweighting and reweighting the raw data the "right" way, so small differences are to be expected.

The last step is then to decimalize the "new" single weight. This is done, as before, by multiplying the new weight by the raw N (i.e., the number of non-duplicate cases) and dividing by the calculated weighted N. This yields a sample size equal to the number of raw cases and still preserves the relative case weights.

To summarize, this rather messy process involves 6 steps:

1. Delete all the duplicate cases from the file. This is the raw N.
2. Crosstabulate the two weights. You may want to include the duplicates in your crosstabulation to check for abnormalities, but be sure to get rid of them before moving on.
3. Calculate the new single weight by adding 1 to each value of each weight and multiplying them together.
4. Calculate the weighted N by multiplying each cell frequency by the appropriate single weight and summing these products.
5. Decimalize the new single weight by multiplying it by the raw N and dividing by the calculated weighted N.
6. Weight the file by multiplying each case by its decimalized weight.

TABLE 7

SINGLE WEIGHT FOR EACH CELL OF TABLE 6

EDUCATION CATEGORIES	TIMES-AT-HOME CATEGORIES 0	1	2	3	4
0	1	2	3	4	5
1	2	4	6	8	10
2	3	6	9	12	15

The shortcoming of this method is exactly the same as that mentioned in our earlier discussion: this procedure yields a better but still imperfectly weighted file because of the bias introduced by weighting in the first place. Just as the weakness is the same, the solution is the same, bringing us to the last option.

Once the investigator has gone to all the trouble of unweighting and reweighting the file, weighting it again by the relative variance is a minor task. As before, one simply calculates the variance of the decimalized single weight (the mean will be 1) and multiplies the single weights by 1/(1 + rel. var. of the weight). Thus, we insert steps 5a and 5b into the 6-step process just summarized.

5a. Calculate the variance of the decimalized single weight.

5b. Multiply the single weights by 1/(1 + rel. var. of the weights).

So much for the mechanics. Users of SPSS will find an example of the control cards necessary to achieve this reweighting and the weighting of an unweighted AIPO file in the Appendix. Table 8 shows the studies we have used that were done between 1960 and mid-1967 for which this procedure should be appropriate.

In addition to the studies listed in Table 8, we encountered three studies in the twilight zone: AIPO 746, 747, and 749 (done in May, July, and August of 1967, respectively). These studies have large sample sizes like their earlier counterparts, but only one weight like the later studies. It would seem that a combination of the two methods should be used with these: select only the raw cases, add one to each weight value, then weight as if they were post-1967 studies. We have also provisionally concluded that AIPO 721 (December 1965) is a mystery. This study has a large sample size but only one weight, labeled "times-at-home", that does not add up as it should. Probably the safest way to deal with this study is to use the data unweighted. Finally, the Roper Center lists five studies during the early period for which weights were not punched: AIPO 637, 638, 639, 640, and 651 (see Table 1). Since we did not use any of these studies, we can offer no advice to the user.

TABLE 8

AIPO STUDIES, 1960 TO MID-1967, USED BY SOCIAL CHANGE PROJECT

STUDY #	DATE	STUDY #	DATE	STUDY #	DATE	STUDY #	DATE
642	3-61	671	4-63	709	3-65	730	6-66
646	3-61	673	5-63	710	4-65	732	7-66
649	8-61	674	6-63	712	6-65	733	8-66
654	1-62	675	7-63	713	6-65	734	9-66
655	2-62	676	7-63	714	7-65	735	9-66
661	7-62	681	12-63	716	8-65	736	10-66
662	8-62	704	1-65	723	1-66	744	4-67
670	4-63	705	1-65	728	5-66		

Up until this point we have tried to avoid discussing the usefulness of these weights, both practically and theoretically. A good theoretical dicussion of the justifications for weighting data files in this manner is beyond the scope of this paper, but may be found elsewhere.[5] From a practical point of view, we do have some observations.

Our first question had to do with the education marginals. How "bad" were the raw data, compared to Census data and to other non-AIPO studies in our possession? And what improvement in education marginals was to be gained by weighting the files? Figure 1 shows the per cent of respondents with less than a high school education, using selected unweighted AIPO data, the Current Population Surveys (CPS), of the Census, Michigan Election Studies, and selected NORC studies.[6]

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[5]Kish (1965).

[6]The following studies were used in all subsequent analyses. Michigan Election Studies: 1952, 1956, 1958, 1960, 1962, 1964, 1966, 1968, 1970, 1972.

NORC/SRS Studies:

Study #		Date	Study #		Date	Study #		Date
NORC	273	1/50	NORC	404	4/57	SRS	4050	3/68
NORC	298	12/51	NORC	447	4/62	SRS	4100	4/70
NORC	325	5/52	SRS	350	11/63	NORC	4119	3/71
NORC	337	2/53	SRS	760	10/64	NORC	5046	11/72
NORC	351	1/54	SRS	868	10/65	NORC	4164	3/73
NORC	370	3/55	SRS	876	2/66	NORC	4187	3/74
NORC	390	6/56	SRS	4011	1/67			

AIPO Studies (After 1954 the data from two studies were pooled for each odd year, yielding 12 time points.):

Study #		Date	Study #		Date
AIPO	502	9/52	AIPO	675	7/63
	531	5/54		710	4/65
	543	2/55		713	6/65
	546	4/55		744	4/67
	586	7/57		747	7/67
	589	9/57		778	4/69
	610	2/59		784	7/69
	614	5/59		825	3/71
	646	3/61		839	10/71
	649	8/61		863	1/73
	671	4/63		868	4/73

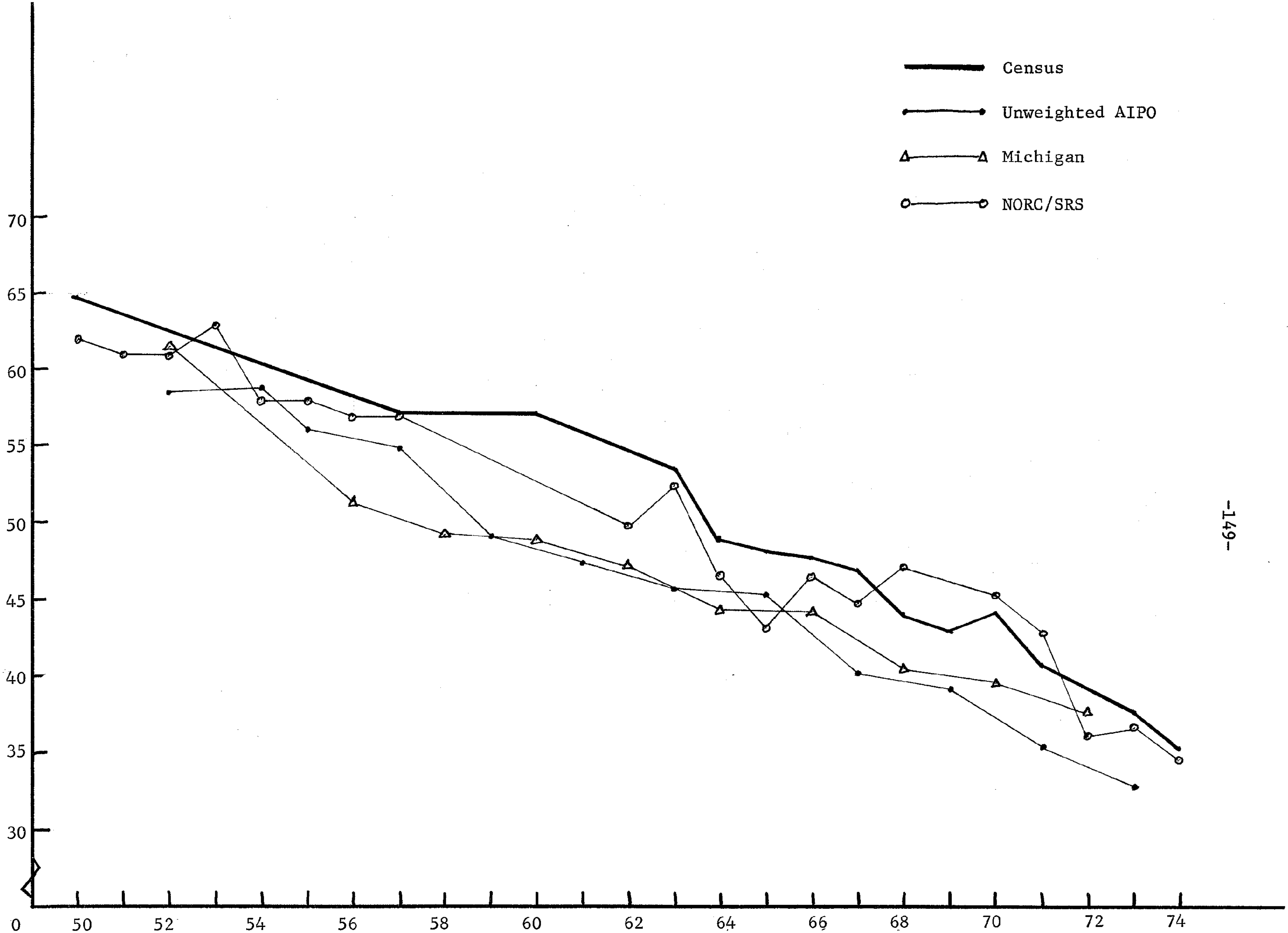

Fig. 1--Per Cent < High School Education

We can readily see that the marginal percentages from AIPO studies are quite similar to those from the Election Studies. Only after 1970 do the AIPO marginals look "worse" than the Election Study marginals, and both sets of studies consistently underestimate the proportion of the population with less than a high school education when compared with the CPS data. There is, unfortunately, a gap in the NORC studies between 1957 and 1962, but the information we do have indicates that NORC tends to better estimate (i.e., the estimates are more like the CPS data) the proportion of the population with less than a high school education though these estimates lack a consistent relationship to CPS data.

In Figure 2 we compared weighted and unweighted AIPO marginals with those from the Current Population Surveys. It is quite apparent that the weighted data do a better job of approximating population proportions than the unweighted data. Figures 3 and 4 show the same data, though this time for the proportion of a sample with a high school diploma. The trends here are less clear-cut. With respect to Figure 3, we would suggest that AIPO tends to over-estimate the proportion of high school graduates, while NORC tends to underestimate the same group. The Michigan Election Studies tend to fall between the other two, generally estimating the proportion with a high school diploma more accurately than NORC or the AIPO raw data. As before, Figure 4 indicates that by weighting the AIPO raw data, better estimates of education marginals are achieved.

Finally, in Figures 5 and 6, the same data are shown for the proportion of the samples with more than a high school education. It is apparent that the AIPO studies do at least as well as the other studies in estimating Census (CPS) data. The Michigan data show consistently higher proportions and the NORC data show inconsistency. Again, applying the weights improves AIPO marginals, as we would expect (Figure 6).

We checked the shifts in the education marginals for significance, and found that the real changes occurs in the least-and most-educated groups (see Table 9). The numbers shown in Table 9 are

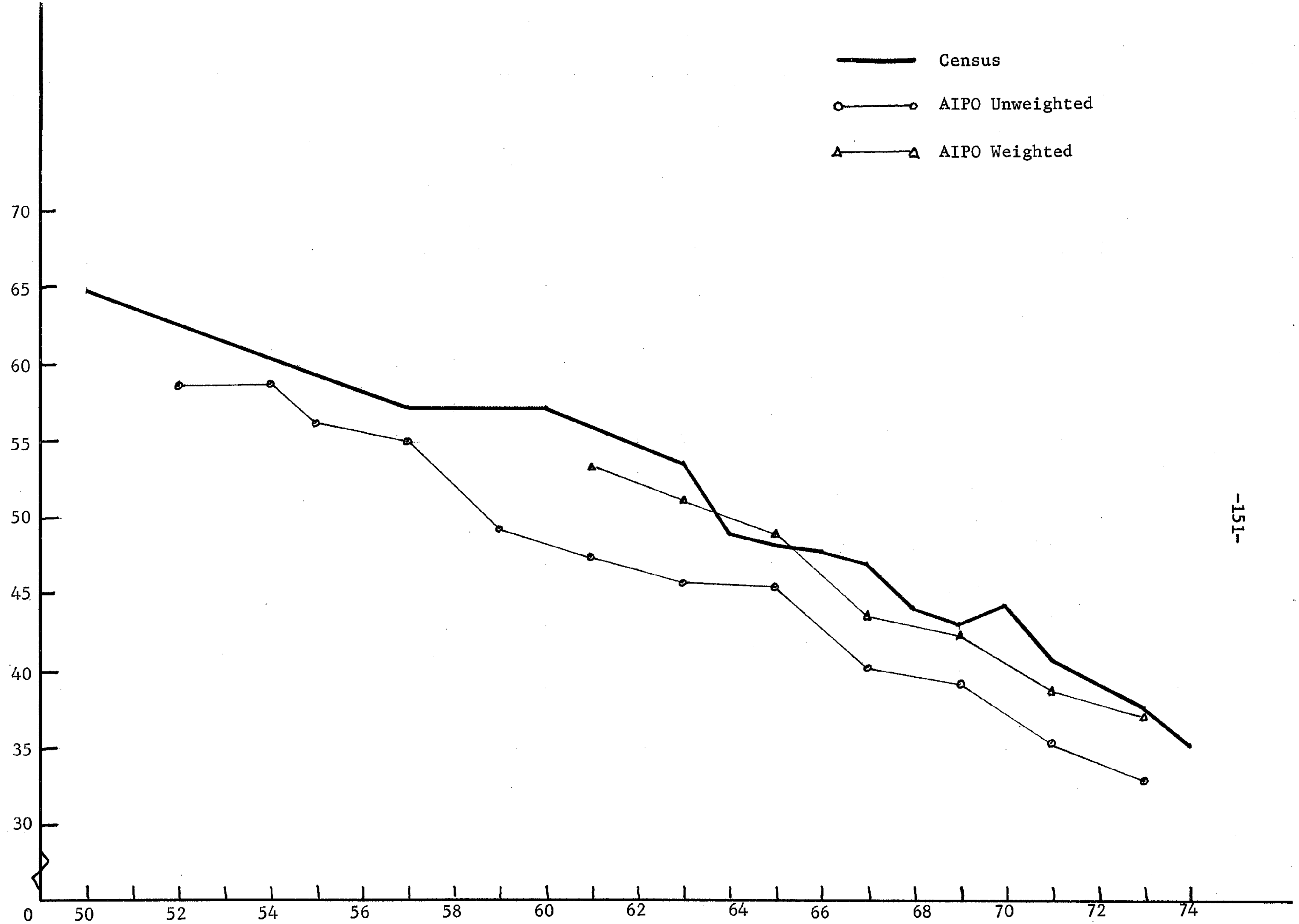

Fig. 2--Per Cent < High School Education

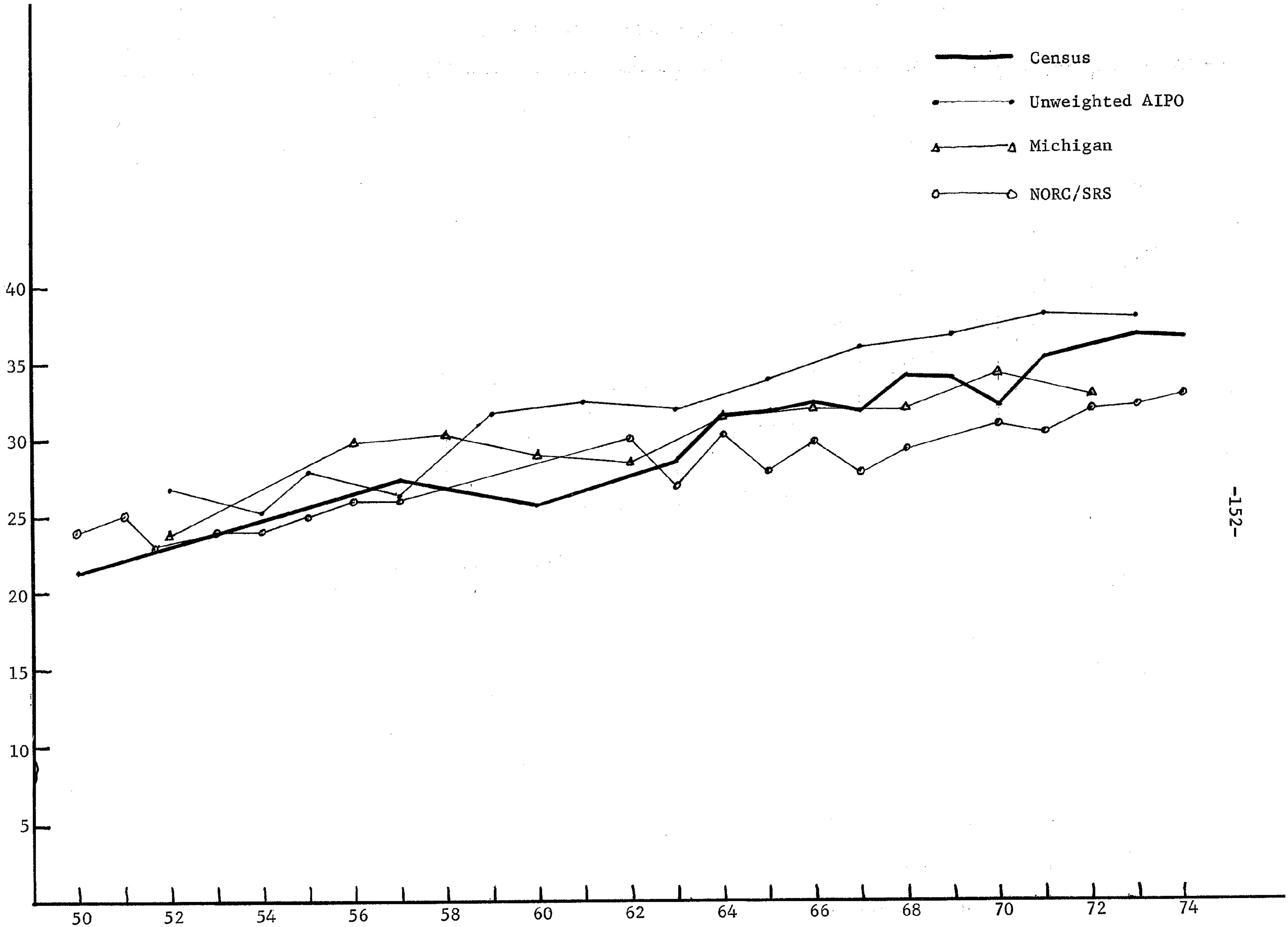

Fig. 3--Per Cent High School Graduates

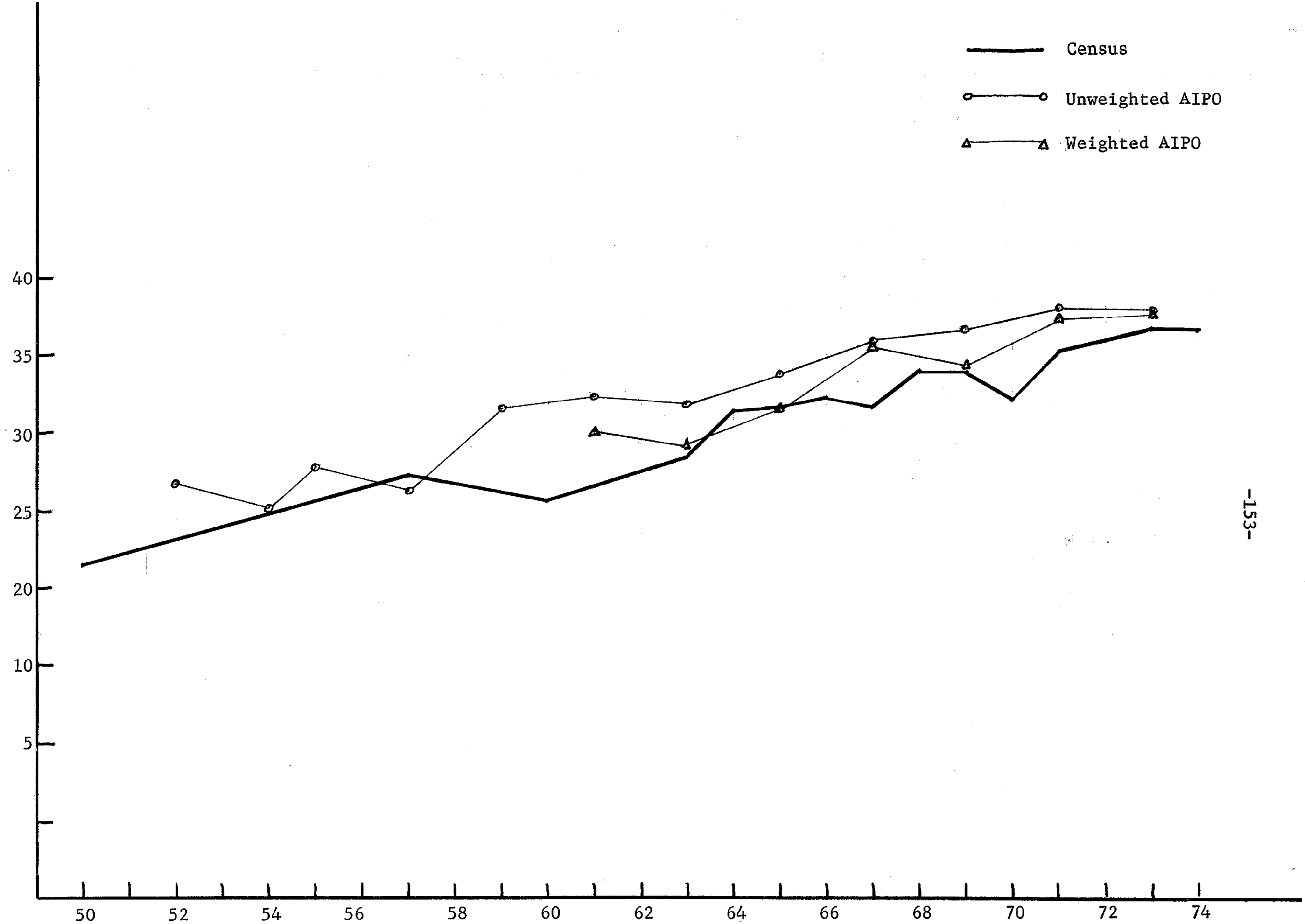

Fig. 4--Per Cent High School Graduates

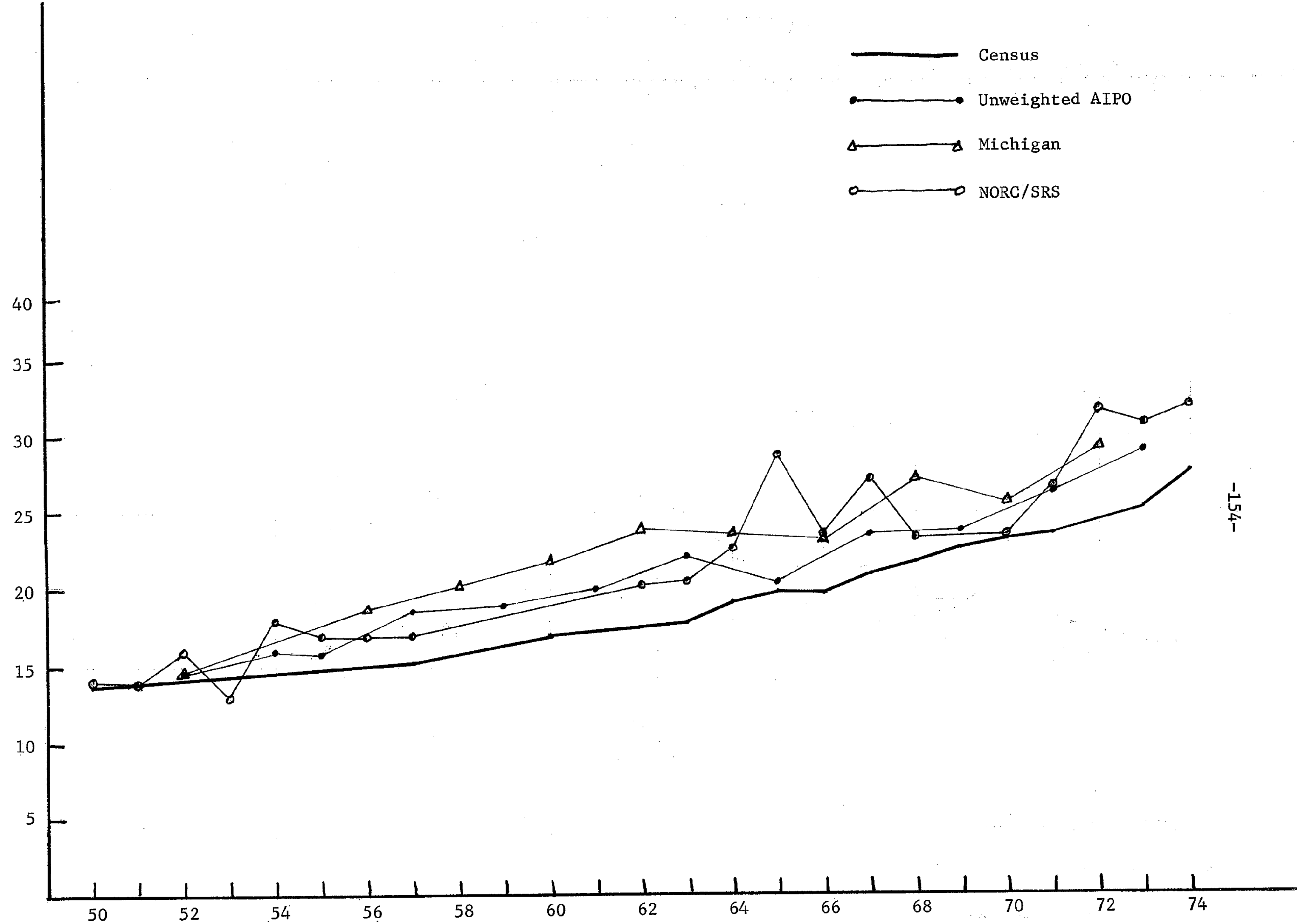

Fig. 5--Per Cent > High School Graduate

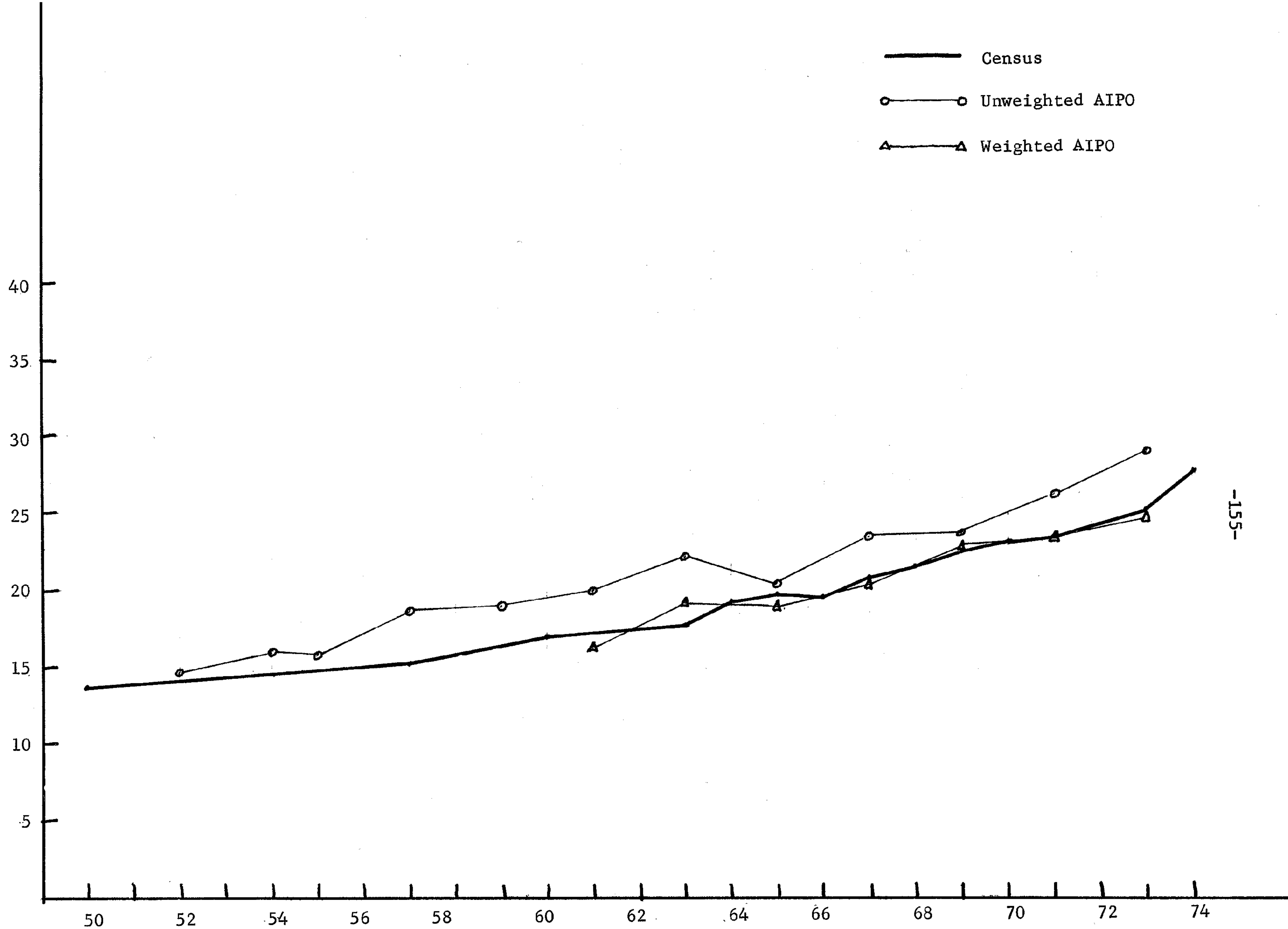

Fig. 6--Per Cent > High School Graduates

TABLE 9

CHANGES IN MARGINAL DISTRIBUTION ON EDUCATIONAL ATTAINMENT CAUSED BY WEIGHTING AIPO FILES

EDUCATION CATEGORY	Year						
	1961	1963	1965	1967	1969	1971	1973
Less than High School Graduate	.061**	.057**	.035*	.042**	.033*	.034*	.042**
High School Graduate	-.024	-.026*	-.019	-.019	-.022	-.005	-.002
More Than High School Graduate	-.037**	-.031*	-.015	-.023*	-.011	-.029*	-.039**

Note: * twice its standard error
** three times its standard error

percentage differences, indicating the change in marginal proportions resulting from using the weights.

These results left us in a bit of a quandry. While it is certainly true that applying the AIPO weights makes the education marginals "look better" in being more like the CPS data, it does not always make them look more like the other studies we are using. Moreover, the larger question that must be answered concerns the value of these improved marginals given the loss in cases occassioned by weighting (from 20 per cent to 40 per cent of the sample). In general, one must ask whether weighting the file makes any difference in the marginal distributions of other variables, and then in the relationships between variables in the file. After all, if one is interested in changes in educational attainment over time, the place to look for data is the Census, not national surveys like the AIPO files.

One variable that has been of particular concern to us, and one which shows up quite often in trend analyses, is cohort or year of birth. We grouped year of birth into four categories, those born before 1907, those born between 1907 and 1923, those born between 1924 and 1939, and those born after 1939. We compared the proportion of the samples in each of the four cohorts using weighted and unweighted AIPO data (see Figures 7 through 10) and found that weighting the files makes no significant difference in the proportion of a sample in each cohort. In no year did we find a correlation between cohort and "weight" as a dichotomous variable. Nor did we find that "weight" ever interacted with the relationship between cohort and year. We concluded that weighting the AIPO studies clearly does not affect the cohort distribution in these studies.

Our next question was whether or not weighting the files made any difference in the marginal distribution of other background variables. Table 10 shows some of the results from this analysis. Here we simply used weight as a variable, creating a four- or six-fold table, and looked for significant percentage differences in marginals in a number of studies for a number of variables. The background items shown were groups as follows:

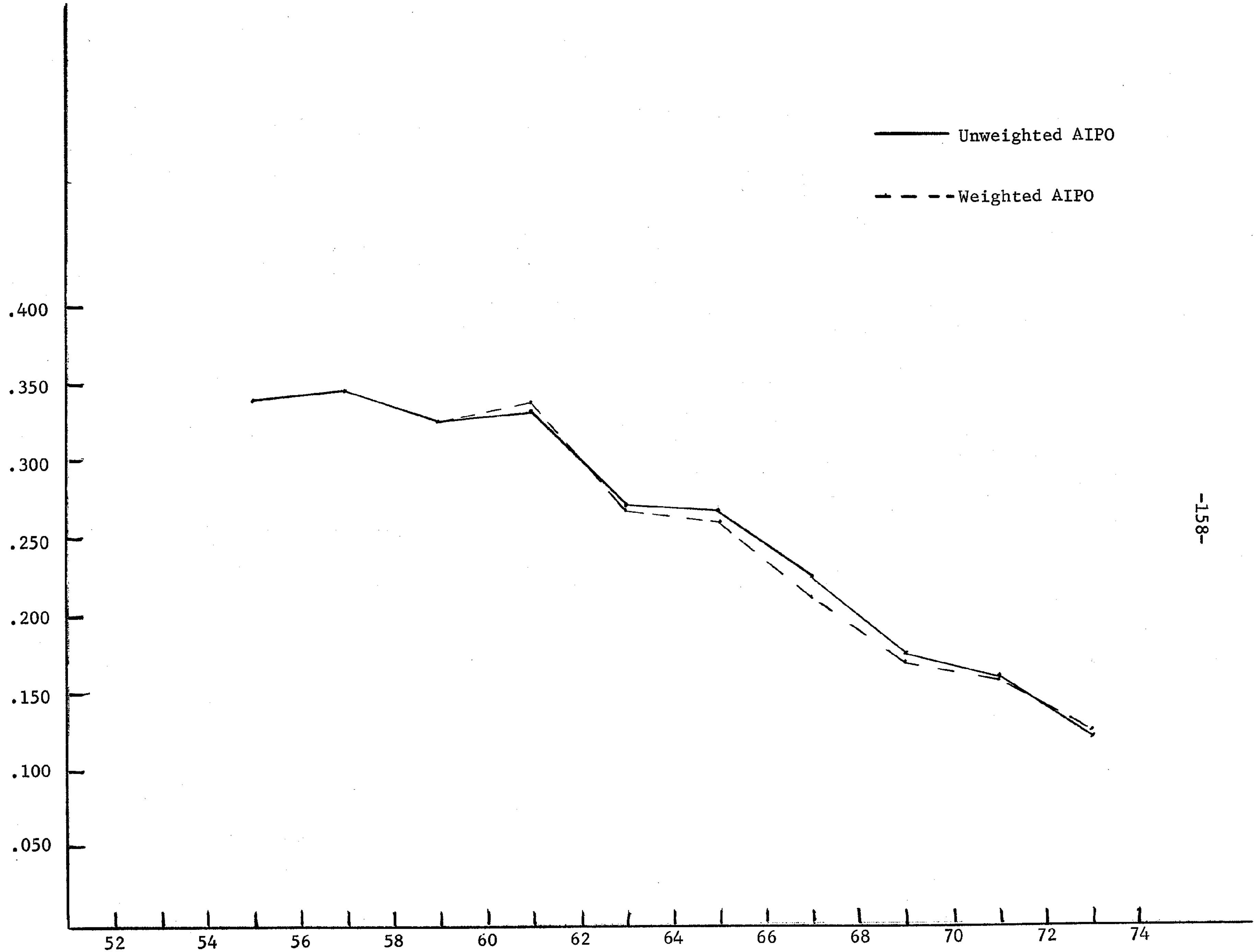

Fig. 7--Proportion of Sample in Pre-1907 Cohort

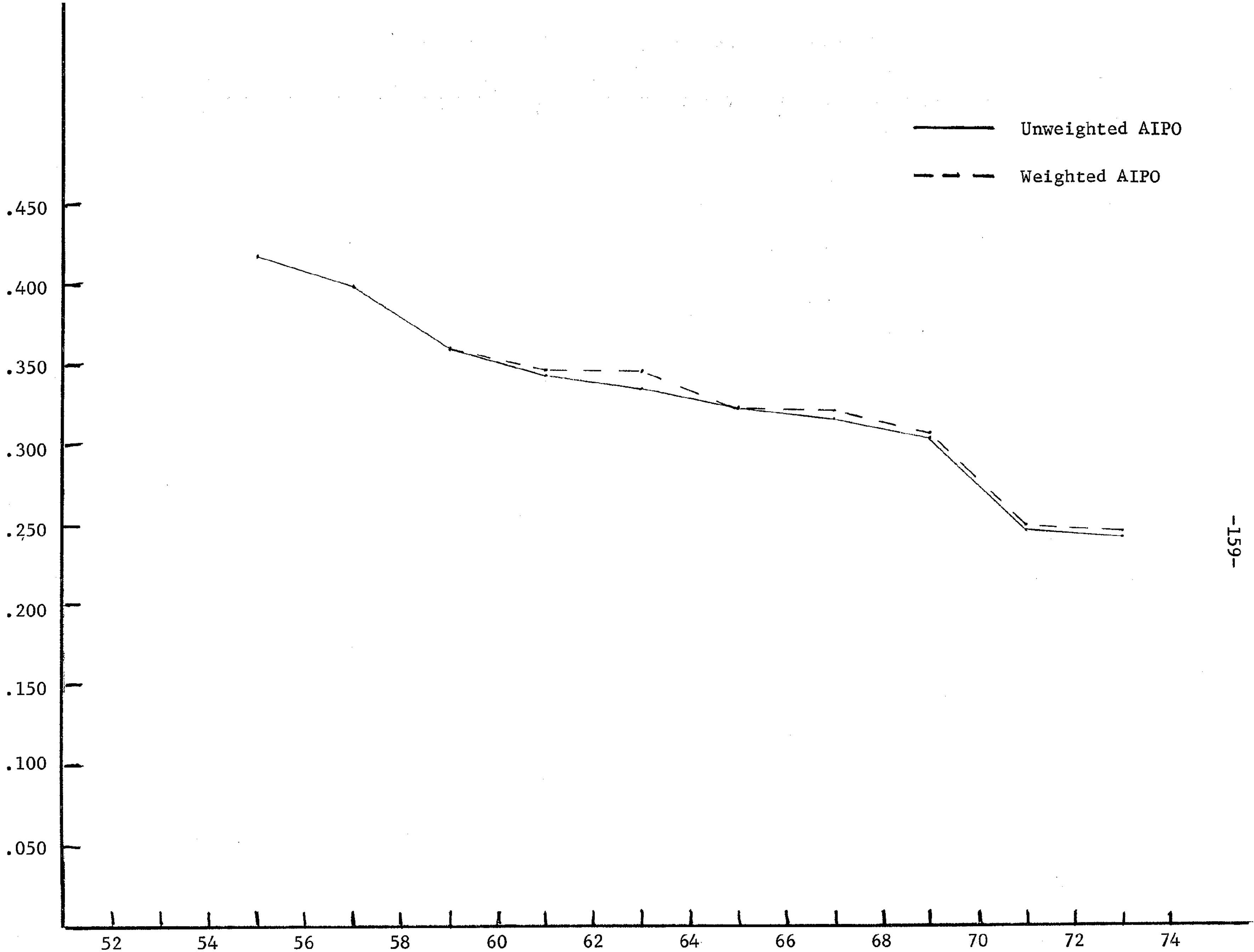

Fig. 8--Proportion of Sample in 1907-1923 Cohort

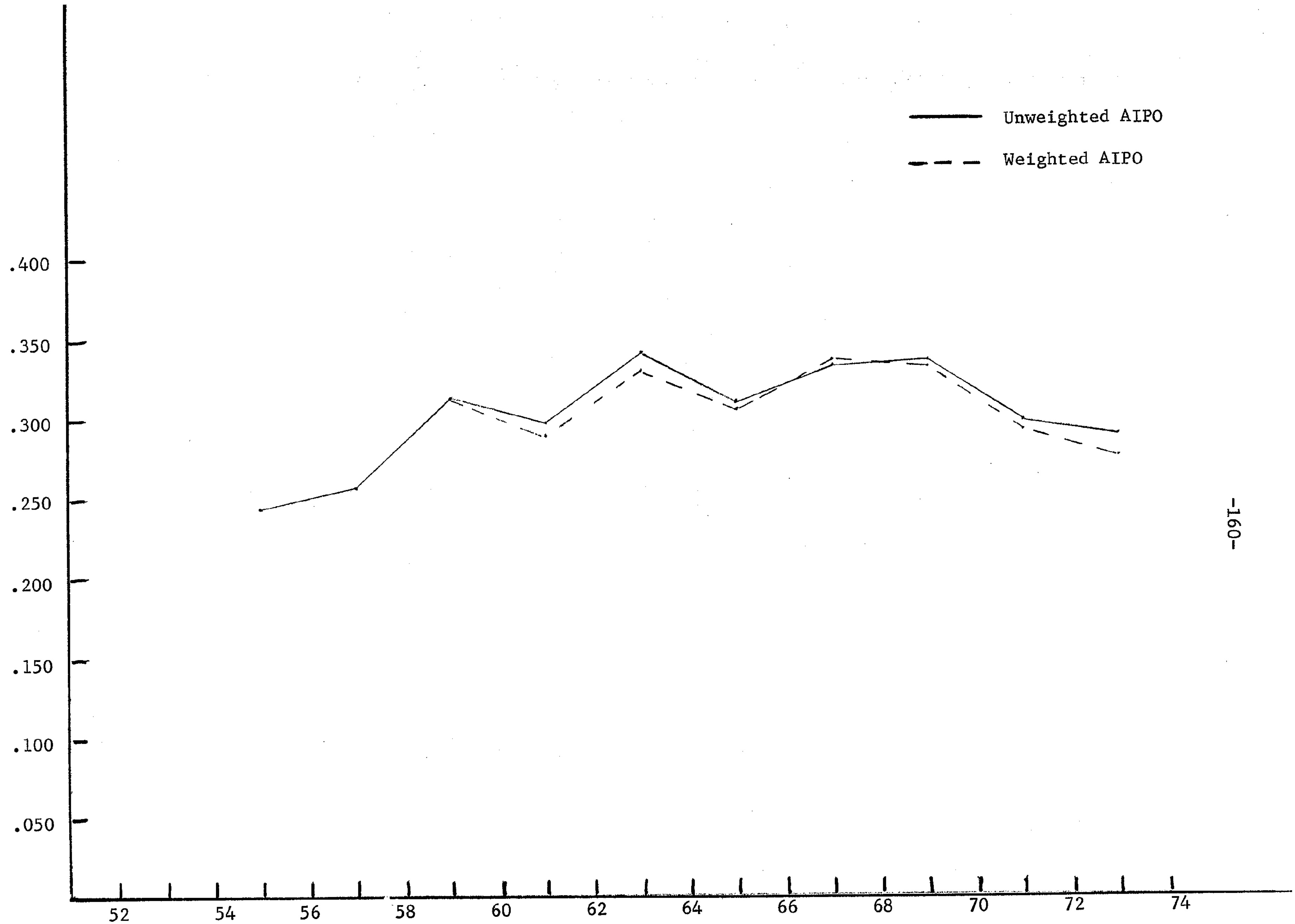

Fig. 9--Proportion of Sample in 1924-1939 Cohort

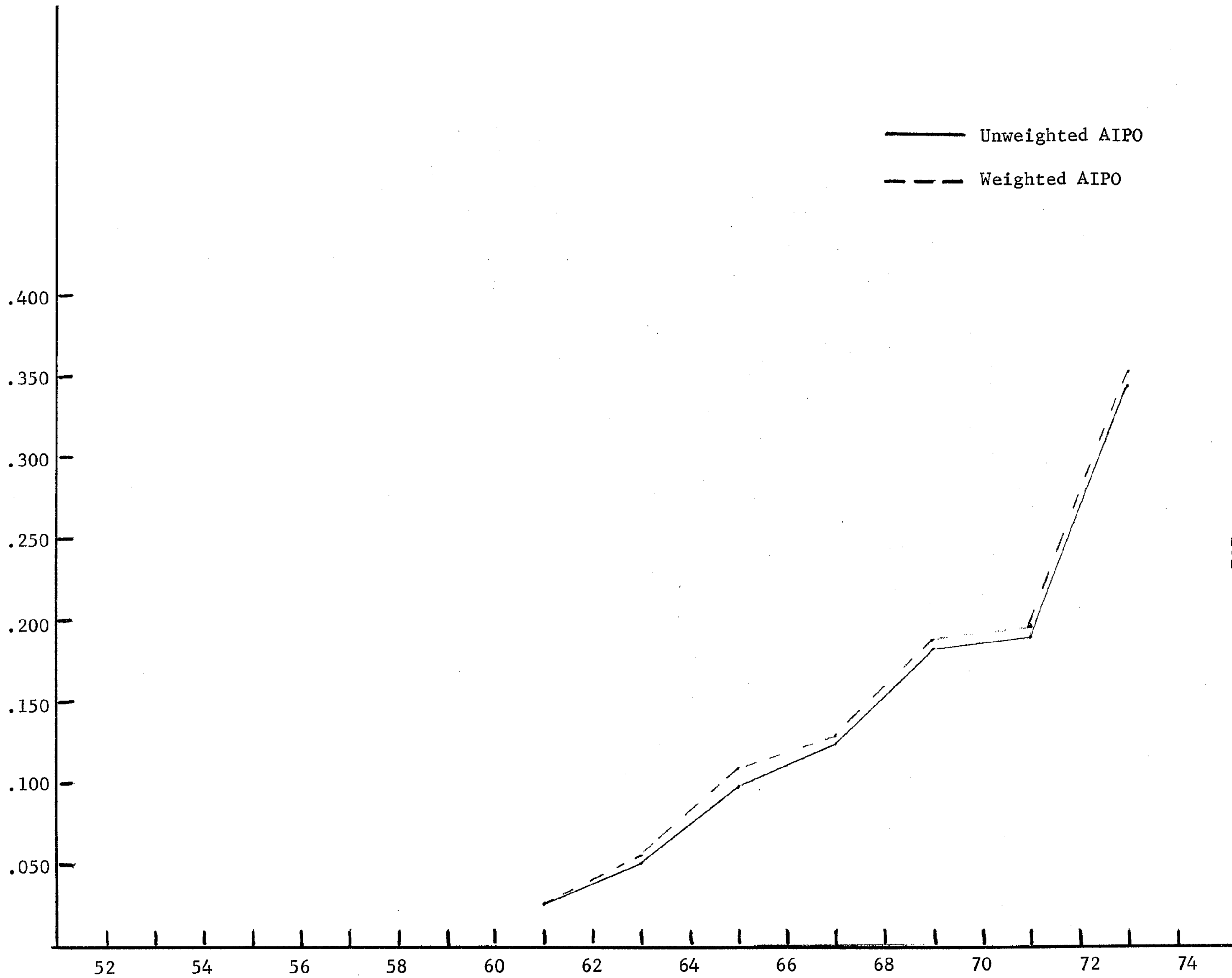

Fig. 10--Proportion of Sample in Post-1939 Cohort

TABLE 10

CHANGES IN MARGINAL DISTRIBUTION OF SELECTED BACKGROUND ITEMS CAUSED BY WEIGHTING AIPO FILES

Variable/ Category	1961	1963	1965	Year 1967	1969	1971	1973
Sex/female	.011	.019	.009	.027	.017	.017	.016
Race/non-white	.009	.005	.008	.009	.002	.003	.002
Region/South	.020	-.019	-.008	-.007	-.006	.011	-.001
Income/more than $5000	-.020	-.014	-.012	-.036*	-.007	-.008	-.005
Occ. Head/ /blue collar	.020	.032*	.060**	.017	.010	.013	.018
/not working	-.003	-.006	-.024*	-.003	-.003	-.003	.001
Religion/ /Catholic	-.003	.006	.002	.002	-.002	-.005	.003
/other or none	-.006	.004	-.002	.001	.007	.000	-.002
Party/ /Republican	-.009	-.006	.008	-.005	-.008	.000	-.010
/Independent	.000	-.004	-.004	-.001	.004	-.006	-.002

Note: * twice its standard error
** three times its standard error

Sex: male, female
Race: white, non-white
Region: non-South, South
Income: less than \$5000, greater than or equal to \$5000
Occupation of Head of Household: white collar, blue collar, not in labor force
Religion: Protestant, Catholic, other or none
Political Party: democrat, republican, independent

In all cases, the categories "no answer" and "don't know" were excluded.

It is apparent that relatively few effects are significantly different from zero in Table 10 (save the education effects shown in Table 9), though most of the variables are affected in the same way over time by weighting. The parameters shown can easily be interpreted as the increases or decrease in the proportion of the sample falling into the criterion category as a result of the use of weights. For example, we notice that weighting the sample tends to increase the proportion of persons with blue collar jobs, the change ranging from 1 per cent in 1969 to 6 per cent in 1965. Thus, in 1965 the unweighted proportion with blue collar jobs was 6 per cent less than the weighted proportion in the same category. Although we rather expected to find significant marginal shifts in income and occupation of the head of the household because of their relatively strong correlation with education, this expectation was not supported very strongly by the data.

We did the same kind of analysis on dependent variables (attitude items) in these files and found essentially no effect. Our conclusion once again, therefore, was that weighting the files does not seem to affect the distribution of responses on any items, save education.

Our last examination had to do with the effects of weighting on multivariate analysis. More specifically, we developed a "demographic model" for the years 1952 to 1973 that plots changes (and consistencies) in the relationships among cohort, sex, educational attainment, and a constructed variable representing race, region of residence, and religious preference.[7] The even years are represented

[7] See Davis (1975).

by Michigan Election Studies and the odd years by AIPO studies. We computed 26 parameters in each of the four cohorts for each year, using the AIPO studies both weighted and unweighted. In a nutshell, we found no reason whatsoever to use weights with AIPO studies. The weighted and unweighted parameters differed from each other often enough, but in no consistent manner; neither was one set consistently closer to the Election Study parameters. Finally, with regard to overall predictions, the use of weights simply made no difference. Our final conclusion was that there is nothing to be gained by weighting AIPO studies. Indeed, we felt that it was to our disadvantage to weight the files for two reasons. First, the weighted sample sizes, when corrected, are considerably smaller than the unweighted sample sizes, yielding more acute "small cell" problems than already exist in surveys of this size. Second, weighting the files is expensive and another source of error for the analyst.

For the reader who wishes to use the weights or test their impact on a particular analysis, Table 11 presents everything you always wanted to know, etc., for the studies we weighted at one time or another.

One might notice particularly the sample-size impact we have mentioned. In the studies done between 1960 and mid-1967 (numbers 646 to 744 in Table 11), the corrected weighted N is about 65 per cent of the raw N. In other words, the analyst has to throw away 35 per cent of the cases to correct for a weighted sample during these years. Given the minimal beneficial effects of weighting, this is a high price to pay. For the later studies, the analyst loses about 20 per cent of the sample by correcting for the weights, and although this is obviously less than the case loss in earlier studies, it is serious enough to question. Moreover, if one is using studies from both periods, one would have to justify weighting some files and not others. In some sense, therefore, 35 per cent case loss has to be considered in all such weighting decisions. Finally, the AIPO studies before 1960 are

TABLE 11

SUMMARY OF INFORMATION GATHERED CONCERNING AIPO WEIGHTS

STUDY	RAW N	CALCULATED WEIGHTED N	VARIANCE OF WEIGHT	CORRECTED WEIGHTED N
646	1502	3518	.507	997
649	1534	3169	.470	1043
662	1499	3360	.561	960
671	1632	3910	.611	1013
673	1658	4089	.596	1039
674	1606	3464	.547	1038
675	1573	3672	.534	1025
676	1588	3569	.574	1009
679	1635	4251	.586	1031
681	1613	4365	.697	951
704	1689	3514	.591	1062
705	1627	3493	.457	1117
709	1531	3539	.404	1090
710	1611	3452	.377	1170
712	1638	3340	.517	1080
713	1640	3574	.495	1096
730	1562	3524	.567	997
732	1503	3504	.508	997
733	1507	3548	.513	996
734	1554	3512	.521	1022
735	1597	3499	.469	1087
736	1609	3530	.507	1068
744	1505	3547	.488	1011
747	1549	3784	.159	1336
778	1607	3626	.253	1283
784	1517	3141	.231	1232
825	1561	3231	.201	1300
839	1558	3211	.238	1258
863	1508	2664	.332	1132
868	1528	2708	.318	1159

generally unweighted (or at least they must be treated as such), and again one must justify inconsistent use of weights if one is using both pre- and post-1960 studies and weighting the latter. Given all of these problems, and the dubious value of weighting the files, our experience suggests strongly that AIPO files should be used without weights. It should be clearly understood, however, that our analysis of the effects of weighting was superficial and clearly directed by our other interests; and that although it is our clear impression that weighting is not worth the trouble, it may be that it is worthwhile in another research context. We do hope, however, that we have been able to ease or eliminate the task of determining the usefulness of weights for others using AIPO studies.

APPENDIX

1. SPSS control cards necessary to weight an AIPO file that has not been previously weighted (mid-1967 to current).

A. Determine the raw and weighted sample sizes. The raw N is given in the codebook. The weighted N can be determined by multiplying each weight by the number of cases with that weight and summing over all weight values. Alternatively, one may save the weight as a variable, weight an SPSS system file, and determine the weighted N by looking at the resulting marginals. If the weight variable is called AIPOWGT, one simply weights the file by inserting the following card before the first procedure card.

```
1               16
WEIGHT          AIPOWGT
```

B. Decimalize the weight by multiplying it by the ratio of the raw N to the weighted N. To do this, create a new variable (AIPOWGT1) which results from the multiplication (assume the raw N = 1500 and the weighted N = 3200).

```
1               16
COMPUTE         AIPOWGT1=AIPOWGT*(1500/3200)
```

C. Calculate the variance of the decimalized weight.

```
1               16
CONDESCRIPTIVE  AIPOWGT1
STATISTICS      1,6
```

Statistic 1 is the mean. The user should see the mean to be sure that it is equal to one. If it is not, the ratio of raw to weighted N is probably wrong. Statistic 6 is the variance.

D. Correct the weight for the bias introduced in weighting the sample by multiplying the decimalized weight by 1/(1+ rel. var. of AIPOWGT1). Let us assume that the relative variance is equal to .365 divided by 1, or .365. A final weight variable is created as follows.

```
1               16
COMPUTE         AIRPWGT2=AIPOWGT1*(1/1.365)
```

E. Weight the file by AIPOWGT2.

```
1               16
WEIGHT          AIPOWGT2
```

If the analyst determines the weighted N by hand rather than by machine, determing the correct weights and weighting the file requires two discrete steps:

```
     1                    16
     COMPUTE              AIPOWGT1=AIPOWGT*(1500/3200)
(1)  CONDESCRIPTIVE       AIPOWGT1
     STATISTICS           1,6

     COMPUTE              AIPOWGT1=AIPOWGT*(1500/3200)
(2)  COMPUTE              AIPOWGT2=AIPOWGT1*(1/1.365)
     WEIGHT               AIPOWGT2
```

Note in step (2) that the two "COMPUTE" cards can be combined. It was shown in this manner because the first "COMPUTE" card in step (2) is the same card used in step (1).

2. SPSS control cards necessary to weight an AIPO file that has previously been weighted by card duplication (1960 to mid-1967).

A. Crosstabulate the two weights. Let us call the education weight AIPOEDUC and the times-at-home weight AIPOTAH.

```
1                    16
CROSSTAB             VARIABLES=AIPOEDUC,AIPOTAH(0,5)/
                     TABLES=AIPOEDUC BY AIPOTAH/
```

This should yield a table like Table 6. Check to make sure that all education duplicate cards are also times-at-home duplicates. The raw N can be determined from this table by subtracting the number of times-at-home duplicates from the weighted N shown in the table. In Table 6 this is 3165 - 1631 = 1534.

B. Calculate the new single weight by adding 1 to each value of each weight and multiplying them together. Then calculate the true weighted N by multiplying each cell frequency by the appropriate single weight and summing these products. Remember to exclude duplicate cases from this process.

C. Decimalize the new single weight by multiplying it by the raw N and dividing by the calculated weighted N. Let us assume that all of the education duplicates are also times-at-home duplicates and that the category for duplicate cards in the times-at-home variable is 5. The user than selects only the original cases, creates one weight from the two in the file, decimalizes the weight, and can determine its variance with the following cards. Let us assume that the raw N = 1500 and the calculated weighted N = 3200.

```
1                    16
SELECT IF            (AIPOTAH NE 5)
COMPUTE              AIPOWGT=(AIPOEDUC+1)*(AIPOTAH+1)
COMPUTE              AIPOWGT1=AIPOWGT*(1500/3200)
CONDESCRIPTIVE       AIPOWGT1
STATISTICS           1,6
```

D. Weight the file. This is accomplished in largely the same manner as shown before.

```
1              16
SELECT IF      (AIPOTAH NE 5)
COMPUTE        AIPOWGT=(AIPOEDUC+1)*(AIPOTAH+1)
COMPUTE        AIPOWGT1=AIPOWGT*(1500/3200)
COMPUTE        AIPOWGT2=AIPOWGT1*(1/1.365)
WEIGHT         AIPOWGT2
```

Thus, this weighting procedure requires 3 discrete steps.

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PROCEDURES FOR EVALUATING TRENDS IN QUALITATIVE INDICATORS

D. Garth Taylor

February 1975

The author wishes to thank John Fry for writing invaluable computer programs; Stephen Fienberg and Leo Goodman for helpful comments; and James A. Davis for assistance in all other areas.

Introduction

In this paper, we will provide methods whereby a researcher starting with a series of proportions or percentage differences collected from sample surveys over some period of time can arrive at a parsimonious description of the change (if any) in variables over that period of time. In the first section, we will consider some examples, showing the kinds of hypotheses to be tested and how to move from the simplest to more complex models for describing change. In the second section, we will discuss more fully the statistical procedures for building and testing these models.

I. Examples of Change and Change Models

When confronted with a set of proportions or percentage differences observed at various points in time, one should determine whether the values: (1) are generally zero (for differences); (2) have a constant non-zero value; (3) show a linear trend over the period of time examined; (4) show a more complex non-linear pattern of change.

Moving down this list, we see that each model is more complex than the one before it. This suggests that an appropriate strategy would be to assess the goodness of fit of the simplest model first. If this model does not describe the data, then the logical thing is to move on to the next most complicated model, continuing to do so until one has arrived at a model that "fits" the data. At each stage, then, it would be helpful to have some statistical criterion for determining whether or not the model does describe the data. If one uses the estimation procedures described in the second part of this paper, there is a chi square test for goodness of fit for each model on the list (the larger the chi square, the worse the fit). The procedure for determining the appropriate model would, then, be to start by fitting the simplest model. If the chi square for the simplest model is not significant, then the model describes the data and there is no need to continue. If the chi square is significant, the researcher is to fit the next most complex model and obtain its chi square value. The chi square will again indicate how well the model fits the data, allowing the researcher to decide whether an even more complicated model is necessary. The difference in chi square values for the various models will become useful for making statements about the statistical significance of improvement in fit given by successive models.

Consider the data in Figure 1, the plot of sex differences over time for the question: "Please tell me whether or not it should be possible for a pregnant woman to obtain a legal abortion if she became pregnant as a result of rape?"

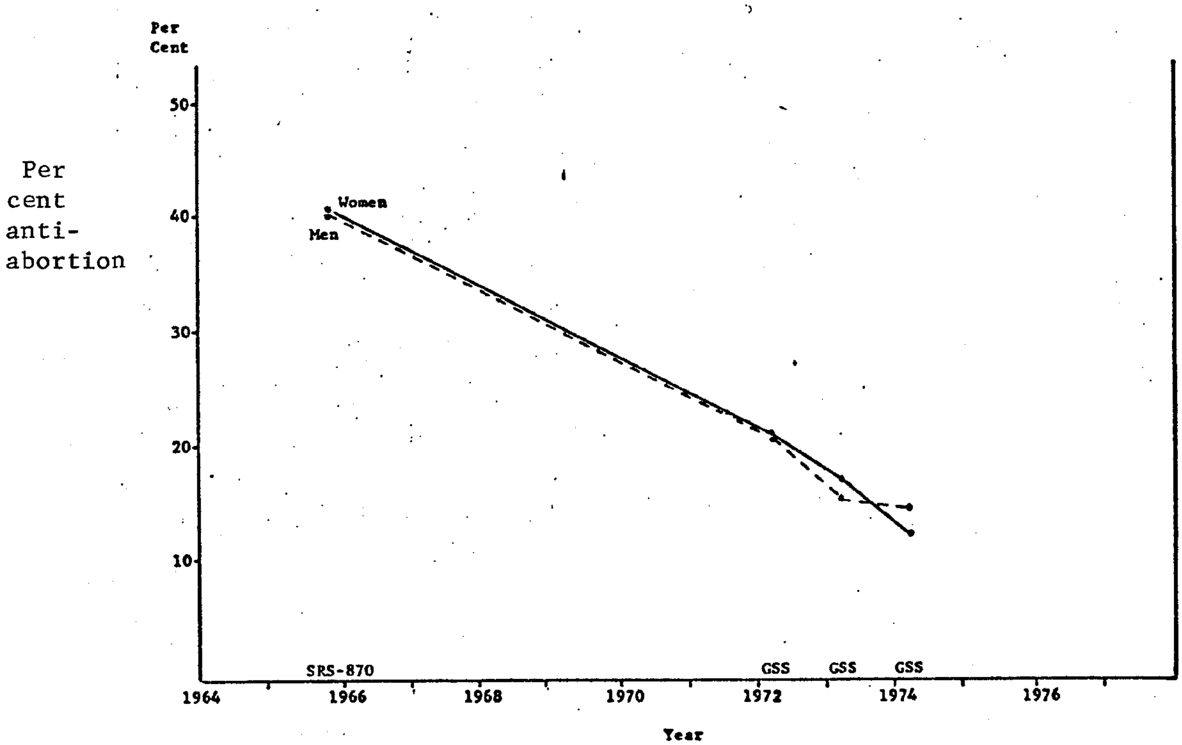

Fig.1.--Sex by Abortion Attitude: Rape

This Figure displays the results from the crosstabulation of sex by abortion attitude for four surveys conducted between 1965 and 1975 (both the raw data and the documentation for this result are presented in Table 1). We note that the overall proportion of people saying that abortion should not be allowed has been declining since 1966; there does not, however, appear to have been much of a sex difference at any time. Using the procedures outlined in the second part of this paper, we test the hypothesis that the difference between men and women on this question has always been zero and obtain a chi square value of 1.8. Since we did not estimate anything from the data, there are as many degrees of freedom as there are data points, four in this case. A chi square of 1.8 on 4 degrees of freedom is not significant at the .05 level, and so we conclude that the hypothesis (that sex differences have always been nil) adequately describes the data and that there is no need to test more complicated hypotheses.

Figure 2 presents a flow chart for the sequence of decisions that would have to be made to sequentially test the four hypotheses in any set of data.

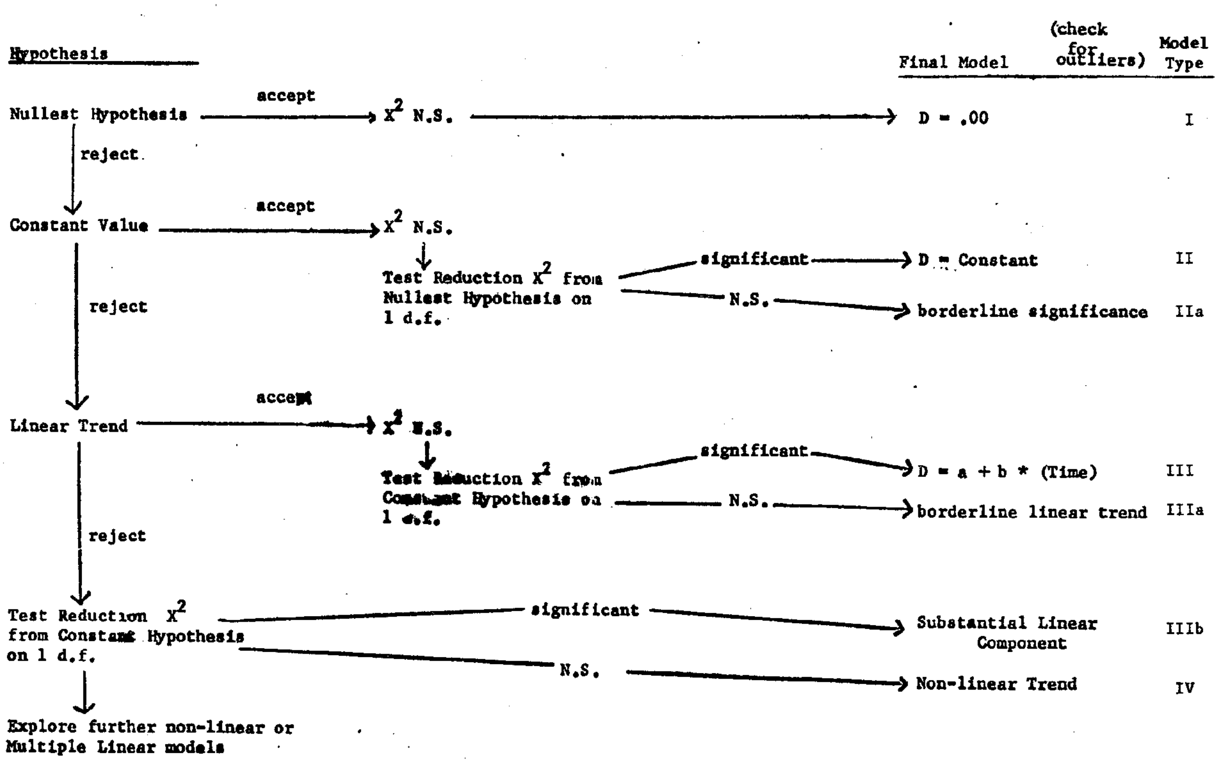

Fig. 2.--Decision Rules for Evaluating Trend Data

TABLE 1

SEX DIFFERENCES FOR ABORTION ATTITUDE: RAPE

Data				
Survey*	SRS870	GSS72	GSS73	GSS74
Date	11/65	3/72	3/73	3/74
Male:				
Per cent No	40.4	20.8	15.6	14.5
(N)	(675)	(751)	(673)	(668)
Female:				
Per cent No	40.2	21.0	17.2	12.6
(N)	(715)	(761)	(778)	(752)

Statistical Analysis

Category Difference (Base=Male)	Hypothesis	model	x^2	df	p	decision
Female	a) no difference	d = 0	1.8	4	$>.05$	accept

Final Model

Female: d = 0

*SRS870 = A survey conducted by the Survey Research Service of the National Opinion Research Center.

GSS = General Social Surveys, conducted by the National Opinion Research Center, funded by the National Science Foundation.

In the example on page 3, we started in the upper left hand corner with the "nullest" hypothesis--that the sex differences were always zero. Since this produced an insignificant chi square value, we accepted the hypothesis, which means that we believe that the small sex differences shown in Figure 1 represent sampling fluctuations around a true value of zero. For a more complicated example, we will examine the educational differences over time for the same question. The results from the four replications of this item are shown in Figure 3. (The raw data and statistical summaries are in Table 2).

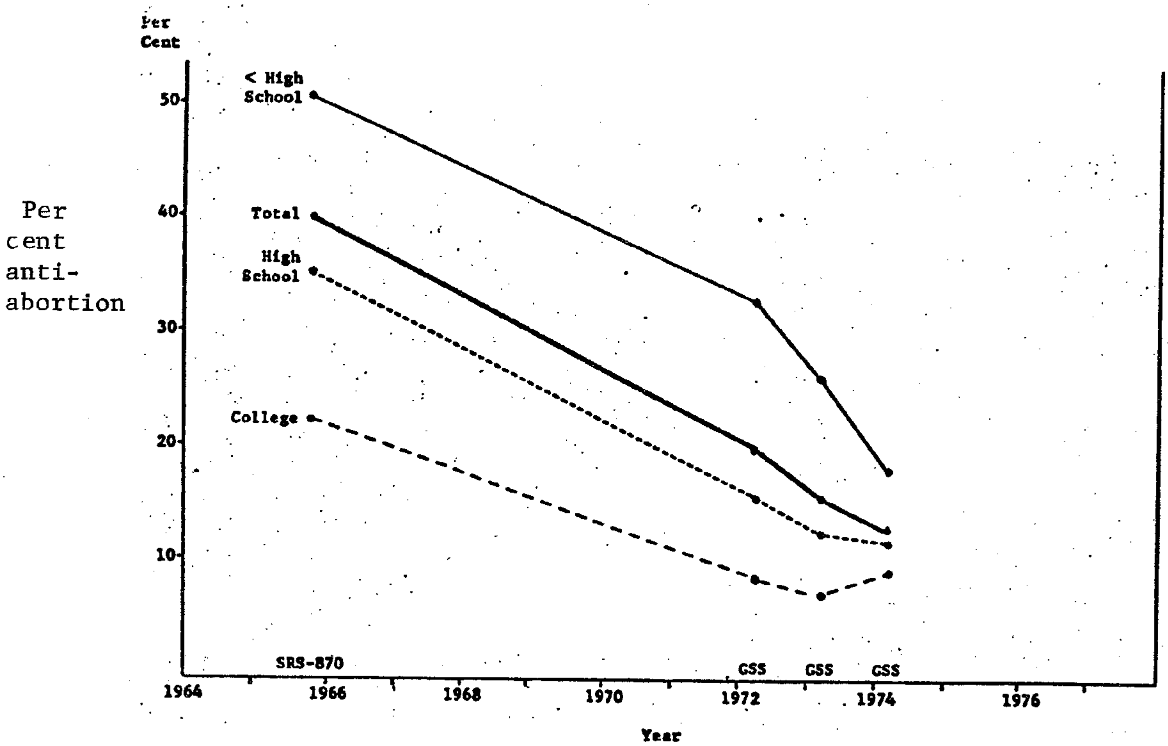

Fig. 3.--Marginals and Education by Abortion Attitude: Rape

A cursory examination of Figure 3 tells us that there have always been educational differences on this question; however, the educational groups seem to be closer together in the seventies than earlier. If the educational groups have always been the same distance apart, the final model should be a constant value for the differences. This is the model one hopes to fit if enduring subgroup differences are hypothesized. If,

TABLE 2

EDUCATION DIFFERENCES FOR ABORTION ATTITUDE: RAPE

Data

Survey	SRS870	GSS72	GSS73	GSS74
Date	11/65	3/72	3/73	3/74
Education category:				
Less than High School				
Per Cent No	50.9	33.3	26.8	18.6
(N)	(709)	(589)	(519)	(473)
High School Graduate				
Per Cent No	35.7	16.4	13.2	12.2
(N)	(342)	(477)	(470)	(426)
College				
Per cent No	23.0	9.0	7.9	9.8
(N)	(330)	(442)	(458)	(469)

Statistical Analysis

Category Difference (Base=<HS)	Hypothesis	Model	x^2	df	p	decision
High school graduate	a) no difference	d = 0	102.8	4	<.05	reject
	b) constant difference	d = dp	10.7	3	*	
College	a) no difference	d = 0	273.4	4	<.05	reject
	b) constant difference	d = dp	34.1	3	<.05	reject
	c) linear change in difference	d = a + bx	14.4	2	<.05	reject
	reduction from linear term		19.7	1	<.05	significant

Final Model

High school graduate	d = -.125	σ = .0130
College	d = -.189	σ = .0122
	d = -1.54 + .0187 (year - 1900)	

however, the educational differences are smaller in the later years than in the earlier years, then the final model should be one which shows a decrease in the percentage difference over time. This is the model one hopes to fit if the hypothesis is that group differences are disappearing (or the population is massifying, in Norval Glenn's terminology) over time.

Let us examine the difference between high school graduates and those with less than a high school education on this question. The simplest hypothesis is that this difference has always been zero. The chi square for this hypothesis is 102.8 on four degrees of freedom (see Table 2). This is clearly significant, and should not be surprising since the inspection of Figure 3 already suggested that there were large educational differences. The chi square for this hypothesis is a baseline for evaluating the contribution of more complex models. It is something like the total amount of variation to be explained in an analysis of variance.

We have rejected the nullest hypothesis and so, following the decision rules in Figure 2, we should test whether or not the difference between high school and less than high school over time can be assumed to have been a constant. Using the techniques described below, we compute a pooled estimate for the percentage difference for these data. This uses up one degree of freedom. When we test the hypothesis that all of the observed percentage differences are equal to this constant value (within the range of sampling variability), we obtain a chi square of 10.7 on three degrees of freedom. We must now ask two questions about this second model: (1) does it fit? and (2) is the pooled difference "significant"?

A chi square of 10.7 on three degrees of freedom is significant at the .05 level if the data are drawn from a simple random sample. The data in our sample, and the data from most social surveys, are drawn from multi-stage samples, not simple random samples. Such chi squares, in order to be used for significance testing, should be corrected to account for sampling procedures. (For an explanation of the reason why chi squares from multi-stage samples should not be taken at face value see Part II.) The usual correction is to divide the obtained chi square value by 2 before making significance tests (Kish 1957).

After making the correction, we obtain a chi square of 5.35 on three degrees of freedom for the hypothesis that the difference between high school graduates and those with less than a high school education has always been a constant value. The chi square is not significant, and we therefore accept the constant difference hypothesis. The answer to the first question, then, is that the model fits; we need go no further in finding an appropriate model.

The pooled difference here is -.125--that is, high school graduates are about $12\frac{1}{2}$ per cent more pro-abortion than people who didn't graduate from high school over the time series considered. The significance test for this pooled percentage difference is the reduction in chi square obtained by using the more complicated model. To find this, we take the chi square for the first model (102.8) and subtract the chi square for the second model (10.7); the reduction in chi square is 102.8 - 10.7 = 92.1. This difference is the amount of improvement accounted for by the second model. Since the second model involved estimating one parameter (the pooled percentage difference), the difference between the two models is accounted for by the one degree of freedom that we have removed from the data. The significance of the pooled percentage difference is the same as the significance of the reduction in chi square between the two models on one degree of freedom. The difference in chi square of 92.1 on one degree of freedom is significant even after the correction for multistage sampling is made. Therefore, the answer to the second question is also yes: the pooled difference is significant.

For an example where a linear model was found to be an appropriate description of change, let us look at Figure 4 and the differences between non-Baptist Protestants and Catholics in response to a different abortion question. The question was "Tell me whether or not you think it should be possible for a pregnant woman to obtain a legal abortion if the family is poor and cannot afford another child." There are very slight differences between the Gallup and NORC versions, which we will ignore for our purposes. The percentage saying "no" to this question is plotted in Figure 4 for Catholics and non-Baptist Protestants. (The data for this figure are in Table 3.) It appears that there are substantial differences between the Catholics and the Protestants. The chi square for zero difference is 94.4

TABLE 3

RELIGIOUS DIFFERENCES FOR ABORTION ATTITUDE: POOR

Data

Survey[a]	AIPO721	SRS870	AIPO788	GSS72	GSS73
Date	12/65	11/65	9/69	3/72	3/73
Protestants[b]					
Per cent No	80.6	79.4	75.3	51.5	42.8
(N)	(803)	(807)	(815)	(756)	(755)
Catholics					
Per cent No	83.8	83.2	82.6	62.1	60.3
(N)	(853)	(327)	(356)	(364)	(358)

Statistical Analysis

Category Difference (Base=Protestant)	Hypothesis	Model	x^2	df	p	decision
Catholic	a) no difference	d = 0	94.4	4	$<.05$	reject
	b) constant difference	d = dp	29.6	3	$<.05$	reject
	c) linear change	d = a + bx	.3	2	$>.05$	accept
	reduction from linear term		29.3	1	$<.05$	signif-icant

Final Model

Catholic: d = -1.34 + .021 (year - 1900)

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[a]SRS870 = A survey conducted by the Survey Research Service of the National Opinion Research Center.

GSS = General Social Surveys, conducted by the National Opinion Research Center, funded by the National Science Foundation.

AIPO721 and AIPO788 are surveys conducted by the American Institute of Public Opinion (Gallup).

[b]Protestants, not including Baptists.

on four degrees of freedom. The hypothesis that the difference is constant produces a chi square of 29.6 on three degrees of freedom; it does not fit at the .05 level. The hypothesis that the difference between non-Baptist Protestants and Catholics has been increasing over time fits the data well--the chi square is .3 and the reduction in chi square accounted for by the linear term is highly significant (29.3 on one degree of freedom). Substantively, although both groups became more pro-abortion between 1966 and 1973, the difference between Catholics and Protestants (not including Baptists) increased by about 2 per cent a year during that time.

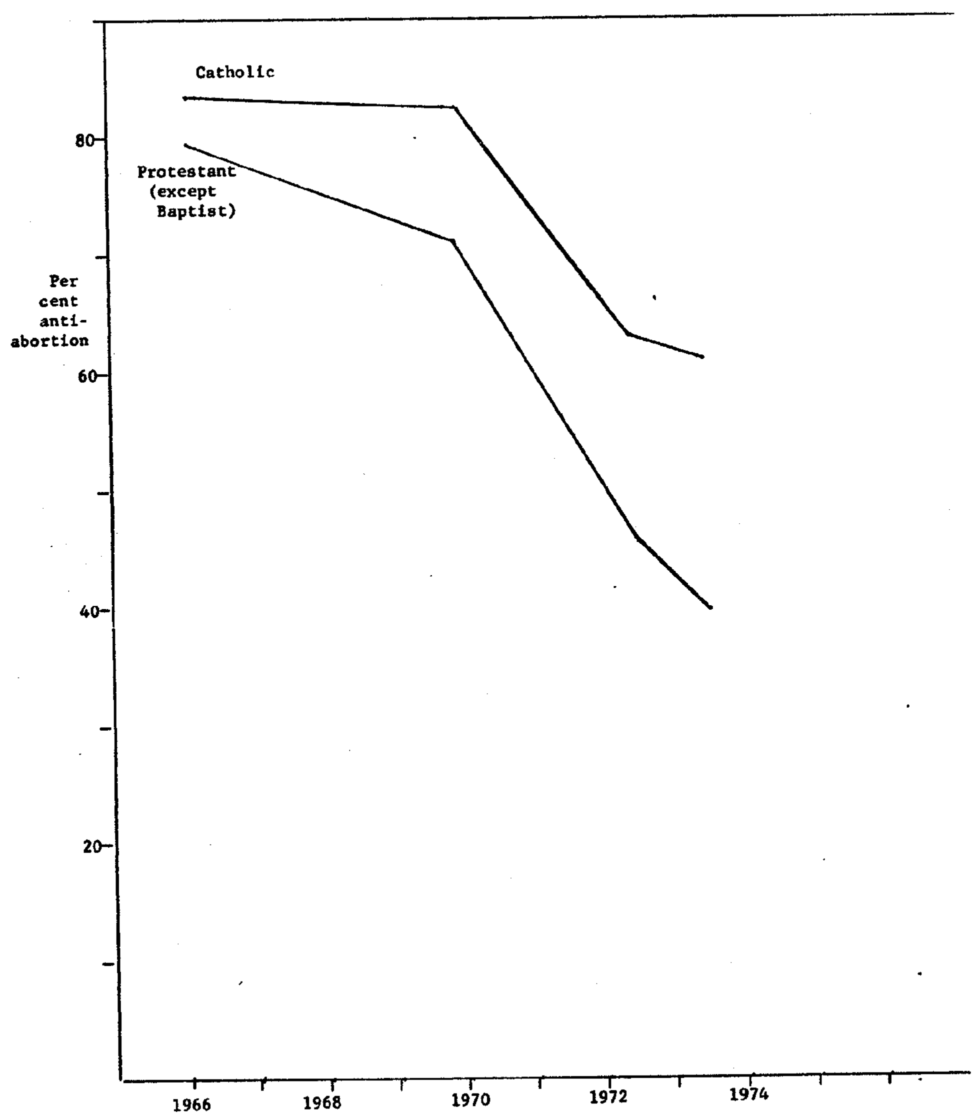

Fig. 4.--Religion by Abortion Attitude: Poor

Following the flow chart for decision rules in Figure 2, we have:

1) rejected the hypothesis that the difference was always zero (x^2= 94.4);
2) rejected the hypothesis that the difference has been constant (x^2= 29.6);
3) accepted the hypothesis that the difference has been changing linearly (x^2= .3);
4) decided that the linear component of change (slope) is significant (x^2=29.3);

and we have estimated the percentage differences to be increasing by 2 per cent a year.

So far, all of the examples have worked. Each set of data has been unambiguously classified into one of the final models in Figure 2. But results are not always so tidy. An example of data that could not be easily classified is the difference between college educated and less than high school on the first abortion question. (The data are presented in Table 2 and Figure 3.) Here, the result was that much is explained by a model of linear change, but the nonlinearity in the data is also significant. The results in this case are ambiguous. Fitting a linear model has, however, added to our understanding of the data and provides a starting point for further analysis of the residual deviations from the linear model. It is possible to use the estimation procedure outlined in Part II to fit a more complicated non-linear model and still remain within the hierarchical structure in Figure 2. Doing so, however, would require choosing from a wide array of non-linear specifications, and we will not treat this issue here. Before moving on, let us recapitulate the main points of the above discussion:

1) We have presented the rationale for and some examples of a series of nested hypotheses for describing change in qualitative indicators. The hypotheses move from simple to complex. The advantage of this technique is that the same decision criterion is used to justify each addition to the model.

2) The system described above can be used to arrive at a parsimonious model for describing change in proportions, percentage differences, or partial percentage differences over time.

3) The hierarchy of models presented encompasses many of the substantive assertions that are made about the dynamics of social change. The models are also the simplest models that can be used to describe change, and should be disproved before any more complex assumptions about change are made by the researcher.

II. Statistical Procedures

In this section, we present the details of the chi square tests--how they were computed and how the parameters for the models in Part I were estimated.

A. The Chi Square Test

The chi square test that we use is a generalization of some methods documented by Leo Goodman (1963) for comparing multiple contingency tables. Let us take as our example the correlation between religion (Catholic vs. non-Baptist Protestant) and abortion attitude at four points in time. These data were analyzed in Part I, where we found that religious differences were increasing over time. The researcher, on beginning the analysis, would be confronted with four percentage tables for these data, as presented in Table 4. Goodman says that, when presented with such a set of tables, the following steps should be undertaken to determine whether or not the percentage differences can be considered the same in all four tables:

1) Compute the percentage difference and the variance for the percentage difference for each table. For the first two rows in Table 4, the percentage difference is (.836 - .791 =) .045. The formula for the variance of a percentage is (p*(1 - p))/N. The variance for the 79.1 per cent in the first row in Table 4 is ((.791)*(1 - .791)/1943 = .000085. The variance of a percentage difference is equal to the sum of the variances for the two percentages that were subtracted to get the percentage difference. To continue the example, the variance of the 83.6 per cent in the second row is ((.836)*(1 - .836))/1180 = .00016. The variance of the difference between these two percentage is (.000085 + .000116 =) .0002. The square root of this quantity is the standard error for the percentage difference, which is reported in Table 4.

2) The second step is to compute an average or pooled percentage difference for the four tables. This procedure will be described later.

TABLE 4

RELIGIOUS DIFFERENCES FOR ABORTION ATTITUDE: POOR

Data				
Survey	AIPO721 SRS870	AIPO788	GSS72	GSS73
Date	11,12/65	9/69	3/72	3/73
Protestants				
Per cent Yes	20.9	29.1	54.7	60.5
Per cent No	79.1	70.9	45.3	39.5
(N)	(1,943)	(601)	(589)	(550)
Catholics				
Per cent Yes	16.4	17.4	37.9	39.7
Per cent No	83.6	82.6	62.1	60.3
(N)	(1,180)	(356)	(364)	(358)
Per cent difference	D = .045	D = .117	D = .168	D = .209
Standard Deviation	σ = .0142	σ = .0273	σ = .0327	σ = .0338

Statistical Analysis

pooled D = .089 σ = .011

weighted regression estimate D = -1.34 + .0209 (year - 1900)

3) The general procedure to decide whether or not all the percentage differences are the same is to compare them all with the pooled percentage difference computed in Step 2. To do this:

   a) Subtract the pooled percentage difference from the observed difference in each table, giving (D_k - pool), where k is the number of tables being compared. In our example, k = 4.

   b) For each table, square the result obtained in 3(a), giving $(D_k - \text{pool})^2$.

   c) For each table, divide the result obtained in 3(b) by the variance for the percentage difference in that table, giving:

$$\frac{(D_k - \text{pool})^2}{V_k}$$

   d) Add up, over all tables, the results obtained in 3(c) giving:

$$\sum_k \frac{(D_k - \text{pool})^2}{V_k}$$

   e) The result from 3(d) is a chi square statistic with (k-1) degrees of freedom. We lost one degree of freedom because we estimated one parameter--the pooled percentage difference. If this chi square statistic is not significant, then the hypothesis that all of the differences are approximately equal to the average difference is accepted. In our example, the chi square for this test was 29.6 on three degrees of freedom. This is significant at the .05 level, and the conclusion is therefore that the percentage differences in Table 4 are not all the same.

The procedures in this paper are an elaboration of Goodman's basic idea for significance testing. As a point of departure we note that another way of looking at the chi square statistic in 3(d) is to express it in the following language:

$$x^2 = \sum_k \frac{(\text{(observed value for a table) minus (value predicted for that table under some hypothesis)})^2}{\text{(variance of observed value)}}$$

df = (k) minus (number of parameters estimated)

The chi square that is obtained serves as the significance test for whatever hypothesis was used to generate the expected values. In our example, the hypothesis was that the D's were all equal and the predicted value for each D was the average percentage difference, which we estimated. The chi square that we obtained indicated that this was not a likely hypothesis.

In Part I, we observed that there are four important hypotheses that should be tested in evaluating trend data. Each gives different predicted values for the proportions or differences in a set of data. The following schematic diagram shows the predicted values that are generated under each hypothesis:

Schematic Diagram

Hypothesis	Predicted Values for Each Table	x^2	Degrees of Freedom
1) zero difference	zero	$\sum_k \frac{(D_k - \text{zero})^2}{V_k}$	(k)
2) constant	weighted average	$\sum_k \frac{(D_k - \text{pool})^2}{V_k}$	(k-1)
3) linear change	weighted least squares estimate	$\sum_k \frac{(D_k - \hat{D}_k)^2}{V_k}$	(k-2)

These models are hierarchical in two important aspects: (1) moving down the list, each model is more complex than the one above it; and (2) if weighted estimation procedures (described below) are used, each model is included in the one below it. It is these two properties that allow the procedures for evaluating trend data to be systematized as they are in Figure 2.

B. Estimation

For the hypothesis of zero difference, there is no estimation involved. The hypothesis assumes a priori that the expected value for each table is zero. Since nothing is estimated, there is no reduction in degrees of freedom. The value of zero is plugged into the chi square test for each table and the resulting fit of this model is assessed on k degrees of freedom.

The hypothesis of a constant difference is the one documented in Goodman's paper. To test this hypothesis, we must estimate one parameter, the average difference.[1] Our criterion for the goodness of fit of the model is a chi square statistic that divides the squared deviation of the observed value from the predicted value by the variance of the observed value. If an observed value has a large variance (usually because of a small case base), then its deviation from the average predicted value will contribute less to the chi square statistic than the deviation for a difference that has a much smaller variance. This mathematical result leads to the following principle of estimation which is used for estimating models that use chi square measures for goodness of fit.

In estimating the parameters for a model, less weight should be given to observations that have larger variances--that is, estimation procedures should weight observations inversely proportional to their variance. These estimates are better than just taking the simple average.

The steps for obtaining the weighted estimate for an average percentage difference are, as described by Goodman:

1) Start with the percentage difference and variance for each table, as before.

[1]With very slight, straightforward modifications, these procedures can be applied to proportions, percentage differences, or partial percentage differences. The language of the discussion here will be in terms of percentage differences.

2) Take the reciprocal of the variance in each table and add these values up, giving:

$$\sum_k \frac{1}{V_k}$$

3) The weight that will be assigned to each difference for computing the average is defined as the reciprocal of the variance for that difference divided by the result in (2). Therefore, the weight for the difference in each table is:

$$W_k = \frac{\frac{1}{V_k}}{\sum \frac{1}{V_k}}$$

4) The weighted average percentage difference that is used to test the hypothesis of a constant difference is the sum of the weight for each table times the difference in each table, giving:

$$D_{avg} = \sum_k W_k * D_k$$

5) The variance for this weighted average, taking a result from Kish (1965) is:

$$V' = \sum (W_k)^2 * V_k$$

Next, we consider linear models. When we hypothesize a linear trend in percentage differences, we must use the same weighting strategy in estimation in order to stay within the hierarchical structure of models in Figure 2. That is, we want a linear regression where each observation is weighted as inversely proportional to its variance. Some readable explanations of how to do this appear in econometrics texts (e.g., Wonnacot and Wonnacot) under discussions of weighted least squares or heteroscedasticity. We will attempt only an intuitive explanation of the procedure here.

The object of a regression analysis is to fit a line to a set of points. The line gives the predicted value for each point. In a study of change, each survey gives one data point. The hypothesis we want to test is that the results from the several surveys are changing systematically over time. We will need some criterion for goodness of fit to decide whether or not our model of change adequately describes the data. It would be advantageous to use the same kind of chi square test we have been using all along so that we can avoid problems associated with having different criteria of goodness of fit for different kinds of models. This means that we should compare the data from a given survey with the result predicted from the regression model and divide by the variance of the observed percentage difference. Results from surveys with large variances (caused by small N's, different sampling procedures, and the like) should have less weight in estimating the model since they contribute less to the measure of goodness of fit. In the language of regression, we do not want to minimize the squared deviations from the model--rather, we want an estimation procedure that minimizes the weighted squared deviations from the regression line, where the weights are defined as before (Step 3).

The formulas for the weighted least squares estimates for a regression of a set of percentage differences on time are (Draper and Smith, 1966:81):

Regression Model: Difference = a + b * (Time)

Estimates:

$$b = \frac{\sum_k W_k * (D_k - \bar{D}) * (T_k - \bar{T})}{\sum_k W_k * ((T_k - \bar{T})^2}$$

$$a = \bar{D} - b * \bar{T}$$

where

W_k = the weight for each percentage difference as before

D_k = the percentage difference in the k^{th} survey

$\bar{D}$ = the simple mean of the D_k

T_k = the time (year and month) of the k^{th} survey

$\bar{T}$ = the mean of the T_k

The discerning regressionist will observe that the difference between these estimates and the ordinary least squares estimates is in the weights in the numerator and the denominator of b. These same weighted least squares principles could apply to estimating more complex models of change if the researcher wanted to stay in this framework of a hierarchical reduction in chi square for each level of complexity added to the model.

C. Outliers

After going through the various estimation procedures and chi square tests in the flow chart in Figure 2, it is a good idea to check the data for outliers before reporting a final model. When comparing surveys over time, outliers are a distinct possibility. "Wild observations" can come from slight differences in question wording or interviewer instructions, differences in sampling procedures from study to study or among survey organizations, or from mechanical errors in processing old studies with incomplete documentation. There does not seem to be an unambiguous procedure for spotting outliers, but the following rule is consistent with much of the literature (Anscombe and Tukey, 1963; Tukey, 1962): An individual observation may be considered an outlier if the chi square for the deviation of that observation from the modeled estimate is too large.

This means that the chi square for testing whether a particular observation is an outlier is:

$$\frac{((\text{observed value}) - (\text{estimate under the model}))^2}{(\text{variance of the observed value})}$$

$$df = \frac{(\text{degrees of freedom in the model})}{(k)}$$

A conservative decision rule is that an observation should be considered an outlier if the chi square for that observation (corrected for sampling procedures) is greater than the chi square for .05 significance on one degree of freedom (3.84).

D. Correction for Sampling

Almost no national survey that has been done has sampled according to a simple random design, yet practically every statistic that has been computed from these survey data has been based on the assumption that the data were drawn from a simple random sample. The problem with this can be most succinctly put this way: the variance estimates are wrong, they are usually too small.

If a sample has been drawn using clustering, weighting, quota, or multistage procedures, it is necessary to increase the usual estimates of the variance by a factor known as the design effect (Kish, 1965: 162). Under some sampling procedures (multistage, clustering, or weighting), the design effect is theoretically knowable; under other procedures (quota) the design effect is not even theoretically knowable. Empirical studies have been carried out on this question and Kist (1957: 159) reports that "For most national surveys of the SRC the actual variances are from 1 to 2 times as great as the [variances obtained using simple random sampling formulas.]"

The rules that we present for deciding on the appropriate model for describing change are based on a chi square test that uses estimates of the variance for proportions or percentage differences. Since the true variance of the statistics we are reporting is expected to be up to twice as large as an estimate based on simple random sampling formulas, a conservative rule would be to divide each chi square statistic obtained by two before making judgments of significance.

E. A Final Methodological Detail

When applying the program of decision rules in Figure 2 it is sometimes possible to arrive at a negative chi square for the contribution of an added parameter. For example, if the chi square for the constant model were 20.8 and the chi square for the linear change were 21.8, we would take the difference and find that the introduction of the linear term accounted for -1.0 chi square, a nonintuitive result. This is not because of rounding error or a fault in the logic of the system. The reasons for this result lie in the distribution theory for these statistics and the fact that the methods we propose here are "approximate" methods (Leo Goodman, personal communication). If this result is observed, it would be best to assume that the added parameter did not add significantly to the explanatory power of the model (e.g., the chi square was zero for the contributions of the linear term in this paragraph).

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STUDIES OF SOCIAL CHANGE SINCE 1948

Report of the NORC Social Change Project

Volume II

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CONTENTS

INTRODUCTION

This is one of two reports on the first two years work of the NORC "Social Change Project" (NSF Grant No. GS-38534).

The Social Change Project is closely tied to NORC's General Social Survey, an annual sampling of the U.S. adult population for the years 1972 through 1977 (NSF Grant No. SOC73-05504A02). By design, the majority of the questions in the General Social Survey are repeated each year and are of the baseline replication type where the item has been used in national surveys prior to 1972. This means that one can both follow short-run changes in the seventies and compare current patterns with the results in the prior baseline surveys. The aim of the Social Change project has been to collect as many of the baseline measures as possible and to analyze changes in selected content areas during the period from the early 1950s to the early 1970s.

As of July 1975, the project staff had obtained some 200 data sets for national surveys in which approximately 400 questions have been repeated since the late 1940s. Most of the surveys have been put in SPSS system-file form, and a computerized index has been developed to locate files with particular items and combinations of items.

Because the project is large, diffuse, and continuing, we have not attempted to produce a single, integrated report. Instead, we have collected various reports and working papers and organized them into two volumes:

Volume I: Methodology. A set of papers on statistical techniques useful for working with survey change data and methodological findings that have emerged from the analyses so far.

Volume II: Substantive Results. A collection of reports dealing in detail with specific areas of change such as Party Identification, Tolerance of Nonconformists, Subjective Social Class, and the like.

Both volumes, as well as individual papers (for the cost of duplication), can be obtained from the NORC Library, 6030 South Ellis Avenue, Chicago, Illinois 60637.

Although the papers have designated authors, the project required the coordinated effort of a large number of people. In addition to the project authors--James A. Davis, Principal Investigator; Rebecca G. Adams, Gregory Gaertner, Karen Newman Gaertner, Thomas Smith, Aaron Wade Smith, and D. Garth Taylor--major contributions were made by: John Fry, Programmer and Research Assistant; Patrick Bova and David Cook of NORC's Library; Susan Campbell, Paige Wickland, and Sylvia Piechocka, Editorial Department; Susan Rand, Mary Lawson, and Ellen Kaufman, Research Assistants; Toshi Takahashi, Mary Okazaki, and Irene Edwards of the NORC Steno Pool; Rita Hinckley, Administrative Assistant to the Director, NORC; and Edmund D. Meyers, Jr., Director of Computation Services.

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James A. Davis

BACKGROUND CHARACTERISTICS IN THE U.S. ADULT POPULATION 1952-1972: A SURVEY-METRIC MODEL

James A. Davis

May 1975

Karen Newman Gaertner, John Fry, D. Garth Taylor, Gregory Gaertner, Tom W. Smith, and A. Wade Smith contributed almost two years of tedious statistical and computer work that made this report possible. I am greatly indebted to their care, hard work, and imagination.

Introduction

We here consider the crosstabulations of Age (Cohort), Sex, Region, Race, Religion, and Educational Attainment in 30 national surveys from 1952 to 1973.

Why?

1) To study the "attainment process" as a dynamic system; that is, to see how social differences in Educational Attainment changed during the first two-thirds of the twentieth century.

2) To show how "d-systems" (Davis, 1976) can be used to construct models using categorical data that are analogous to econometric models.

3) To provide a tool for examining sample biases in national surveys.

Variables and Model

The first variable is Cohort, or respondent's age recoded to year of birth (more exactly, reported age at interview subtracted from the year of the study). To use Year and Cohort is an arbitrary but nontrivial decision, because Year, Cohort, and Age have a tricky interlock. If we know any two, the other is determined. (If the respondent was born in 1900 and was interviewed in 1960, he must have been age 60 at the time of the interview.) Consequently, we cannot generally introduce Age, Cohort, and Year (often called Period) as separate variables in the same analysis (see Mason, 1973). The choice of excluded variable is arbitrary. We chose to keep Year because it seemed odd to study social change and exclude year. We chose to keep Cohort to make sure that at least one variable in the model would change appreciably over 20 years. Of necessity, Age will disappear, but we can keep our eyes open for trends associated with later years and earlier cohorts, and these can just as easily be described as Age effects. We grouped the cases into four cohorts, as shown in Table 1.

To form the grouping we simply worked with the data (prior to running any crosstabulations) until we got reasonable case bases across the study period, 1952-1973. Although the cuts are arbitrary, we can

TABLE 1

AGE COMPOSITION OF COHORT GROUPS, 1947-1974

Year	Cohort			
	Vietnam	World War II	Dep.	World War I
1974	18-34	35-50	51-67	68+
1973	18-33	34-49	50-66	67+
1972	18-32	33-48	49-65	66+
1971	18-31	32-47	48-64	65+
1970	18-30	31-46	47-63	64+
1969	18-29	30-45	46-62	63+
1968	18-28	29-44	45-61	62+
1967	18-27	28-43	44-60	61+
1966	18-26	27-42	43-59	60+
1965	18-25	26-41	42-58	59+
1964	18-24	25-40	41-57	58+
1963	18-23	24-39	40-56	57+
1962	18-22	23-38	39-55	56+
1961	18-21	22-37	38-54	55+
1960		21-36	37-53	54+
1959		21-35	36-52	53+
1958		21-34	35-51	52+
1957		21-33	34-50	51+
1956		21-32	33-49	50+
1955		21-31	32-48	49+
1954		21-30	31-47	48+
1953		21-29	30-46	47+
1952		21-28	29-45	46+
1951		21-27	28-44	45+
1950		21-26	27-43	44+
1949		21-25	26-42	43+
1948		21-24	25-41	42+
1947		21-23	24-40	41+

give the four categories some verisimilitude as follows:

World War I. The oldest cohort consists of persons born in 1906 or earlier. At an extreme, the handful of respondents 80 and older in the 1952 study were born in 1872 or before and reached age 16 in 1922 or before.[1]

Interwar. The Interwar Cohort was born between 1907 and 1923 and reached age 16 between 1923 and 1939, the boom and depression years between World War I and World War II.

World War II and Korea. The third cohort was born between 1924 and 1939 and reached age 16 between 1940 and 1955. Their critical years for Educational Attainment span the period from World War II through the Korean war.

Vietnam. The youngest group, those born in 1940 and after and reaching age 16 in 1956 and after, did not become eligible for sampling until the early 1960s. By the end of the decade, however, they were becoming a substantial portion of the adult population, as will be shown later.

For the Vietnam Cohort we dropped the lower age to 18 from 21 because national surveys moved their age limit to 18 with the advent of the "18 year old vote." (The Constitutional Amendment was ratified in 1971.) In a biological sense the Vietnam cohort is artificially larger than its predecessors, but adulthood was actually increased sociologically (or at least politically) by three years during the late 1960s in the same way that cities have grown by annexing adjacent suburbs.

The second variable is Sex, Male and Female.

The third variable combines Race, Region, and Religion into a typology, or "social stereotypology" (stereotype). For the rationale,

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[1] In terms of the Attainment process it is useful to consider the year in which these groups reached age 16--near the time they decided whether or not to complete High School.

we begin with Table 2, the crosstabulation of Region (Census South vs. All Other or "North"), Race (White vs. Nonwhite) and Religion (Protestant, Catholic, Jewish, Other, and None and No Answer), combining all cases from 10 Michigan Election studies, 1952 to 1972.

The variables are strongly associated: Catholics are predominantly (84.5 per cent) Northern Whites; most Nonwhites (73.5 per cent in the North, 92.8 per cent in the South) are Protestants; Southern Whites are strongly (87.1 per cent) Protestant.

To avoid small cell sizes, to finesse problems of causal ordering, and for simplicity, the 16 cells in Table 2 are collapsed into a sixfold typology in Table 3.

"Yankees" (39 per cent), Northern Catholics (18 per cent), Northern Blacks (5 per cent), Southern White Protestants (23 per cent), Southern Blacks (5 per cent), and All Other (9 per cent) will be treated as a single six-category nominal variable.

The fourth variable is Educational Attainment, trichotomized as Less than High School Graduate, High School Graduate, and More than High School.

Figure 1 shows how these variables are specified as a d-system model. The model is specified within Cohort (i.e., there are four submodels) because statistical analysis shows many of the coefficients vary significantly from Cohort to Cohort. This is one of the main empirical results and will be described in detail later.

Within each Cohort group we take Sex and Stereotype as prior and Education as the dependent or sink variable. The diagram shows double-headed arrows between Sex and Stereotype since they have no plausible causal order. Statistical analysis, however, shows that Sex is unrelated to Stereotype in any Cohort. We will, therefore, end up with a "Simon-Blalock" model with a zero coefficient that enables us to avoid choosing a causal direction for these two variables. The d-system approach requires that one category of each variable be choosen as a "base" or reference point (Davis, 1976). We chose Male for Sex, Yankee for Stereotype, and Less than High School for Education.

TABLE 2

REGION, RACE, AND RELIGION, 1952-1972 POOLED

Region	Race	Protestant	Catholic	Jewish	Other, None No Answer	Total
North	White	6,790	3,125	463	576	10,954
	Nonwhite	639	169	1	60	869
South	White	3,963	368	43	176	4,550
	Nonwhite	830	35	0	29	894
		12,222	3,697	507	841	17,267

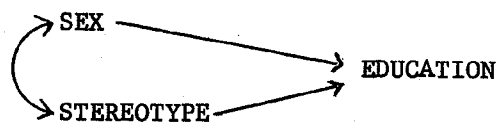
TABLE 3

DATA FROM TABLE 2 IN TYPOLOGY

Group	Region	Race	Religion	N	Proportion
Yankees	North	White	Protestant	6,790	.393
Northern Catholics	North	White	Catholic	3,125	.181
Northern Blacks	North	Black	Any	869	.050
Southern White Protestants	South	White	Protestant	3,963	.230
Southern Blacks	South	Black	Any	894	.052
Other		any other		1,626	.094
			Total	17,267	1.000

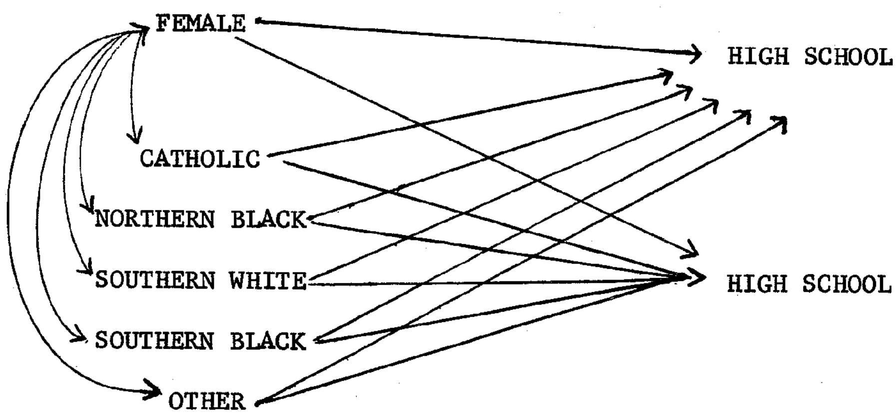
(a) Schematic

<u>Within Cohort</u>



(b) Categories

<u>Within Cohort</u>



Base Categories: Sex = Male; Stereotype = Yankee; Education = Less Than High School.

Fig. 1--D-System Model for Background Variables

The system is thus set up to pose these questions: How did the Educational Attainments of Yankee Males change from Cohort to Cohort? How did the Educational Attainments of Women and members of various ascriptive social groups compare with those of Yankee Men? How have these Attainment differences changed from Cohort to Cohort? To what extent has Cohort turnover increased or decreased social differences in Educational Attainment?

Data

To estimate the parameters in the model we used 30 national surveys spread over the years 1952 to 1973. Ten are University of Michigan election year studies for the even years 1952 to 1972 (save for 1954 when only a token survey was fielded); the remaining twenty, two a year in odd years are American Institute of Public Opinion (Gallup) surveys [2] (no 1953 AIPO file was available in the project files when analysis began).

The Michigan studies are multistage area probability samples with predesignated respondents. The AIPO studies are multistage area probability samples with quotas applied at the final level.[3] All are designed to represent the adult U. S. population living in non-institutional quarters. Although the designs differ in terms of textbook sampling theory the two sets "should" give similar results for similar questions. Therefore, we will pool all 30 sets in the analysis, while keeping a weather eye open for systematic differences between odd and even years.

Table 4 lists the files, dates, and N's.

Estimating the Parameters

All numbers (source values, arrow coefficients, intercept constants) in the model are proportions, p's, or differences in proportions, d's. In each survey the values are estimated from cross-

---

[2] Michigan studies were obtained through the courtesy of the Interuniversity Consortium for Political and Social Research; the AIPO studies were provided by the Roper Public Opinion Research Center, Williamstown, Massachusetts.

[3] For a discussion of AIPO sampling designs, see Hastings, 1975, Appendix A-1.

TABLE 4

STUDIES AND N's

Year	Michigan Election Series	AIPO Study Number	N
1973		863, 868	2,987
1972	x		2,679
1971		825, 839	3,056
1970	x		1,621
1969		778, 784	3,083[a]
1968	x		1,608
1967		744, 747	2,992[a]
1966	x		1,278
1965		710, 713	3,214[a]
1964	x		1,631
1963		671, 675	3,168[a]
1962	x		1,284
1961		646, 649	3,008[a]
1960	x		837
1959		610, 614	3,069
1958	x		1,282
1957		586, 589	3,014
1956	x		1,730
1955		543, 546	3,052
1954			
1953			
1952	x		1,763
Total	10	20	46,356

[a] Original files are weighted in terms of "times at home" and Education. For this analysis the files were adjusted to remove the weights (i.e., to count each case in the file equally).

tabulations, as explained in Davis (1976). In addition, we must decide whether--across the twenty years of studies--each value: is always zero (for d's, not, of course, for p's); is always some constant, $\hat{d}$ or $\hat{p}$; show a linear trend; or shows a nonlinear trend. The statistical rationale, drawing on results in Goodman (1963), is given in an appendix to this paper. Assuming the reader to be familiar with the Appendix, we proceed to consider the estimates.

Cohort

Table 5 gives the Cohort proportions, 1952 to 1973. The figures document the facts of life. Proportions in the World War I and Interwar Cohorts decline steadily, while proportions in the two younger groups increase.

Table 6 reaches the same conclusions in a more rigorous fashion. To illustrate the techniques explained in the Appendix, we will walk through the numbers in some detail.

Row 1 gives the pooled proportions, $\hat{p}$, estimated as a weighted average of the yearly proportions, with weights inverse to the estimated sampling variance of each proportion.[3]

Row 2 with its large chi squares and small probabilities shows that none of the series can be fitted with its constant, $\hat{p}$.

Row 3 tells us what happens when we try to fit the four series with linear trend lines, using weighted least squares, with weights for each year inverse to the sampling variance. Taking each Cohort in turn:

> The data for World War I do not fit ($p < .01$). Inspection of the computer output, presenting the contribution of each year to the total chi square, however, showed that 1955 contributed

---

[3]N's in Table 2 were applied along with the sample proportions (p) and (1-p). Since the studies are multistage (cluster) samples, textbook formulas will tend to underestimate the sampling variances (Kish, 1957). Using the common empirical rule of thumb that clustered variances are twice as large, the computer was programmed to multiply all estimated variances by 2 (or, when relevant, all standard deviations by 1.414) here and throughout the analyses in this paper.

TABLE 5

PROPORTION IN EACH COHORT

Year	World War I	Interwar	World War II and Korea	Vietnam
1973	.121	.245	.290	.345
1972	.144	.250	.276	.329
1971	.161	.249	.299	.290
1970	.176	.278	.279	.266
1969	.175	.306	.337	.183[a]
1968	.211	.304	.319	.165
1967	.225	.318	.334	.124[a]
1966	.226	.333	.310	.131
1965	.267	.324	.312	.096
1964	.252	.342	.334	.073
1963	.272	.336	.342	.050
1962	.298	.354	.323	.024
1961	.333	.344	.298	.025[a]
1960	.326	.378	.296	-
1959	.325	.361	.314	-
1958	.332	.397	.271	-
1957	.344	.399	.257	-
1956	.335	.412	.252	-
1955	.338	.418	.244	-
1954	-	-	-	-
1953	-	-	-	-
1952	.431	.410	.159	-

[a]Outlier in Table 4.

TABLE 6

STATISTICAL TESTS FOR DATA IN TABLE 3

Result	Cohort						
	World War I				Vietnam		
	Total	(-1955)	Interwar	WW II and Korea	Total	(-1961 and 1967	(-1961, 1967, 1969
1) $\hat{p}$	.238	.233	.328	.290	.091	.117	.112
2) Test B							
Chi Square	920.7	849.5	328.2	219.6	1786.5	1408.2	136.0
Prob.	<.001	<.001	<.001	<.001	<.001	<.001	<.001
3) Test C							
Chi Square	36.2	23.4	17.6	144.9	83.8	26.8	11.4
Prob.	.007	.138	.515	<.001	<.001	<.002	.182
4) Test B-C							
Chi Square	884.5	826.1	310.6	74.7	1702.7	1381.4	124.6
Prob.	<.001	<.002	<.001	<.001	<.002	<.001	<.001
5) r^2	.957	.969	.943	.321	.961	.979	.989
6) b	-.0135	-.0142	-.0090	+.0041	+.0256	+.0288	+.0295
7) Type	IIIb	III	III	IIIb	IIIb	IIIb	III

11.127 to the total chi square of 36.2. After removing this apparent outlyer (second column from the left), we get a nice fit for the linear estimates, with the probability of .138 and an r^2 of .969.[4]

The Interwar estimates give a "classic" type III or linear trend result, with Test C producing a probability of .515 and and r^2 of .943.

The World War II and Korea data give a bad linear fit (probability for Test C = <.001), although the B-C test shows significant improvement. Inspection of the raw data in Table 5 tells us why: the trend is curvilinear. Proportions in this cohort increase from 1952 to 1969, but decrease afterwards.

The Vietnam Cohort gives a bad fit on the initial run. After removing 1961 and 1967 (with individual chi squares of 17.783 and 19.487) we get some improvement and finally obtain linear fit after removing 1969, which had an individual chi square of 13.589 on the second run. (Readers nervous about plucking outliers will note the consequences are merely to change the regression slopes in the third decimal.)

Three of our four series show quite reasonable linear trends (see the r^2's in row 5 of Table 6). To avoid curve fitting, we can obtain the World War II and Korea proportions by subtraction. Thus, equations for the four Cohort proportions, 1952 to 1973:

$$P_{\text{World War I}} = 1.17 - .0142 * (\text{Year}-1900) \quad (1)$$

$$P_{\text{Interwar}} = .91 - .0090 * (\text{Year}-1900) \quad (2)$$

$$P_{\text{Vietnam}} = -1.81 + .0295 * (\text{Year}-1900) \quad (3)$$

$$P_{\text{World War II and Korea}} = 1.00 - [\ (1) + (2) + (3)\ ] \quad (4)$$

(Equation 3, of course, should not be applied for years prior to 1962, since it will give negative proportions.)

---

[4] r^2's were computed from unweighted regression since we were in a hurry and we weren't sure how to obtain them from our weighted regression computer program. Weighted and unweighted regressions give virtually identical results since the N's are spread out evenly across the study years.

Equations 1 through 4 have two uses. Technically, they enable one to produce estimated cohort distributions for any year one chooses, perhaps to check other data sets against the model--perhaps for simulations of the sort presented later in this paper. Substantively, they document perhaps the strongest social change in America in the last twenty years. While the coefficients look small, a steady decrease of 2.3 per cent each year (.0142 + .0090 = .0232) in the older cohorts--and hence a 20-year increase of 46 per cent--represent a massive change, at least by comparison with other parameters in the model. Table 7 illustrates and gives one some "feel" for the fit of the estimates.

In 1952, 87.4 per cent of the adult population came from cohorts born in 1923 and before. By 1972, 59.0 per cent were from cohorts born after 1923, and almost a third (31.4 per cent) were from cohorts reaching age 16 in 1956 and after. The changing of the guard is not total (the groupings were chosen to prevent this), but it is substantial.

Sex

The second parameter to be estimated is the proportion Female within each cohort. Table 8 gives the raw figures.

Table 9 summarizes the statistical analysis of sex composition over time within the four cohorts.

The Interwar and Vietnam results are clearly of the type designated Case II in the Appendix. We can fit the data handily with pooled constants of .519 for Interwar and .542 for Vietnam.

For the World War I cohort, things are more complex. On the first run, the data fell in Case IV (i.e., significant fluctuations across the years but no linear trend). Inspection of the raw numbers in Table 8 suggests differences between the odd years (AIPO) and the even ones (Michigan). Analyzing the two groups separately confirms this impression. The AIPO results can be fitted by a constant, $\hat{p}$ = .451. The Michigan data hover between a constant, $\hat{p}$ = .552, and a linear trend. Parsimony argues for the constant, but demography (sex differentials in mortality in the later ages) suggests the linear trend is more apt, and we chose the latter.

TABLE 7

COHORT PROPORTIONS IN SELECTED YEARS

Cohort	Source	Year 1952	1962	1972
World War I	Raw Data	.431	.298	.144
	Equations	.432	.290	.148
Interwar	Raw Data	.410	.354	.250
	Equations	.442	.352	.262
World War II and Korea	Raw Data	.159	.323	.276
	Equations	.128	.339	.276
Vietnam	Raw Data	-	.024	.329
	Equations	-	.019	.314

TABLE 8

PROPORTION FEMALE BY COHORT AND YEAR

Year	World War I	Interwar	World War II and Korea	Vietnam
1973	.460	.479	.538	.527
1972	.622	.581	.552	.542
1971	.460	.504	.544	.505
1970	.588	.550	.531	.599
1969	.423	.480	.543	.534
1968	.562	.541	.577	.568
1967	.408	.478	.551	.580
1966	.553	.548	.550	.577
1965	.480	.519	.541	.542
1964	.580	.509	.564	.537
1963	.471	.518	.539	.554
1962	.561	.510	.588	.432
1961	.474	.528	.545	.557
1960	.532	.533	.590	
1959	.449	.498	.579	
1958	.493	.534	.571	
1957	.450	.537	.590	
1956	.514	.552	.605	
1955	.431	.521	.571	
1954				
1953				
1952	.543	.527	.565	

TABLE 9

STATISTICAL TESTS FOR DATA IN TABLE 5

Result	World War I Total	World War I SRC	World War I AIPO	Interwar	WW II and Korea	Vietnam
1) $\hat{p}$	.486	.552	.451	.519	.558	.542
2) Test B						
Chi Square	74.3	10.5	7.7	20.3	10.7	8.8
Prob.	.001	.310	.568	.501	.968	.990
3) Test C						
Chi Square	78.1	4.8	7.7	19.6	6.0	8.3
Prob.	.001	.779	.532	.353	.996	.689
4) Test B-C						
Chi Square	-	5.7	0.0	0.7	4.7	0.5
Prob.	-	<.02	N.S.	>.30	<.05	>.30
5) r^2	.023	.611	.001	.023	.427	.029
6) b	+.0018	+.0039	.0000	-.0009	-.0024	-.0018
7) Type	IV	II ? III ?	II	II	II-III	II

Why the odd-even difference? We do not know for sure, but suspect that the quota element in the AIPO samples may force a constant sex composition in all age groups, whereas the full-probability methods in the Michigan series allow the changing sex composition in the oldest cohorts to come through.

The results for the World War II and Korea Cohort are also a bit ambiguous. A constant $\hat{p}$ of .558 fits very well, but there is a significant ($p < .05$) linear trend, a decrease in females over time. Sticking with demography against parsimony, we opt for the constant.

We are now ready to state the next four parameters in the model: the proportion Female in each of the cohorts.

$$\text{World War I Cohort} = .31 + .0039 * (\text{Year} - 1900) \qquad (5)$$

$$\text{Interwar Cohort} = .519 \qquad (6)$$

$$\text{World War II and Korea Cohort} = .558 \qquad (7)$$

$$\text{Vietnam Cohort} = .542 \qquad (8)$$

<u>Stereotype</u>

To add the third variable, the Region-Race-Religion typology, we must examine: (a) correlations between Sex and Stereotype categories in each cohort; and (b) the intercept values (i.e., the Stereotype category proportions for males in each cohort).

Luckily there is no association between Sex and Stereotype in any of the Cohort groups. When we ran the percentage differences for Female vs. Male by Northern Catholic, Northern Black, Southern White Protestant, and Other we found that $\hat{d}$ = .000 fits the data in each Cohort-by-Year data set. Substantively, this confirms one's expectation that sex ratios are identical in subcultural groups. Technically, it absolves these survey houses from the occasional allegation they under-represent black males. Methodologically, it allows us to use Sex and Stereotype in the same model without worrying about causal direction.

The results for the "intercepts" are rather interesting but need some explanation for readers unfamiliar with d-systems. Consider, for example, Figure 2, the results for Sex and Stereotype in the Interwar Cohort. For the moment we take the numbers at face value without worrying about how they were estimated. We arbitrarily treat Sex as the prior variable with a value of .519 (Eq. 6). In theory there should be arrows running from Female into each of the five non-base categories, but we know their values to be zero, so we leave them out. The technique requires each category of the second variable to have an intercept value, namely the proportion in the category for those in the base category of the source (i.e., men). Thus, the .211 intercept value for Catholic means that .211 of the males in the Interwar Cohort are Northern White Catholics.

To find the total proportion Catholic following flow graph principles, we multiply the source value times its arrow and add the residual--(.519 * .000) + (.211) = .211. That is, the intercept values are estimates of the marginal proportions for the Stereotype groups in the special case where the second variable is independent of the first.

When the intercept proportions were run across years within Cohorts, all 20 runs (five non-base categories of Stereotype by four Cohort groups) fell in Case II. Thus, the data show constant Stereotype proportions over time within Cohorts. Table 10 summarizes.

In the absence of interactions we can estimate the standard deviations of the sampling distributions of the $\hat{p}$'s (as explained in Davis, 1976; see also Footnote 3 of this paper). These are shown below and to the right of the pooled proportions. If we now think of each row in Table 10 as a set of k proportions with known standard deviations, we can use the techniques explained in the Appendix to test whether the proportions are homogeneous; that is, whether the Stereotype categories are independent of Cohort.

The four Catholic proportions are not homogeneous (chi square for Test B = 75.7 for 3 d.f.). However, when the .153 value for World War I is removed, the other three do not differ significantly from p = .211 (chi square = 1.6, p = .667). Presumably, these results reflect the direct and indirect contributions of turn-of-the-century immigration, such that the Northern Catholic proportion increased .058 in Cohorts born after 1906.

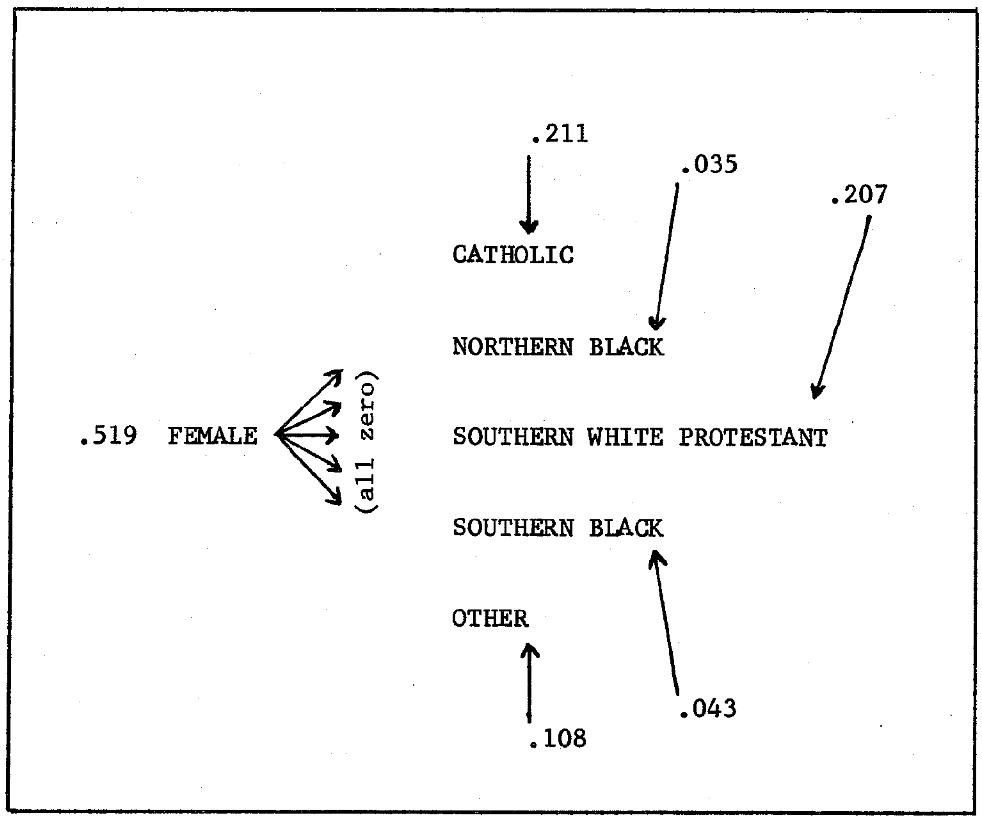


Fig. 2--Sex and Stereotype Group Within
Interwar Cohort

TABLE 10

INTERCEPT VALUES FOR STEREOTYPOLOGY

Category	Cohort							
	World War I		Interwar		World War II and Korea		Vietnam	
	$\hat{p}$	$\sigma\hat{p}$	$\hat{p}$	$\sigma\hat{p}$	$\hat{p}$	$\sigma\hat{p}$	$\hat{p}$	$\sigma\hat{p}$
Catholic	.153	.0065	.203	.0066	.214	.0075	.211	.0089
Northern Black	.026	.0029	.035	.0030	.048	.0039	.038	.0055
Southern White Protestant	.224	.0075	.207	.0067	.195	.0072	.191	.0112
Southern Black	.049	.0039	.045	.0034	.038	.0035	.042	.0058
Other	.101	.0054	.110	.0051	.113	.0058	.190	.0112
Yankee (by subtraction)	.447		.400		.392		.328	

Proportions for Northern Black vary significantly among cohorts (chi square = 21.0, $p < .001$), showing a general but not perfect pattern of increase from earlier to later cohorts. The increasing proportion Northern Black in the population presumably reflects the epochal migration of southern blacks to northern cities under the impetus of industrialization and war-induced economic opportunities.

The proportion for Southern-White-Protestant (.224, .207, .195, .191) are significantly heterogenous (chi square = 9.9, $p = .019$) and show a pattern of steady, albeit small, declines.

For Southern Blacks, the four proportions are homogeneous. The pooled value, $\hat{p} = .043$, fits the data (chi square = 4.7, $p = .192$).

The residual category, Other, is not homogeneous (chi square = 52.5, $p < .001$). When, however, the Vietnam Cohort value, $\hat{p} = .190$, is removed, the other three are easily fitted with the constant, $\hat{p} = .108$ (chi square = 2.6, $p = .536$). The proportion Other was a steady .108 until the Vietnam Cohort, where it jumped to .190. Since Other is a melange of Jews, Southern White Catholics, Other Religions, and No Religion, this trend is difficult to interpret. Project staff who have worked closely with the raw data suspect that an increased proportion of "No Religion" in the youngest Cohort is the main factor, but no hard evidence has been evaluated.

We can now add the following parameters for Stereotype Intercept Values to the model:

Catholic	(if Cohort = WWI)	= .153	(9a)
	All other	= .211	(9b)
Northern Black	(World War I)	= .026	(10a)
	(Interwar)	= .035	(10b)
	(World War II)	= .048	(10c)
	(Vietnam)	= .038	(10d)
Southern White Protestant			
	(World War I)	= .224	(11a)
	(Interwar)	- .207	(11b)
	(World War II)	= .195	(11c)
	(Vietnam)	= .191	(11d)
Southern Black		= .043	(12)
Other	(All Other)	= .108	(13a)
	(Vietnam)	= .190	(13b)

To find a theme in these 13 numbers, let us calculate the proportion Yankee in the four cohorts by summing the category intercepts and subtracting their total from 1.000. Thus, Table 11.

Because other categories increase in newer cohorts, the proportion Yankee (Non-Southern White Protestant) must decline. In the Cohorts born in 1906 or earlier, .446 were Yankees and two-thirds (.670) were White Protestants. By the time we reach persons born in 1940 and after, Yankees had dropped to .327 and White Protestants to .518.

Equations 9a-13b and Table 11 underline a rather dramatic aspect of American social history in this century. At the turn of the century something like two-thirds of the population was White Protestant and 45 per cent were in the Yankee subculture that has dominated American life from the Pilgrim Fathers to Richard Nixon. Under the onslaughts of Catholic immigration, black fertility, and in the case of other possibly rapid secularization, the figures among the youngest adults are rather different: one third Yankee and a scant half (.518) White Protestant.

Education

To analyze Educational Attainment, its association with Cohort, and its relationship with Sex and Stereotype, we begin with the intercept values--the Educational Attainment of those Lords of Creation, Northern White Protestant Males. Table 12 gives the raw data.

The proportions are "constant" across time (as one would expect, since relatively few persons add substantial schooling during the adult years) and quite different among cohorts (each pair of adjacent proportions at the bottom of Table 12 is significantly different.) Table 13 helps us see the pattern.

In the World War I Cohort (persons reaching age 16 in 1922 or before), two-thirds (.687) failed to complete High School; of those who did complete High School, about half went on to a year or more of College.

TABLE 11

IMPLIED PROPORTIONS IN 9a-13b

Cohort	Yankee	Southern White Protestant	Total White Protestant
World War I	.446	.224	.670
Interwar	.396	.207	.603
World War II	.395	.195	.590
Vietnam	.327	.191	.518

TABLE 12

INTERCEPT VALUES FOR EDUCATION
(Proportions among Yankee Males)

Year	High School				College			
	World War I	Interwar	World War II	Vietnam	World War I	Interwar	World War II	Vietnam
1973	.143	.242	.414	.382	.167	.341	.345	.455
1972	.110	.296	.307	.368	.096	.278	.474	.488
1971	.280	.365	.466	.504	.160	.189	.317	.307
1970	.170	.481	.354	.400	.132	.182	.378	.422
1969	.163	.324	.421	.481	.114	.258	.273	.405
1968	.105	.337	.434	.409	.140	.297	.368	.500
1967	.142	.408	.404	.400	.213	.279	.335	.475
1966	.109	.205	.230	.414	.152	.288	.328	.552
1965	.185	.314	.407	.548	.180	.276	.313	.310
1964	.145	.325	.352	.353	.203	.265	.375	.294
1963	.226	.444	.366	.346	.164	.213	.354	.423
1962	.175	.300	.340	.455	.105	.243	.358	.455
1961	.171	.371	.399	.385	.163	.254	.286	.462
1960	.113	.473	.238	-	.094	.236	.381	-
1959	.175	.350	.390	-	.187	.230	.349	-
1958	.146	.416	.414	-	.180	.303	.343	-
1957	.137	.353	.393	-	.149	.188	.246	-
1956	.184	.365	.417	-	.149	.222	.264	-
1955	.155	.356	.412	-	.151	.189	.247	-
1952	.119	.263	.236	-	.155	.234	.327	-
1) p	.158	.344	.381	.425	.155	.239	.324	.415
2) σ	.010	.013	.014	.026	.010	.011	.014	.025
3) Test B								
Chi Square	12.4	23.4	16.3	5.6	8.3	13.6	13.7	9.4
Prob.	.928	.322	.751	.999	.993	.885	.882	.986
4) Type	I	I	I	I	I	I	I	I

TABLE 13

EDUCATION AND COHORT FOR WHITE, NORTHERN, PROTESTANT MALES

(Modeled Data)

Education	Cohort			
	World War I	Interwar	World War II and Korea	Vietnam
College	.155	.239	.324	.415
High School	.158	.344	.381	.425
Grade School[a]	.687	.417	.296	.150
	1.000	1.000	1.000	1.000

[a]By subtraction.

For the Interwar Cohort (persons reaching age 16 between 1923 and 1939), High School completion increased .270 (.687 - .417 = .270). However, only 41 per cent of these High School Graduates went on to College (.239/.239 + .344 = .410), possibly because of the Great Depression, though we have no hard evidence on this. Consequently, the College proportion increased .084.

For the World War II Cohort (persons reaching age 16 between 1940 and 1955), there was another jump in High School completion (.417 - .296 = .121) and a return to the "half college" proportion among High School Graduates. This gives a group spread that is essentially even across the three categories of Education and a .101 increase in College.

For the Vietnam Cohort (persons reaching age 16 in 1956 and after), High School completion shows further growth (.296 - .150 = .146) and the College-High School ratio is again close to 50-50.

This extraordinary improvement in Educational Attainment is, of course, familiar, but one is always impressed with the figures. For example, the proportion of High School "drop outs" in the Vietnam Cohort is about the same as the proportion of College attenders in the World War I category!

We can now add the following parameters (education intercept values) to the model:

HIGH SCHOOL =	(World War I)	.158	(14a)
	(Interwar)	.344	(14b)
	(World War II and Korea)	.381	(14c)
	(Vietnam)	.425	(14d)
COLLEGE =	(World War I)	.155	(15a)
	(Interwar)	.239	(15b)
	(World War II and Korea)	.324	(15c)
	(Vietnam)	.415	(15d)

Now let us see how the numbers work out for Americans who are Female, instead of Male, or in Stereotype groups other than Yankee. Table 14 gives the estimates for Sex differences.

TABLE 14

D's FOR SEX AND EDUCATION

	Cohort			
	World War I	Interwar	World War II and Korea	Vietnam
High School				
1) $\hat{d}$	+.055	+.048	+.113	+.085
2) $\sigma\ \hat{d}$	.009	.010	.012	.018
3) Test A				
Chi Square	42.9	31.7	112.4	24.5
Prob.	.005	.083	.001	.322
4) Test B				
Chi Square	7.3	9.3	17.2	4.2
Prob.	.997	.987	.698	.999
5) Type	II	II	II	I
College				
1) $\hat{d}$	+.011	-.037	-.097	-.137
2) $\sigma\ \hat{d}$	.009	.009	.010	.018
3) Test A				
Chi Square	13.4	26.1	102.4	62.0
Prob.	.921	.248	.001	.001
4) Test B				
Chi Square	11.8	7.5	11.1	5.7
Prob.	.945	.997	.960	.999
5) Type	I	I	II	II

The first row in Table 14 gives the pooled sex difference in High School within Cohort and across years. For example, the +.055 in the left-hand column means that Females were 5.5 per cent more likely to report High School than Males, averaged across typology groups and years, within the World War I Cohort.[5]

For High School, all four d's are positive. Women are consistently more likely to report High School graduation. The d for Vietnam is not strictly significant (Prob. for Text A = .322), but we will keep it on the basis of comparison with Census data (to be discussed later). The d's are not homogeneous (chi square = 21.9, $p < .001$ for Test B), but fall into two clumps. We can fit the data nicely with d's of +.052 for World War I and Interwar and +.105 for World War II and Korea. Thus:

$d_{\text{Female-High School}}$ =

(Interwar and World War I)	+.052	(14a)
(World War II and Korea and Vietnam)	+.105	(14b)

For College, the d's form a progression from virtually zero to negative; that is, men and women showed no difference in proportion College in the World War I group, but in later cohorts women were less likely to report College (chi square = 93.7, $p < .001$ for Test B on the $\hat{d}$'s). We decided to take the Interwar $\hat{d}$ at face value, although it is not significant, giving the following:

$d_{\text{Female-College}}$ =

(World War I)	.000	(15a)
(Interwar)	-.037	(15b)
(World War II and Korea)	-.097	(15c)
(Vietnam)	-.137	(15d)

To interpret these findings we can add Yankee Females to the modeled data in Table 13, obtaining the results for Females by adding or subtracting the appropriate values from Equations 14a through 15d. The results appear in Table 15.

---

[5]With three variables, Sex-Stereotype-Education, the question of interaction effects arises, but they turned out to be negligible in the data sets we ran. In the dozens of conditional d's run for this section of the analysis, only six significant interactions occurred (applying Test B across conditions rather than times) and they showed no consistency across years or effects.

TABLE 15

EDUCATION, SEX, AND COHORT FOR WHITE NORTHERN PROTESTANTS

Education	Sex	Cohort: World War I	Interwar	World War II and Korea	Vietnam
College	Male	.155	.239	.324	.415
	Female	.155	.202	.227	.278
Female	d	.000	-.037	-.097	-.137
High School	Male	.158	.344	.381	.425
	Female	.210	.396	.486	.530
Female	d	+.052	+.052	+.105	+.105
Grade School	Male	.687	.417	.296	.150
	Female	.635	.402	.287	.192
Female	d	-.052	-.015	-.009	+.042
College, along High School, and College	Male	.495	.410	.460	.494
	Female	.425	.338	.318	.344
Female	d	-.070	-.072	-.142	-.150

The third row, Grade School, is a good place to begin. We see that in the World War I Cohort Females were <u>more</u> likely to be graduated from High School (d = .052), but their advantage declines with later cohorts and reverses for the Vietnam group. Thus, a traditional educational advantage of Females over Males has eroded and possibly reversed.

Turning to the proportion of High School Graduates going on for one or more years of College (estimated by the proportion College divided by the sum of College and High School), we see negative signs (Female High School Graduates are less likely to go on to College) and increasing magnitudes (the feminine deficit is stronger in the newer cohorts). However, for reasons discussed below, we should not take the difference between -.097 and -.137 too seriously.

Since the Female advantage in High School has eroded and the Female disadvantage in College among High School Graduates has increased, the result is a sharp, progressive growth of the Sex difference in College.

In absolute terms Female Educational Attainments have improved steadily from Cohort to Cohort, but not as fast as Male Attainments. Consequently, the relationship between Sex and Education has shifted from curvilinear (Males more likely to drop out of high school and more likely to enter college) to a clear-cut Male advantage.

Next, let us apply the same analysis to the five Stereotypology groups: Northern Catholics, Northern Blacks, Southern White Protestants, Southern Blacks, and Others. The detailed statistical results will not be presented to save space; instead, Table 16 gives the final estimated coefficients after applying the tests in the Appendix to the time series data (finding no time trends within cohorts) and then testing the intra-Cohort effects for homogeneity.

To interpret the figures, let us look at High School Completion, summing the coefficients for College and High School to get differences in High School Completion between Yankee Males and those in various other Stereotype categories (Table 17). Beginning with the proportions and reading across the rows of Table 17, we see a steady increase in High School for all groups. In particular, the two Black groups move

TABLE 16

COEFFICIENTS FOR TYPOLOGY AND EDUCATION, WITHIN COHORT

Coefficient	Cohort			
	World War I	Interwar	World War II and Korea	Vietnam
College				
Southern Black	-.144	-.144	-.144	-.144
Northern Black	-.121	-.121	-.121	-.121
Southern White Protestant	-.030	-.030	-.030	-.030
Northern Catholic	-.071	-.071	-.071	.000
Other	.000	+.038	+.148	+.148
High School				
Southern Black	-.145	-.291	-.263	-.101
Northern Black	-.104	-.195	-.136	.000
Southern White Protestant	-.065	-.122	-.067	.000
Northern Catholic	.000	.000	.000	.000
Other	-.028	-.028	-.150	-.150

TABLE 17

COEFFICIENTS AND PROPORTIONS FOR HIGH SCHOOL DIPLOMA AMONG MALES
(Summed from Table 11)

Category	Cohort			
	World War I	Interwar	World War II and Korea	Vietnam
p				
Southern Black	.024	.148	.298	.595
Northern Black	.088	.267	.448	.719
Southern White Protestant	.218	.431	.608	.810
Northern Catholic	.242	.512	.634	.840
Other	.285	.593	.703	.838
Yankee	.313	.583	.705	.840
d				
Southern Black	-.289	-.435	-.407	-.245
Northern Black	-.225	-.316	-.257	-.121
Southern White Protestant	-.095	-.152	-.097	-.030
Northern Catholic	-.071	-.071	-.071	.000
Other	-.028	+.010	-.002	-.002
Mean	-.142	-.193	-.167	-.080

from less than 10 per cent in World War I to strong majorities in the Vietnam Cohort. Southern Blacks, by 1940 (World War II and Korea) ahd High School completion rates as high or higher than Yankees in the World War I groups! But, since Yankee proportions were also increasing, it is equally useful to look at the columns, especially for d's. From left to right:

In the World War I Cohort the Stereotype groups were strung out in a clear-cut order: Yankee-Other-Northern Catholics-Southern White Protestants-Northern Black-Southern Black.

In the Interwar Cohort, Yankee High School Completion jumped .270, Others and Catholics increased about the same amount, but Blacks and Southern Whites improved less, so their d's became more negative. As a result, the subgroup differences in High School around 1940 were as strong as or stronger than they had been at the turn of the century.

In the World War II and Korea Cohort, the gap began to close for Blacks and Southern Whites, while Catholics kept the same distances from Yankees and Others dropped trivially.

Finally, in the Vietnam Cohort, the Catholic disadvantage disappears, the Southern White coefficient nears zero, and the Black coefficients drop substantially. But the Black coefficients are still far from zero. The gap between Northern Blacks and Yankees is as large as the Catholic gap for World War I. The gap for Southern Blacks in the Vietnam group is about as large as their World War I baseline.

In sum, all social groups in the United States have shown a phenomonal increase in High School Completion in this century, but the gap between Yankees and other major groups remained substantial until after World War II. In the Vietnam Cohort, differences among the three White categories are trivial, but Blacks, especially Southern Blacks, are far from equality in High School Completion.

Table 18 gives the relevant figures for college. We can use the figures in Table 18 to summarize the patterns for each group.

TABLE 18

ESTIMATES OF PROPORTION OF HIGH SCHOOL GRADUATES GOING ON TO COLLEGE (Among Males)

Category	Cohort			
	World War I	Interwar	World War II and Korea	Vietnam
Proportions				
Southern Black	.458	.642	.604	.455
Northern Black	.386	.442	.453	.409
Southern White Protestant	.573	.485	.484	.475
Northern Catholic	.347	.323	.399	.494
Other	.544	.467	.671	.672
d (vs. Yankee)[a]				
Southern Black	-.037	+.232	+.144	-.039
Northern Black	-.109	+.032	-.007	-.085
Southern White Protestant	+.078	+.075	+.024	-.019
Northern Catholic	-.148	-.087	-.061	-.001
Other	+.049	+.057	+.211	+.178

[a] See Table 12 for Yankee proportions.

Southern Blacks are consistently disadvantaged in High School Completion, especially the Interwar and World War II and Korea Cohorts. However, among those with High School diplomas, the college rate is not consistently below Yankees. The key problem for Southern Blacks is High School Completion.

Northern Blacks show a declining disadvantage in High School Completion and a persistent, albeit small and not entirely consistent, disadvantage in College.

Southern White Protestants, despite lower High School Completion, show higher College proportions for High School Graduates in the early Cohorts, but the differences disappear over time. In the Vietnam Cohort their Educational pattern is essentially the same as Yankees.

Northern Catholics, prior to Vietnam, were lower in both High School and in College attendance among High School Graduates. In the Vietnam Cohort these differences vanish and their Educational pattern is virtually the same as for Yankees.

Others show little difference in High School Completion, but an increasing advantage in College. Since the group is so heterogeneous we cannot interpret the result.

In a nutshell: Subgroup differences in Educational Attainment declined very little prior to World War II. Differences among White groups vanished in the Vietnam Cohort, leaving a declining but nontrivial Race difference as the major obstacle to equality in Education among major social groups in contemporary America.

Validity

The data have a certain amount of prima facie credibility because they include 46,356 cases from 30 national surveys by two outstanding survey organizations. Furthermore, the figures show a pleasing amount of internal consistency: the linear trends are smooth and the fixed parameters show only insignificant wobbles from year to year. Save for Sex composition in the World War I Cohort, the Michigan

Election and AIPO Studies give virtually identical results, despite the differences in their sampling techniques. Nevertheless, it is useful to compare our parameters with other data sets. To illustrate, we shall use the U. S. Census 1970 Public Use Sample and the NORC General Social Surveys for 1972, 1973, and 1974.[6]

To proceed, we draw on the following useful property: with d systems (like log linear models) one can always construct a full crosstabulation table from the system parameters and an appropriate N.[7] That is, one can choose an arbitrary year and N and proceed to construct the full 144 cell (4 x 2 x 6 x 3) crosstabulation for Cohort-Sex-Stereotype implied by the model or any appropriate table collapsing variables or categories. To illustrate, let us consider the 1970 Census sample, beginning with Cohort. Table 19 gives the necessary figures.

---

[6]The General Social Survey (GSS) is an annual sampling of continental U. S. adults (18 years of age and older) living in non-institutional quarters. The survey employes a multistage area probability sample with quotas at the block level and is supported by a grant from the National Science Foundation.

[7]For example, given some appropriate N and year we can find the sub-N's for each Cohort from Equations 1-4. Within each Cohort we wish to construct a crosstabulation for Sex by Stereotype. The marginal proportions for the four Stereotype groups are given in Equations 9a-13b, Yankee can be found by subtraction and N's found by applying these proportions to Cohort N's. Within each Stereotype group the proportion Female is given in Equations 5-8 and the proportion Male by subtraction from 1.000 (the sex proportion is, of course, identical in each Stereotype group within a cohort). Applying these proportions to the Stereotype category N's, we have the frequencies for Sex by Stereotype within each Cohort. We now wish to construct a table within each Cohort where the rows are Sex by Stereotype and the columns are Education. We begin with Yankee Males, applying the proportions in Equations 14a-15d to get High School and College and then obtaining Grade School by subtraction. For Males in other Stereotype categories we add or subtract the numbers in Table 16 for High School and College and then find Grade School by subtraction. We now have the educational proportions for Males in all Stereotype groups. For Females, we add or subtract the coefficents in Equations 14a-15d with the results for Males in the same Stereotype category. When the educational proportions are applied to the N's in the Sex by Stereotype rows, we will have a frequency table for Cohort-Sex-Stereotype-Education that has the desired system parameters and adds up to the desired N.

TABLE 19

COHORT PROPORTIONS, MODELED AND CENSUS, 1970

	Model				
Cohort	Proportion	Sampling Standard Deviation	Census	diff[a]	diff/sigma
Vietnam	.255	.005	.299	(+.044)[b]	8.800
World War II and Korea	.289	.006	.276	(-.013)	2.167
Interwar	.280	.006	.261	(-.019)	3.167
World War I	.176	.004	.164	(-.012)	3.000

[a]Mean absolute difference = $|.02|$.

[b]Differences in parentheses are significant at the .05 level.

To fill in Table 19, we:

(1) Obtained the cohort distribution (recoding age) in the 1970 Census sample, N = 13306.

(2) Found the model's cohort distribution for N = 13306, Year = 1970, from Equations 1-4.

(3) Calculated the standard deviations of the theoretical proportions for N = 13306 (as usual, correcting for multi-stage sampling, perhaps over-correcting here).

(4) Found the differences between the observed (Census) and expected (model) proportions.

(5) Divided the differences by the sigmas in step (3) recognizing as significant (at .05) any two-sigma discrepancies.

Table 19 indicates significant differences between the model and the 1970 Census. Census results have a greater proportion in the Vietnam cohort and smaller proportions in the older cohorts. In absolute terms, however, the results are not bad since the average absolute discrepancy is .022.

One's impluse is to infer that the model is "biased" since Census results are generally considered the yardstick. However, more detailed study is called for, because a number of other possibilities for explaining this discrepancy come to mind:

The model data are spread out over 20 years, whereas the Census data are collected for one specific month.

The model data are based on personal interviews with respondents, while the Census data are reports by household informants.

Survey interviewers are generally more experienced than Census enumerators.

The Census universe probably includes "group quarters" cases (e.g., soldiers, students, prisoners) generally excluded from survey sampling frames.

Question wordings may not be identical.

Similar analyses can be made for other variables in the model. It is generally more instructive, however, to examine non-source variables in terms of model parameters. Consider, for example, Sex and

Education in the 1970 Census. John Fry of NORC has written an interactive computer program (MODDRIVE) that generates crosstabulations for the full model or a model with variables collapsed out, given arbitrary N's and Years. The program may be used as follows:

(1) The appropriate crosstabulation is run off on the test data.

(2) The MODDRIVE program creates a crosstabulation for the same N and Year.

(3) The modeled data are run through CATFIT, a computer program for statistical analysis of d-systems. CATFIT gives the parameters and their standard errors (i.e., the sampling statistics for samples of exactly that size from a universe with the model's parameter values).

(4) The test crosstabulation is run through CATFIT to obtain the parameters.

(5) Observed and expected results are compared as in Table 19.

For Sex by Education within Cohort, we have the following parameters:

Base proportions:

1) Proportion Female

2) Proportion High School among Males

3) Proportion College among Males

d's:

1) Female to High School

2) Female to College

Table 20 gives the results.

To interpret Table 20, consider, for example, the d from Female to High School in the Vietnam Cohort. The figures tell us:

(a) The model d equals +.105

(b) In samples of size 3977 (the number of Vietnam cases in the 1970 Census sample) this d has a standard deviation of .024.

(c) The actual Census crosstabulation gives a d of +.067.

TABLE 20

SEX BY EDUCATION WITHIN COHORT
(Model vs. 1970 Census)

Cohort	Result	Female	Among Males: High School	Among Males: College	d's: Female High	d's: Female College
Vietnam	Model					
	Value	.542	.392	.427	+.105	-.137
	Sigma	.013	.017	.018	.024	.023
	Census	.516	.384	.395	+.067	-.074
	Diff.	(-.026)[a]	-.008	-.032	-.038	(+.063)
	Diff/Sigma	2.000	.471	1.778	1.583	2.739
World War II and Korea	Model					
	Value	.558	.334	.307	+.105	-.097
	Sigma	.011	.016	.016	.023	.020
	Census	.525	.310	.323	+.120	-.102
	Diff.	(-.033)	(-.034)	+.016	+.015	-.005
	Diff/Sigma	3.000	2.125	1.000	.652	.250
Interwar	Model					
	Value	.519	.296	.211	.052	-.037
	Sigma	.011	.016	.014	.021	.018
	Census	.519	.271	.210	.057	-.036
	Diff.	.000	-.025	-.001	+.005	+.001
	Diff/Sigma	.000	1.563	.071	.238	.056
World War I	Model					
	Value	.583	.131	.128	.052	.000
	Sigma	.014	.016	.016	.021	.020
	Census	.575	.131	.139	.040	.004
	Diff.	-.008	.000	+.011	-.012	+.004
	Diff/Sigma	.571	.000	.688	.571	.016
	Mean	-.017	-.017	-.002	-.008	+.016

[a]Values in parentheses are significant at the .05 level.

(d) The Census d is less positive, the discrepancy being -.038.

(e) The difference is not significant at the .05 level.

For Table 20, as a whole, we draw these conclusions:

1) The model has more Females than the Census, but only in the World War II and Vietnam Cohorts.

2) The High School and College proportions for the base category Male give a pretty fair fit.

3) The d's for sex and Education fit nicely save for the College d in the Vietnam Cohort, discussed above. The model gives a strongish -.137 for the Female deficit in College in the Vietnam Cohort. The Census estimate of -.074 is significantly less extreme, although clearly non-zero. The result confirms our decision to treat the value as non-zero, but it suggests we should be cautious about inferring an accentuation in the d from World War II and Korea to Vietnam. (The 1972, 1973, and 1974 NORC General Social Surveys, to be discussed later, give an average of -.110 for this parameter.)

A similar analysis can be made for Stereotype and Education, although we have to collapse our Stereotype groups to White, Northern Black, and Southern Black, respecifying the system with White as the base category (because the Census does not ask Religion). Table 21 gives the results, a la Table 20.

We interpret Table 21 as follows:

1) The model has fewer Northern Blacks than the Census. All four discrepancies are significant as is the average of +.017. No such differences appear for Southern Blacks.

2) Educational proportions in the base category White are reasonably compatible with the Census figures. The Census gives about .025 fewer High School Graduates and about +.010 more College, but the discrepanices are not uniform or consistently significant.

3) The d's (race differences in Education) are generally compatible.

To summarize Tables 19, 20, and 21: the model generally matches the 1970 Census user sample, the important discrepancies being:

1) The Census estimates a higher proportion in the Vietnam Cohort, possibly because of differences in sampling frames.

TABLE 21

STEREOTYPE BY EDUCATION WITHIN COHORT
(Model vs. 1970 Census)

Cohort	Result	Proportions: Northern Black	Proportions: Southern Black	Proportions: High School[b]	Proportions: College[b]	d's: Northern Black High	d's: Southern Black High	d's: Northern Black College	d's: Southern Black College
Vietnam	Model								
	Value	.038	.043	.451	.365	+.033	-.070	-.146	-.168
	Sigma	.004	.004	.013	.013	.064	.058	.054	.048
	Census	.060	.041	.412	.375	+.104	+.007	-.169	-.184
	Diff.	(+.022)[a]	-.002	(-.039)	+.010	+.040	+.077	-.023	-.016
	Diff/Sigma	5.500	.500	3.000	.769	.625	1.328	.426	.333
World War II and Korea	Model								
	Value	.048	.043	.407	.265	-.103	-.232	-.118	-.137
	Sigma	.004	.004	.011	.010	.049	.044	.038	.038
	Census	.072	.045	.389	.287	-.069	-.236	-.136	-.171
	Diff.	(+.024)	+.002	-.018	(+.022)	+.034	-.004	-.018	-.034
	Diff/Sigma	6.000	.500	1.636	2.200	.694	.091	.474	.895
Interwar	Model								
	Value	.035	.043	.340	.201	-.165	-.259	-.102	-.126
	Sigma	.004	.004	.011	.010	.048	.033	.038	.031
	Census	.050	.037	.310	.197	-.031	-.216	-.075	-.072
	Diff.	(+.015)	-.006	(-.030)	-.004	(-.134)	+.043	+.027	+.054
	Diff/Sigma	3.750	-1.500	2.727	.400	2.792	1.303	.711	1.742
World War I	Model								
	Value	.026	.043	.170	.136	-.088	-.130	-.103	-.126
	Sigma	.004	.006	.011	.010	.051	.030	.034	.017
	Census	.034	.050	.159	.149	-.026	-.086	-.096	-.086
	Diff.	(+.008)	.007	-.011	+.013	+.062	+.044	+.007	(+.040)
	Diff/Sigma	2.000	1.167	1.000	1.300	1.216	1.467	.206	2.353
	Mean	+.017	.000	-.025	+.010	+.001	+.023	-.002	+.012

[a] Values in parentheses are significant at the .05 level.

[b] Within base category, Northern White.

2) The Census shows fewer young females in the Vietnam and World War II and Korea categories. One suspects that the surveys underestimate the notoriously "never-at-home" younger adult males.

3) The Census shows higher proportions of Northern Blacks, but no general race discrepancy. No good reason for the Northern Black discrepancy comes to mind.

Similar analyses were carried out for the 1972, 1973 and 1974 NORC General Social Surveys. No significant discrepancies were observed for d's, but two consistent differences in marginal distributions turned up. Table 22 summarizes.

The General Social Survey, like the Census, shows more Northern Blacks than the model, the difference being significant in each year.

The General Social Survey, unlike the Census, shows an excess of College and a deficit in High School, the differences again being significant in each year. Whether these differences come from coding conventions or sampling is unknown.

All other differences are either trivial or inconsistent from year to year.

Substantive Projections

The computer program used to check validity can also be used to draw substantive conclusions. In d-systems, inferences about associations and variable distributions can be drawn following the principles of linear flow graphs (Davis, 1976); but in a system as complex as ours, exactly the same results can be obtained more easily with the computer program. For example, if we wish to estimate the increase in College from 1955 to 1965, we can ask the program to run off the Educational distributions for the years 1955 and 1965 with a convenient N, say 1000, and compare the proportions.

The enterprise is much like "computer simulation," with a crucial difference. Each number in the result is based on a statistical estimate rather than an attractive a priori assumption. The closest analogy, perhaps, is the econometric model. In this sense, we use the

TABLE 22

OBSERVED - EXPECTED PROPORTIONS,
MODEL VS. NORC GENERAL SOCIAL SURVEY

Variable	Category	General Social Survey 1972		1973		1974		Average
Cohort	Vietnam	-.003	(.188)[a]	-.022	(1.294)	-.014	(.778)	-.013
	World War II	-.004	(.250)	+.025	(1.563)	+.003	(.188)	+.008
	Interwar	+.018	(1.200)	+.013	(.813)	+.002	(.125)	+.011
	World War I	-.011	(.846)	-.016	(1.231)	+.009	(.818)	-.006
Sex	Female	-.047[b]	(2.765)	-.013	(.722)	-.012	(.667)	-.024
Stereotype	Yankee	-.088[b]	(5.176)	-.067[b]	(3.722)	+.065[b]	(3.333)	-.032
	Northern Catholic	+.015	(1.071)	+.001	(.071)	-.007	(.500)	+.003
	Northern Black	+.028[b]	(4.000)	+.042[b]	(6.000)	+.035[b]	(5.000)	+.035
	Southern White Protestant	-.023	(1.643)	+.009	(.643)	-.099[b]	(7.071)	-.038
	Southern Black	+.054[b]	(7.724)	+.007	(1.000)	+.004	(.571)	+.022
	Other	+.014	(1.273)	+.008	(.615)	+.002	(.154)	+.008
Education	College	+.036[b]	(2.571)	+.055[b]	(3.438)	+.061[b]	(3.813)	+.051
	High School	-.043[b]	(2.688)	-.040[b]	(2.353)	-.037[b]	(2.056)	-.040
	Less than High School	-.003	(.176)	-.015	(.833)	-.024	(1.333)	-.014

[a]Values in parentheses equal 0-E/sigma 0.

[b]Significant at .05 level.

phrase "survey-metric model" to stress the similarity, while calling attention to an important difference--these models use only the categorical metric characteristic of surveys.

In the light of the results in the previous section, three corrections were made in the parameters:

1) The intercept values for Northern Black were shifted to the Census estimates (.060, .072, .050, and .034, for Vietnam, World War II, Interwar, and World War I, in Equations 10a-10d) since both the Census and the NORC results suggest such a correction. Of mathematical necessity, the Yankee proportions are reduced, a plan that is somewhat arbitrary, but reasonable since the Northern Catholic results in the General Social Survey match the model.

2) Proportions Female in Vietnam and World War II were changed to the Census values (.516 for Equation 8 and 525 for Equation 7).

3) The coefficient for Female to College in the Vietnam Cohort was changed to the Census estimate -.074 (Equation 15d).

Table 23 shows results for various runs of the computer model.

The numbers are about what one would expect from the previous discussions since the adjustments are not drastic and the independence of Sex and Stereotype means that two-variable tables will not differ much from three-variable tables in their patterns.

The results for Educational d's, however, do have something to say. While the figures show the patterns implied by the within-cohort parameters, the absolute changes are small and discouraging to those who favor increasing equality. Although the Vietnam Cohort shows a remarkable convergence in school completion rates for these social groups, the extrapolations for 1976 and 1980 are surprisingly close to the extrapolation back to 1948. Such sluggish response is inevitable in Cohort processes. Even in 1980, about 45 per cent of the adult population will be from pre-Vietnam cohorts, and the social inequalities of their educations in the 1920s through the 1950s will be preserved, as in amber, for many years to come. If, as the students of Achievement argue, Education is the central variable in group SES differences, this country will retain a discouraging amount of intergroup Educational

TABLE 23

SELECTED MODEL RESULTS FOR YEARS 1948-1980

Result		Data Base								
		1948	1952	1956	1960	1964	1968	1972	1976	1980
Cohort										
	Vietnam	-	-	-	-	.08	.20	.31	.43	.55
	World War II	.03	.13	.22	.31	.33	.30	.28	.25	.23
	Interwar	.48	.44	.41	.37	.33	.30	.26	.23	.19
	World War I	.49	.43	.37	.32	.26	.20	.15	.09	.03
Sex										
	Female	.509	.517	.524	.529	.533	.537	.538	.538	.537
Stereotype										
	Yankee	.408	.404	.400	.396	.388	.379	.370	.360	.351
	Northern Catholic	.183	.186	.189	.193	.196	.199	.202	.206	.209
	Northern Black	.043	.046	.049	.052	.052	.051	.050	.049	.048
	Southern White	.215	.213	.211	.209	.206	.204	.201	.199	.196
	Southern Black	.043	.043	.043	.043	.043	.043	.043	.043	.043
	Other	.108	.108	.108	.108	.114	.124	.134	.143	.153
Education										
	College	.162	.171	.180	.190	.210	.235	.260	.285	.310
	High School	.243	.258	.274	.289	.310	.333	.355	.378	.401
	Less Than High School	.596	.571	.546	.521	.480	.432	.385	.337	.289
Educational d's										
Female (vs. Male)										
	College	-.019	-.027	-.037	-.046	-.051	-.057	-.062	-.066	-.069
	College and High School	+.038	+.032	+.026	+.020	+.016	+.016	+.016	+.019	+.024
Stereotype (vs. Yankee)										
College										
	Southern Black	-.141	-.141	-.141	-.141	-.140	-.137	-.136	-.137	-.138
	Northern Black	-.110	-.107	-.105	-.105	-.107	-.111	-.115	-.121	-.126
	Southern White	-.029	-.029	-.029	-.030	-.029	-.027	-.026	-.026	-.027
	Northern Catholic	-.063	-.063	-.062	-.062	-.055	-.043	-.035	-.029	-.024
	Other	+.026	+.038	+.051	+.063	+.089	+.114	+.134	+.146	+.151
College and High School										
	Southern Black	-.353	-.358	-.363	-.369	-.360	-.344	-.329	-.319	-.309
	Northern Black	-.239	-.228	-.221	-.219	-.218	-.216	-.214	-.214	-.212
	Southern White	-.117	-.116	-.115	-.114	-.106	-.095	-.084	-.076	-.067
	Northern Catholic	-.041	-.039	-.039	-.041	-.033	-.023	-.017	-.016	-.017
	Other	+.001	+.002	+.004	+.005	+.024	+.042	+.050	+.048	+.039

differentials long after the equalitarian shifts of the last 15 years have become old history.

A Note on Methods

The results reported here are not novel. Save for the introduction of Religion, the differences are familiar to those who work with Census data. And for Religion, these findings were anticipated (and greatly stimulated) by Andrew Greeley's work.[8]

If there is something novel in the materials presented, it is in method. Here, we think we have presented some potentially useful tools. D-systems seem to form a practical technique for studying social change through pooling surveys, for assessing the agreement of multivariate contingency tables, and for developing sociological analogues to econometric modeling. Although the statistics are nothing more than glorified percentage tables, their system character, in particular their analysis through flow graph techniques, means there is no reason the survey analyst must adopt multiple regression to indulge in causal analysis, change studies, extrapolation, and all the other heady and dangerous stunts pulled off by econometricians.

We also feel the technique has considerable possibilities for classroom use. Given the parameters in this system, or in any other (NORC is now working on a model incorporating Father's and Respondent's occupation), a computer simulation can be constructed for most any computer. Students can be sent to the computer with questions (e.g., "Have race differences in education changed in the last 20 years?") and receive scientifically responsible answers from simple percentage tables. In addition, the student will be spared the apparatus of significance testing and the iffy character of results from a single sample. There is no reason why sociologists cannot develop and disseminate similar models on a variety of variables so that students can learn sociology as a laboratory science without having to suffer term-long courses in statistics before entering their "labs."

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[8] See Greeley, (1974: Chapters 2 and 3).

APPENDIX

Evaluating Trends in Proportions and Differences in Proportions from Multiple Surveys

Assume we have a set of proportions (e.g., Table 1) or differences in proportions (e.g., Table 5) from sample surveys over some period of time. We wish to decide whether the values:

A. are generally zero (when examining differences but not, of course, proportions);

B. have a constant non-zero value;

C. show a linear trend for the time in question; or

D. show a more complex pattern of change.

Using Goodman's techniques for comparing contingency tables (Goodman, 1963) one can make three tests.

A. Null Hypothesis for d's

The most general null hypothesis asserts that all d's could be independent samples from a universe where d = .00. To test the hypothesis, one:

1) squares each d, divides the squared value by its variance, and sums;

2) evaluates the sum as chi square with K degrees of freedom, where K is the number of samples.

If chi square is not significant, one accepts the null hypothesis.

B. Constant Value for d's or p's

The next null hypothesis asserts that all d's or p's could be independent samples from the same universe value. To test the hypothesis, one:

1) finds the pooled value, weighting each estimate by the reciprocal of its variance, as explained by Goodman;

2) subtracts each value from the pooled estimate, squares K results, divides each squared result by its variance, and sums;

3) evaluates the sum as chi square with K-1 degrees of freedom.

If chi square is not significant, one concludes that the values are not significantly different across time and/or studies.

C. Linear Trend for d's and p's

To test for a linear trend in the data, one:

1) runs a weighted regression for Year and p or d, weighting each proportion or d inversely to its variance (see Theil, 1971: 244-248);

2) calculates the difference between each value and its predicted level ($\hat{Y}$), squares the difference, divides by the variance of the value, and sums;

3) evaluates the sum of chi square with K-2 degrees of freedom.

It is also possible to examine differences among the A, B, and C chi squares. A-B has one degree of freedom and tests the null hypothesis that fitting a constant does not improve the model. B-C also has one degree of freedom and tests the null hypothesis that fitting a linear trend does not improve fit in comparison with the model using a constant. B-C is thus analogous to testing whether a regression line differs significantly from zero.

A Typology of Outcomes

Table 1 gives a classification of possible outcomes and suggests how to interpret the results.

TABLE 1

A TYPOLOGY OF TEST OUTCOMES
(+ = significant, - = nonsignificant)

A	B	C	A-B	B-C	Type	Interpretation
-					I	d = .00
+	-		+	-	II	Constant
			-	-	IIa	Borderline constant
+	+	-		+	III	Linear trend
				-	IIIa	Borderline linear trend
+	+	+		+	IIIb	Rough linear trend
				-	IV	Non-linear trend

If A is not significant, we conclude that we can fit the data by assuming d is zero at all times. It is possible (though rare) for A-B or B-C to be significant when A is not. If so, we can fit the data better with a constant or a trend, but these alternative models are more complicated and not necessary. Parsimony suggests the d = .00 interpretation.

If A is significant but B is not, we can fit the data with a constant non-zero value, but not with a constant zero. If, in addition, A-B is significant and C is not, we have a type-case constant model. If neither A-B nor B-C is significant, one may interpret the results as a constant with borderline significance. The failure of A-B weakens the case for the model, but the failure of C and significance of A imply that linear trends or constant zeros are not plausible alternatives. It is also possible that B-C is significant. This means a linear model can improve fit, but the non-significance of B says that this is not necessary. Thus, the data show some tendency toward linear trend, but a linear model is not required. Parsimony argues for choosing the constant model.

When A and B are significant but C is not, the data show a linear trend since a straight line model fits the data, while constants and d = .00 do not. The significance of B-C confirms the linear interpretation, and its non-significance puts it in the borderline linear trend category.

When A, B, and C are all significant, interpretation depends on the outcome for B-C. If it is significant, one concludes that a linear model improves fit, but the straight line cannot account for the data. In such a case, there may be a monotonic curve at work, imperfectly approximated by the straight line, or the data may contain clear outliers (see below). "Rough linear trend" describes both possibilities. If, however, B-C is not significant, the suggestion is one of complex or erratic fluctuation that cannot be described by either a constant or a straight line. Again, inspection of outliers is called for.

If the data are proportions rather than d's, the A test is omitted since the existence of at least one non-zero proportion in the set is ipso facto rejection of the hypothesis that the common universe value is zero. Otherwise, exactly the same scheme applies to proportions.

A Note on Outliers

When comparing surveys over time, "outliers" are a distinct possibility. "Blips" in the trends can come from slight differences in question wording, differences in sampling procedures from study to study or among survey organizations, or from mechanical errors in processing old studies with incomplete documentation.

There seems to be no unambiguous procedure for spotting such deviant cases, but it seems useful to have a consistent rule. I have used the following:

1) Except for non-linear trends and rough linear trends, there is no necessity to spot outliers unless they stand out like sore thumbs.

2) To define outliers, I use a chi square value (v. the modeled estimate) that would be larger for 1 d.f. than the general alpha value. Since I generally use the .05 level (after correcting for multistage sampling), I use a cell chi square of 5.000, which is a bit above .02, as a criterion.

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COMMUNISM, CONFORMITY, COHORTS, AND CATEGORIES: AMERICAN TOLERANCE IN 1954 AND 1972-73

James A. Davis

December 1974

This paper is a revision of "A Survey-Metric Model of Social Change--IV. Tolerance of Atheists and Communists in 1954 and 1972-73." Data for 1954 were provided by the Interuniversity Consortium for Political and Social Research, for 1972-73 by the National Opinion Research Center National Data Program under grants from the National Science Foundation and the Russell Sage Foundation. The analysis reported here draws heavily on unpublished research by Ann Stueve of the University of California, Berkeley. A. Wade Smith and John Fry assisted in preparation of the data and tables. Stephen Fienberg Leo Goodman, Joel Levine, and Arthur Stinchcombe provided helpful comments.

Introduction

In 1954, Samuel A. Stouffer studied tolerance of Communists, Atheists, and Socialists in a 4,933-case national sample. His classic monograph, Communism, Conformity, and Civil Liberties, ventured this forecast:

> The data showed that (A) the older generation was less tolerant of nonconformists than the younger generation; also, that (B) within each group the less educated were less tolerant than the better educated.
>
> The fact also was brought out that (C) the older generation tended to have much less education than the younger--reflecting the big change in American school attendance in the past thirty years.
>
> Can we then forecast, we asked, that if external conditions are unchanged the younger people will be more tolerant when they grow older than their elders are now?
>
> . . . Much evidence points in this direction . . . (C) more of the people who are moving from youth to middle age (are) better educated than their elders. . . .
>
> On the other hand, (D) even if the people who are now 30 may still be more tolerant when they reach 60 than their elders, they may on the average be somewhat less tolerant than they are now. This is suggested by the tendency, among people at the same educational level, for the older ones to be . . . less tolerant . . . (Stouffer, 1955, p. 107; capital letters inserted).

The Argument in Graph Terms

Stouffer is talking about three variables--cohort ("generation"), educational attainment, and tolerance--and three static propositions:

(A) The older the cohort, the less the tolerance.

(B) The greater the education, the greater the tolerance.

(C) The older the cohort, the less the education.

Following Stinchcombe (1968, pp. 130-148) the three propositions can be represented by the linear flow graph in Figure 1.

As is conventional in flow graphs, we have added two residuals: E for education and T for tolerance. Technically, they represent the constants in equations for the system ("intercepts" for the slopes associated with the coefficients). Substantively, they may be viewed as the contribution of all variables excluded from the model.

Stouffer adds a dynamic proposition:

(D) Net of all other variables, tolerance will decline with time.[1]

Nothing is said about two other matters that turn out to be relevant. Taking his silence as deliberate, we add two other propositions:

(E) Cohort change completely accounts for change in education.

(F) The coefficients A, B, and C do not change over time.

As will be explained later, propositions A through F imply the "change graph" in Figure 2. (The symbol, delta, Δ, may be read as the difference in value between a later and an earlier time.)

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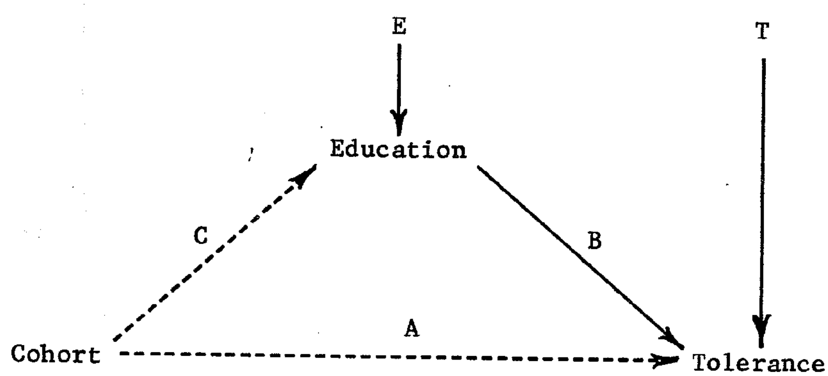
[1]Stouffer does not distinguish between "period" and "age" effects in proposition D, although my impression is he is talking about age. Since the two are confounded in our analysis, we will call the time effect "period-age."



NOTES: For cohort, older is the positive end, younger the negative.
Solid lines indicate positive coefficients.
Dashed lines indicate negative coefficients.
E and T are constants or "intercept" values.

Fig. 1.--Flow Graph for Propositions A, B, and C

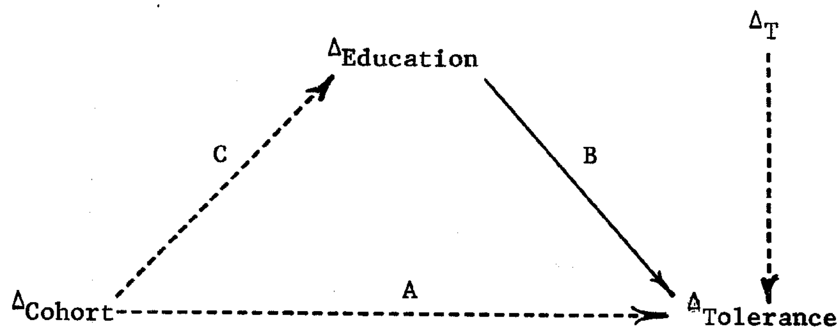


Fig. 2.--Change Graph for Stouffer's Argument

If the six propositions are correct, Stouffer's implicit dynamic argument may be read off Figure 2.

(1) Δ_{Cohort} will be negative (the mean "oldness" of the population will decline over time).

(2) $\Delta_{Education}$ will be positive, since it equals $\Delta_{cohort} * C$ and both have negative signs. (The departure of less well-educated, older cohorts will raise education.)

(3) $\Delta_{Tolerance}$ will have one negative and two positive components.

$$\Delta_{Tolerance} = (\Delta_{Cohort} * A) + (\Delta_{Cohort} * C * B) + (\Delta_T)$$

That is:

(a) Δ_T will be negative (from proposition D).

(b) $\Delta_{Cohort} * A$ will be positive since both terms are negative. (The declining proportion of less tolerant oldsters will raise tolerance.)

(c) $\Delta_{Cohort} * C * B$ will be positive since B is positive and the other two terms negative. (The declining proportion of less well-educated oldsters will raise tolerance.)

In brief, Stouffer's prophecy boils down to:

Cohort replacement will tend to increase tolerance directly and also via an increase in education levels.

Period-age will tend to decrease tolerance.

Since the components have opposite signs, it is impossible to predict whether the net change in tolerance will be positive or negative.

We will now proceed to check these propositions with national survey data.

Data

The original Stouffer study was an area probability sample of the American population 21 years of age and over living in private households, with a completion rate of 84 per cent (see Stouffer, 1955, Appendix A). In 1972 and 1973, the National Opinion Research Center (NORC) repeated nine of the original Stouffer tolerance items in its General Social Survey.[2] The GSS is a "modified probability" sample of the same universe, except that age is expanded to include persons 18-20 years old. By pooling the two GSS files and excluding 93 persons under 21 and 18 cases lacking information on all three variables, we have 3,006 cases for comparison with Stouffer's 4904 (4933 minus 29 cases lacking information on all three variables). We will use these two data sets to check Stouffer's forecast over an 18- to 19-year interval.

In the original Stouffer questionnaire, age is coded 21-29, 30-39, 40-49, 50-59, and 60 and older. For simplicity we grouped them 21-39, 40-59, and 60 plus and dubbed the groups, Young, Middle Aged, and Older. We can find the same cohorts in the 1972 and 1973 surveys by adding 18 or 19[3] to these numbers, which also include a "new generation"

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[2] The General Social Survey is an annual national sampling supported by the National Science Foundation that replicates a wide variety of sociological variables. Data from the study are disseminated to any interested person, at cost, immediately upon completion of the coding and keypunching, through the cooperation of the Roper Public Opinion Research Center, Williams College, Williamstown, Massachusetts. The Stouffer data were obtained through the courtesy of the Inter-University Consortium for Political and Social Research.

[3] In point of fact, the tape used for 1972 had age coded in ten-year units. Thus, cohort definitions for 1972 (but not for 1973) are off from one to two years. The discrepancy has little or no practical effect, but should be borne in mind by anyone seeking to continue or extend this analysis in his own use of the General Social Survey data.

of adults who reached age 21 in 1955 and after. This gives four cohort groups for analysis:

(1) The Older Cohort

Persons age 60 or older in 1954 and 79 or older in 1973. They were born in 1894 or before and reached age 16 in 1910 or earlier.

(2) The Middle Age Cohort

Persons age 40 to 59 in 1954 and 59 to 78 in 1973. They were born between 1895 and 1914 and reached age 16 between 1911 and 1930.

(3) The Younger Cohort

Persons age 21 to 39 in 1954 and 40 to 58 in 1973. They were born between 1915 and 1933 and reached age 16 between 1931 and 1949.

(4) The New Generation

Persons under age 21 in 1954 and 21 to 39 in 1973 (21 to 38 in 1972). They were born in 1933 or later and reached age 16 in 1949 and after. Persons in the New Generation were too young for the Stouffer study but appear in the 1972-73 data.

The second variable, educational attainment, was assessed by these questions:

Stouffer: "What is the last grade you finished in school?" (Seven pre-coded answers from "None" to "College graduate.")

General Social Survey: "(a) What is the highest grade in elementary or high school that you finished and got credit for? (b) Did you ever get a high school diploma? (c) Did you complete one or more years of college for credit?"

We assume that persons saying "yes" to (c) match Stouffer's "College, not graduate" and "College graduate" categories; persons answering "yes" to (b) but not (c) match Stouffer's "High School (12)" and all others match Stouffer's "None," "Grammar School (1-6)," "Grammar School (7-8)" and "High School (9-11)" categories. The three groups will be dubbed "COLLEGE," "HIGH SCHOOL," and "GRADE SCHOOL."

The tolerance items, taken verbatim from Stouffer, appear in Table 1. A similar trio of Stouffer-GSS items dealing with "a person who favored government ownership of all the railroads and all big industries" are not included in this report because preliminary inspection of the data showed their pattern to be about the same as that for Atheists and Communists.

Analysis

Flow graph models such as Figures 1 and 2 can be estimated using regression techniques (for such an analysis of these data, see Stinchombe, 1974). Nevertheless, we shall use a different, but closely related, technique for handling categorical data with flow graphs because (a) no level of measurement assumptions are required, (b) the technique gives us interesting information about interactions and differential category effects that would be swept under the rug in regression analysis, and (c) arbitrary personal preference.

The method is simple enough; we will develop it by example as we move along. The Appendix reviews the key concepts. For a more detailed explanation, see Davis (1974). Before proceeding, it is necessary to discuss alternative models for change data.

TABLE 1

WORDING OF COMMUNIST AND ATHEIST ITEMS

Question	Response Categories
There are always some people whose ideas are considered bad or dangerous by other people. For instance, somebody who is against all churches and religion . . .	
A. If such a person wanted to make a speech in your city (town, community) against churches and religion, should he be allowed to speak, or not?	Yes, allowed to speak Not allowed Don't know No answer
B. Should such a person be allowed to teach in a college or university, or not?	Yes, allowed to speak Not allowed Don't know No answer
C. If some people in your community suggested that a book he wrote against churches and religion should be taken out of your public library, would you favor removing this book, or not?	Favor Not favor Don't know No answer
Now, I should like to ask you some questions about a man who admits he is a Communist.	
A. Suppose this admitted Communist wanted to make a speech in your community. Should he be allowed to speak, or not?	Yes, allowed to speak Not allowed Don't know No answer
B. Suppose he is teaching in a college. Should he be fired, or not?	Yes, fired Not fired Don't know No answer
C. Suppose he wrote a book which is in your public library. Somebody in your community suggests that the book should be removed from the library. Would you favor removing it, or not?	Favor Not favor Don't know No answer

Change Models

Consider a prior categorical variable, K, e.g., cohort, and a dependent dichotomy, e.g., the proportion GRADE on education, with measures of K and Y in independent samples of the same universe at $Time_I$ and $Time_{II}$, e.g., 1954 and 1972-73. (We do not assume a panel design with repeated measures on the same subject.)

To pick a change model, the relevant data are the proportions Y for each category of K at each time. Table 2 gives a schematic layout.

Reading across the top row of Table 2, we see:

> p_{aI} and p_{aII}, the proportions Y for cases in the a category of k at $Time_I$ and $Time_{II}$.
>
> d_a, the percentage difference between p_{aI} and p_{aII}.
>
> v_{aI}, the variance of p_{aI}, following the usual textbook formula for estimating the variance of a proportion.
>
> v_{aII}, the variance for p_{aII}.
>
> $v_{aI} + v_{aII}$, the variance for d_a, following the usual textbook formula.

Goodman (1963, pp. 97-8) gives simple methods for testing the following hypotheses in contingency tables with conditional d's:

OR {
- (1) The d_k's differ among each other.
- (2) Each d_k estimates a common universe value, d.

  OR {
  - (a) which is zero
  - (b) which is not zero.

TABLE 2

FRAMEWORK FOR ANALYZING CHANGE IN A CATEGORICAL SYSTEM

Category of K	Proportion Y Time I	Proportion Y Time II	d_k	v_I	v_{II}	v
K_a	p_{aI}	p_{aII}	$p_{aII}-p_{aI}$	$\frac{(p_{aI})(1-p_{aI})}{N}$	$\frac{(p_{aII})(1-p_{aII})}{N}$	$v_{aI}+v_{aII}$
K_b	p_{bI}	p_{bII}	$p_{bII}-p_{bI}$	etc.	etc.	etc.
K_c	p_{cI}	p_{cII}	$p_{cII}-p_{cI}$	etc.	etc.	etc.
etc.	etc.		etc.	etc.	etc.	etc.

Let us consider how to interpret such tests when Goodman's techniques are applied to change data. A test has been made for significant changes in the marginal proportions of K. Figure 3 gives a typology of possibilities.

Case (0) Identical Systems, No Change. If there is no change in the marginals for K and d=0, we infer no change in y (Δ_y=0), no change in K (Δ_k=0), and no change in the K-Y coefficients. (To see the reason for inferring stable coefficients, we remember that each coefficient is a difference in proportion Y for two categories of K. If these proportions do not change, the differences between them do not change.) Thus, we infer the K by Y tables at Times I and II are identical, save for N and random error.

Case (0) serves as a benchmark by defining "stability" and is useful for deciding when data sets are sufficiently similar to justify pooling them into a common file.

Case (1) "Demographic" Change. Here we have a change in the level of the prior variable, K, but d=0--there are no changes in Y within categories of K. Necessarily, the K-Y coefficients do not change. In such models, the total change in Y is given by multiplying each change in K_i by its K_i-Y coefficient and summing. (Of course, if the coefficients are all zero, changes in the level of K will not produce changes in Y.)

When we interpret a linear equation by saying "a unit increase in X will be followed by a (value of coefficient) change in Y," we are using model (1). Following Stinchcombe (1968, Chapter 3), we call this a "demographic" model because it accounts for change in a dependent variable by changes in the population composition for a prior variable.

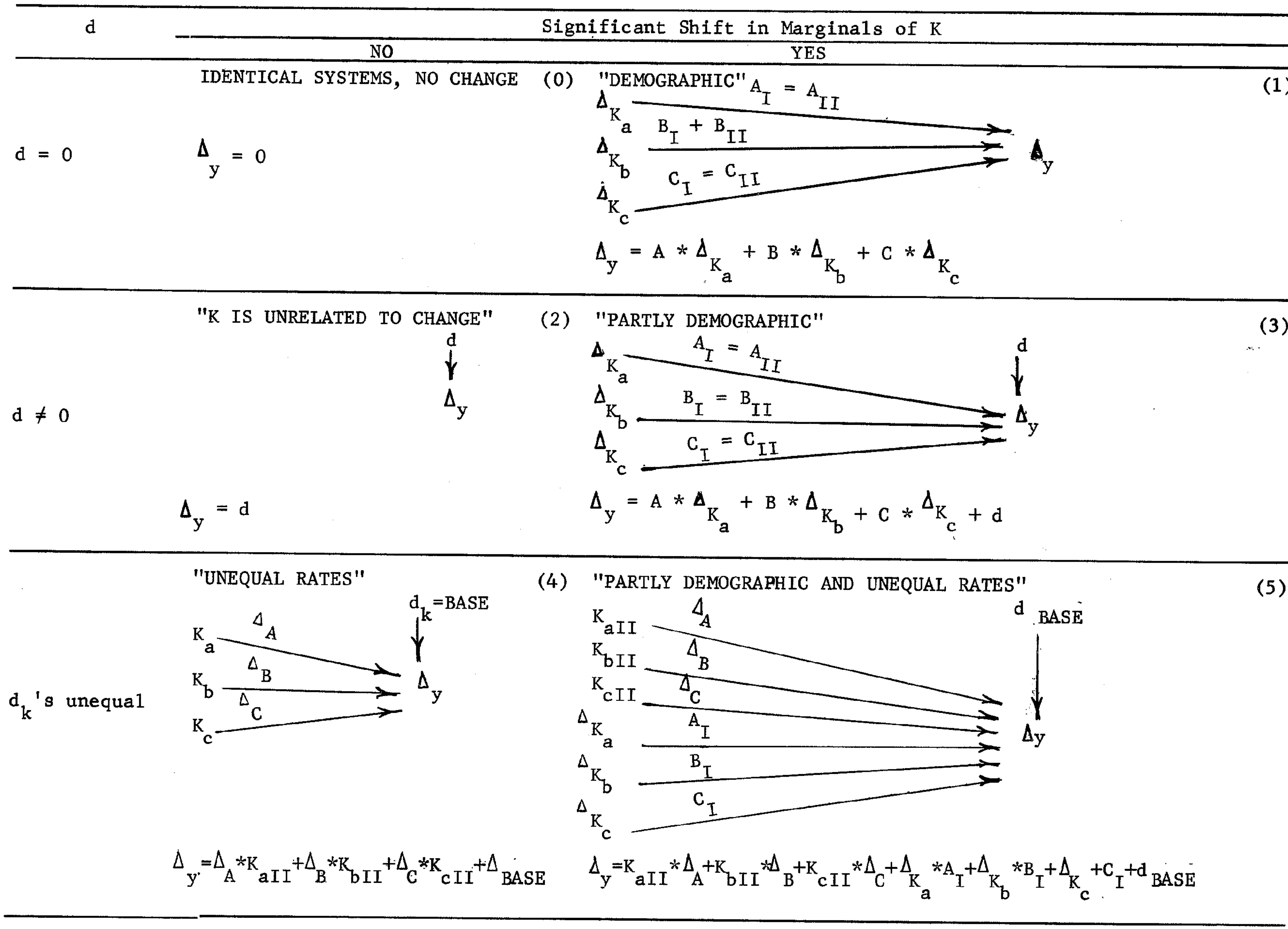

Fig. 3.--A Typology of Change Models

Case (2) K Unrelated. In Case (2) there is an identical change in Y within each category of K and no change in the marginals for K. Since the K-Y coefficients are constant and K does not shift in level, the change in Y, estimated by the value of d, has nothing to do with variable K. K may or may not be associated with Y, but it has nothing to do with the observed change in Y.

Case (3) Partly Demographic. This combines Cases (1) and (2). Since the level of K changes and there is no variation in the d's, demographic change occurs. Since d is other than zero, there are also changes in Y within categories of K that cannot be accounted for by differences between K's categories. In this model, demographic change accounts for part, but not all, of the change in Y.

Case (4) Unequal Rates. Here we have a situation where the d's are unequal--the changes in Y have different magnitudes in different categories of K. Table 3 gives a hypothetical example.

In the base category of K (see the Appendix for a discussion of base categories), d equals +.200, while in K_a it is +.040, and in K_b it is -.300. Inevitably, the coefficients (the difference in proportion Y between K_c and the base and between K_b and the base) change from Time I to Time II. The right-hand panel in Table 3 shows the differences between the Time I and Time II d's for K_b and K_a. The same numbers would emerge if we compared the base d with the d's for the other categories. Thus:

$$\Delta_{\text{Coefficient C}} = (C_{II} - C_I) = d_c - d_{\text{Base}}$$

TABLE 3

HYPOTHETICAL EXAMPLE OF A TYPE 4 MODEL

Category of K	Constant Proportion	Proportion Y		d_k	Coefficient		Change in Coefficient
		Time I	Time II		Time I	Time II	
K_b	.400	.500	.200	-.300	+.400	-.100	-.500
K_a	.350	.200	.240	+.040	+.100	-.060	-.160
K_{BASE}	.250	.100	.300	+.200	--	--	--
Total	1.000	.295	.239	-.056			

$$\Delta_y = (-.500 * .400) + (-.160 * .350) + .200 = -.056$$

The expression, $\Delta_{\text{Coefficient}}$, may be viewed as a measure of relative degree of change. If it is positive, the category has increased more (decreased less) in proportion Y than the base; if negative, the opposite; if zero, the category and the base show identical values of d.

It is easy to show (when the K marginals are constant) that the total change in Y is given by multiplying each K marginal by its value of $\Delta_{\text{Coefficient}}$ and summing.

Substantively, we may view a case (4) model as one in which change in Y is accounted for by differential rates of change among categories whose marginal proportions remain constant. Sociological theories of "massification and differentiation" (Glenn, 1967) employ this sort of model.

Case (5) Partly Demographic and Unequal Rates. The final model might better be called the "kitchen sink" since it includes aspects of models (1) through (4). With changing marginals for K and unequal values of d_k, the total change in Y is decomposed into three parts: (1) the Time II marginals for K times their change in coefficient; (2) the marginal change in K times the original Time I coefficients; and (3) the value of d in the base category of K. The first may be viewed as a contribution from unequal rates, the second as the contribution from "demographic change," and the third as a frame of reference. Case (5), in fact, is the general model. The other cases occur when particular parameters are set to zero. Figure 4 gives the general flow graph for K and Y.

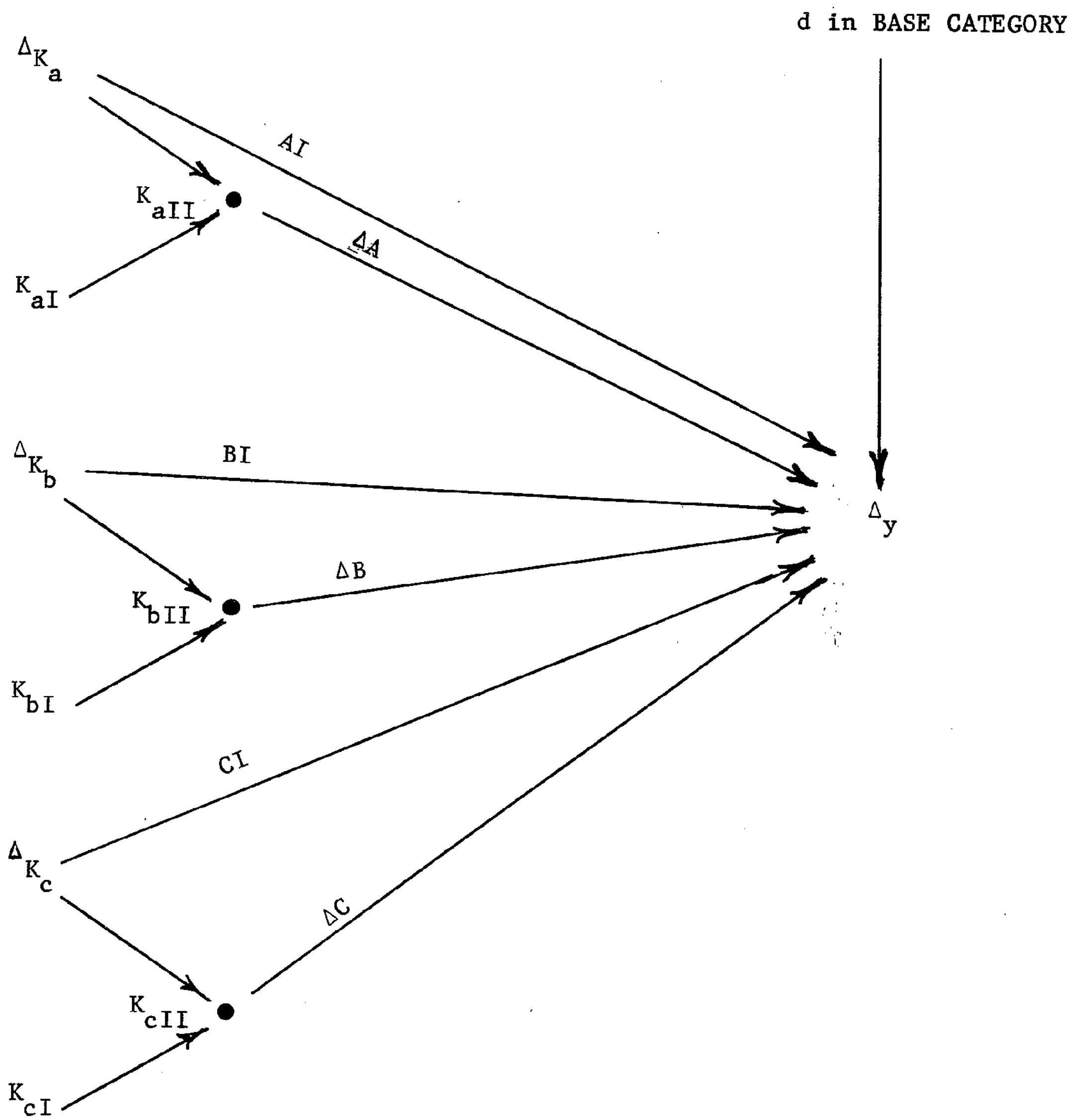

Fig. 4.--General Flow Graph for Change in Proportion "Y" as a Function of a Prior Categorical Variable, K

Calculations necessary to choose a model will be explained as we analyze the actual data. For now, we merely note Stouffer's implicit change model (Figure 2) implies Case (1) data for change in educational attainment and Case (3) for change in tolerance.

We now turn to analysis of the Stouffer data in 1954 and 1972-73.

Change in Cohort and Education

Table 4 gives the distribution of cases into the four cohort groups for 1954 and 1972-73. To test the significance of the Δ_k parameters, we first calculated the variance for each difference, as in Table 2, and took its square root to get the standard deviation. These formulas assume simple random sampling (SRS). It is well known that multistage samples of the sort analyzed here tend to have higher variances. Since a number of studies have shown that multistage variances are typically twice as large as SRS variances (Moser and Kalton, 1972), we shall routinely multiply the v's by 2 and the standard deviations by 1.5 (a conservative approximation of $\sqrt{2}=1.414$). The adjusted sigmas are next multiplied by two to give conventional .95 confidence levels. Since the changes for Older and Younger Cohorts are well outside the two sigma confidence bands, the deltas are significant. The +.419 increase for the New Cohort is inherently significant and was not tested.

Table 4 confirms the facts of life. The Older Cohort's shares of the adult population have declined appreciably. The Older and Middle groups made up 58 per cent of Stouffer's sample; they are only 24 per cent of the 1972-73 cases. The New Generation, too young for Stouffer's study, now make up about 42 per cent of the population 21 and older.

TABLE 4

COHORT DISTRIBUTIONS, 1954 AND 1972-73

Cohort[a]	1954 Proportion	1972-1973 Proportion	$\Delta_k 2\sigma_d$ [a]
Older	.202	.017	-.185 (.018)
Younger	.423	.346	-.077 (.033)
New Generation	.000	.419	+.419 (----)
Middle	.375	.218	-.157
Total	1.000	1.000	.000
Total cases	4,904	3,006	
Total no answer	29	111[b]	
Total N	4,933	3,117	

[a]Definitions given in text.

[b]Includes 93 cases of respondents age 18 to 20.

Table 5 gives educational attainment by cohort for 1954 and 1972-73. To model the first two variables, cohort and education, we must choose between cases (1), (3), and (5) since there are changes in our K variable. The calculations suggested by Goodman in his 1963 article are simple, but, as they may be relatively unfamiliar, we will review them step by step. (Table 6 gives the figures.) In row (1) we see the 1954 proportions for the three cohort groups (the New are excluded since there are no 1954 data for them); in row (2), the 1972-73 proportions; in row (3), the within-cohort changes, d_k. Row (4) gives the estimated variances for the differences, with no correction (as yet) for multistage sampling.

The next step is to estimate d, the pooled change. Goodman tells us that d is the weighted average of the d_k's where the weights are inverse to the v's. Row (5) gives the weights, obtained by finding the reciprocal of each variance, summing, and dividing each by the sum. To find d, we multiply each d_k by its weight, as shown in row (6). The row sum is -.033, our estimate of the common within-cohort change in proportion GRADE, assuming no interactions.

Row (7) gives Goodman's test for differences among the d_k's, the interaction effects. We subtract each d_k from d, square the difference, divide by v_k, and sum. The sum, 2.68, is distributed as chi square with degrees of freedom equal to K-1. To correct for multistage sampling, we divide the sum by two (which is tantamount to multiplying each v_k by 2), obtaining 1.34. For two degrees of freedom, $p > .50$.

TABLE 5

EDUCATIONAL ATTAINMENT BY COHORT 1954 AND 1972-73

(Proportions)

Year	Cohort	Education			Total	N
		GRADE	HIGH	COLLEGE		
1954	OLDER	.762	.138	.100	1.000	930
	MIDDLE	.652	.177	.171	1.000	1,761
	YOUNGER	.428	.366	.206	1.000	1,976
	NEW	--	--	--	--	--
	Total	.579	.249	.172	1.000	4,667[a]
1972-73	OLDER	.646	.125	.229	1.000	48
	MIDDLE	.603	.209	.188	1.000	627
	YOUNGER	.412	.320	.269	1.001	1,001
	NEW	.223	.376	.401	1.000	1,218
	Total	.378	.316	.306	1.000	2,894[a]

[a]N's differ from Table 4 because of "No Answer" cases on Education: 237 in 1954, 112 in 1972-73.

TABLE 6

STATISTICAL TESTS FOR EDUCATIONAL CHANGES WITHIN COHORT

Category	Calculation	Older	Middle	Younger	Total
GRADE	(1) p_I	.762	.652	.428	
	(2) p_{II}	.646	.603	.412	
	(3) d_k	- .116	- .049	- .016	
	(4) v_k	.004959	.000511	.000366	
	(5) w_k	.041	.400	.559	
	(6) $w_k * d_k$	- .00476	- .01960	- .00894	- .033 = d
	(7) $\frac{(d_k - d)^2}{v_k}$	1.389	.501	.790	2.68
	(8) $\frac{d_k^2}{v_k}$	2.713	4.699	0.699	8.111
COLLEGE	(1) p_I	.100	.171	.206	
	(2) p_{II}	.229	.188	.269	
	(3) d_k	+ .129	+ .017	+ .063	
	(4) v_k	.003775	.000324	.000279	
	(5) w_k	.038	.445	.517	
	(6) $w_k * d_k$	+ .00490	.00757	.03257	+ .045 = d
	(7) $\frac{(d_k - d)^2}{v_k}$	1.869	2.420	1.161	5.450
	(8) $\frac{d_k^2}{v_k}$	4.408	.892	14,226	19.526

Having inferred homogeneity among the d_k's, we may test the significance of d, the pooled estimate, by squaring each d_k, dividing it by v_k, and summing. The sum is distributed as chi square with K degrees of freedom. For the sum 8.111/2=4.056, $p > .20$. We infer d = .000. There is no reliable within-cohort change in the proportion GRADE from 1954 to 1972-73.

The bottom panel in Table 6 gives similar steps for analyzing within-category change in the proportion COLLEGE. The adjusted chi square for interaction, 2.725, is not significant ($p > .20$), but the adjusted chi square for d, 9.763, is significant ($.05 > p > .02$). We infer a significant increase, +.045, in the proportion COLLEGE within each cohort.

Technically, the upshot is simple: For COLLEGE we must add a residual change of +.045 to our model. Substantively, this result is a bit of a mystery.

Could the result be produced by non-random sampling biases? It could if the General Social Survey was biased toward higher education or the Stouffer study was biased toward lower education. Indirect evidence suggests this is not the case. In a separate analysis, we tabulated GRADE-HIGH SCHOOL-COLLEGE in the well known University of Michigan Election Studies (for 1952, 1956, 1958, 1960, 1962, 1964, 1966, 1968, 1970, 1972) and ran the least squares trend lines for the marginal proportions. We got a good fit ($R^2 = .931$, standard error of the estimate = .0189 for GRADE SCHOOL; $R^2 = .904$, standard error of the estimate = .0138 for COLLEGE). Although there were no election studies in 1954 or 1973, we can use the regression equations to estimate what SRC would have obtained for these years. These results appear in Table 7.

TABLE 7

MARGINAL PROPORTIONS FOR EDUCATION IN MICHIGAN ELECTION SERIES, STOUFFER, AND GENERAL SOCIAL SURVEY

Year		Grade	High School	College	Total
1954	Stouffer	.579	.249	.172	1.000
	Michigan[a]	.559	.269	.172	1.000
	Difference	+.020	-.020	.000	
1972-73	General Social Survey	.378	.316	.306	1.000
	Michigan[a]	.368	.344	.288	1.000
	Difference	+.010	-.028	+.018	

[a]See text for explanation of regression estimates.

The Stouffer-General Social Survey figures are very close to the Michigan estimates. Since the Michigan sample is technically excellent and carried out in essentially the same way for both study periods, the bias explanation is not sufficient. Whether the result can be explained--by adult education, differential mortality, immigration, some sort of changing bias in many survey organizations, or type I error--is unknown.

We now know we must use a Case (3) model for change in cohort and education. The parameters required are the Δ_k's from Table 4, the COLLEGE residual, +.045, and the K-Y coefficients. Since the model assumes constant coefficients, we pool the estimates from 1954 and 1972-73. The technique is exactly the same as that for estimating the pooled d's.

Middle Cohort was chosen as the base category for cohort and HIGH SCHOOL as the base for education. Table 8 gives the results. The pooled differences (1954 only for the New Cohort) confirm Stouffer's (C) proposition--the older generation tends to have much less education. Compared to the Middle Cohort, the Old are higher in proportion GRADE (+.106) and lower in proportion COLLEGE (-.066), while the Young and Middle Cohorts are lower in GRADE (-.215 and -.380) and higher in COLLEGE (+.047 and +.213). Figure 5 arranges all of these parameters as a flow graph model for cohort and education, as in Case (3) in Figure 3.

By multiplying source values by coefficients and summing, we can account for the marginal shift in education between 1954 and 1972-73 as shown in Table 9. The numbers may be interpreted as follows. First, we apply the residual (.000 or +.045) to the base category

TABLE 8

COEFFICIENTS FOR COHORT AND EDUCATION

Education Category	Cohort Comparison	Difference in Proportions 1954	1972-73	Pooled	Adjusted Chi Square	Prob.	d.f.
GRADE	OLD v. MIDDLE	+.110	+.043	+.106	19.05	<.001	2
	YOUNG v. MIDDLE	-.224	-.191	-.215	128.85	<.001	2
	NEW v. MIDDLE	--	-.380	(-.380)	130.66	<.001	1
COLLEGE	OLD v. MIDDLE	-.071	+.041	-.066	14.40	<.001	2
	YOUNG v. MIDDLE	+.035	+.081	+.047	11.15	<.01	2
	NEW v. MIDDLE	--	+.213	(+.213)	42.36	<.001	1

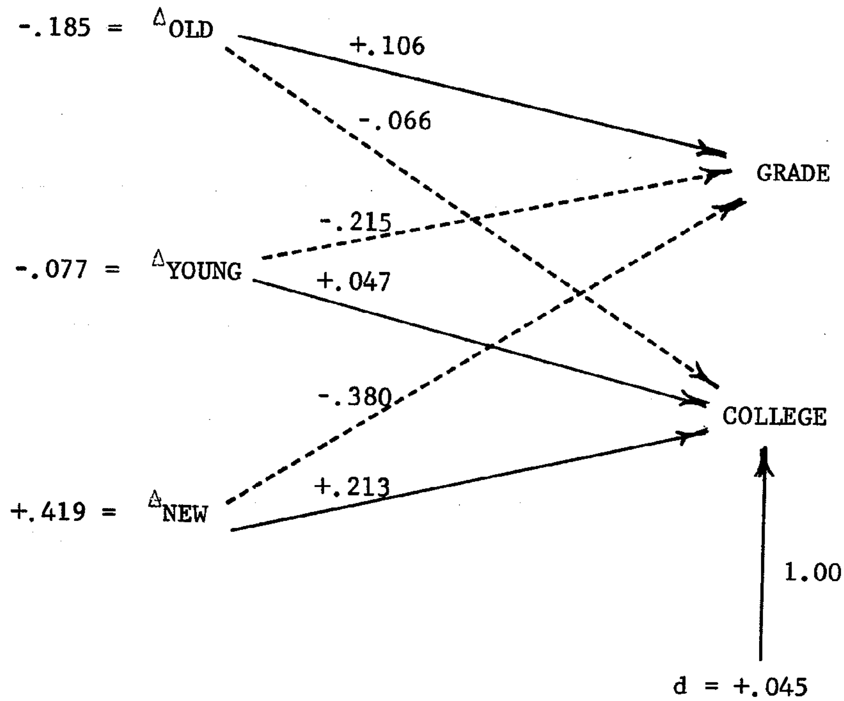

Fig. 5.--Flow Graph Model for Cohort and Education, 1954 and 1972-73

TABLE 9

MARGINAL SHIFT IN EDUCATION BETWEEN 1954 AND 1972-73

Change in GRADE				
Prior	OLD:	-.185 * +.106	-.0196	
Base category	MIDDLE:		.0000	(-.033)
Later				
	YOUNG:	-.077 * -.215 = +.0166	-.1426	
	NEW:	+.419 * -.380 = -.1592		
		Total	-.1622	(-.1952)
		Raw data	-.201	
Change in COLLEGE				
Prior	OLD:	-.185 * -.066	+.0122	
Base category	MIDDLE:		+.045	
Later				
	YOUNG:	-.077 * +.047 = -.0036	+.0852	
	NEW:	+.419 * +.213 = +.0888		
		Total	+.1424	
		Raw data	+.134	

since this is our estimate of the increase within the base group. Then, we see how other categories raise or lower the total because of their change in marginal proportions and greater or lesser education. The Old Cohort raises COLLEGE +.0122 and lowers GRADE -.0196 because it is less well educated and declining in size. The two newer cohorts have the opposite effect. They raise COLLEGE and lower GRADE.[4]

The modeled changes in COLLEGE are quite close to the raw data, but less so for GRADE because we decided to treat the residual value (-.033) as unreliable.[5] To a considerable degree the results confirm Stouffer's prediction. Cohort changes of the sort he predicted--the replacement of older, less well educated Americans by younger, better educated ones--account for most, but not all, of the increased educational attainment between 1954 and 1972-73.

Cohort, Education, and Tolerance

We come now to the dependent variable, change in levels of tolerance. After eliminating the generally small number of "no answers" and "don't knows," we dichotomized each item to make the "more tolerant" response positive. The original codebook marginals allow us to see the general trend, shown in Table 10.

---

[4]The Young Cohort actually shows miniscule effects in the opposite direction. They are better educated than the Middle Cohort, but their "share of the market" is declining. The strong contributions coming from New Cohort more than offset these effects.

[5]This illustrates an interesting difference between this method and regression analysis. In regression models, the means must come out correctly, but the calculated coefficients may differ from the data because of interaction effects. In the categorical approach the coefficients are estimated from the data and the fitted means may differ from the modeled figures.

TABLE 10

MARGINAL DISTRIBUTIONS FOR TOLERANCE ITEMS, 1954 AND 1972-73
(Proportion More Tolerant)

Item	1954		1972-73		Δ
	Proportion	N	Proportion	N	
Atheist					
Speech. . .	.382	(4800)	.662	(3069)	+.280
Book . . .	.373	(4664)	.710	(3013)	+.337
Teacher . .	.124	(4740)	.419	(2990)	+.295
Communist					
Speech . .	.282	(4701)	.573	(3024)	+.291
Book . . .	.289	(4566)	.577	(2995)	+.288
Teacher . .	.064	(4701)	.380	(2905)	+.316
Average	.252		.554		+.301

Each of the items shows a distinct increase in tolerance. Although the marginals differ, each shows a net increase rather close to the average change of +.301. In 1954, these six items show an average of .252 choosing the more tolerant alternative, while in 1972-73 the proportions rose to an average of .554. The delta's for the Atheist items are about the same as those for Communists, suggesting that the decline in the Cold War spirit cannot provide a simple explanation for the changes. Whether, as Stouffer predicted, cohort and educational changes can give an explanation is the question we now address.

We tabulated cohort by education by each of the six tolerance items within the 1954 and 1972-73 studies. Since each of the six items gave about the same pattern of proportions, the results are pooled in Table 11. Thus, each proportion in Table 11 is the average of six tolerance proportions and each base N is the average of the six bases.

In Table 11, if we read up each column, the proportions increase; in each year and each educational level, the older cohorts are less tolerant. If we read across each row, the proportions increase (save for Older-COLLEGE in 1954); within cohort and year, the better educated are more tolerant. Finally, if we examine the diagonals in each "box," the upper right percentage is always greater than the lower left; each cohort and educational group was more tolerant 18.5 years later. Thus, Stouffer's cohort and education differences still hold but he was incorrect in part of his prediction. As each group aged, it became <u>more</u> tolerant, not <u>less</u> tolerant.

TABLE 11

COHORT BY EDUCATION BY TOLERANCE, 1954 AND 1972-73

(Mean Proportion Giving More Tolerant Response Averaged Over Six Items)

Cohort	Less than High School		High School Graduate		College	
	1954	1972-73	1954	1972-73	1954	1972-73
Older	.142 (709)	.185 (31)	.228 (128)	.361 (6)	.208 (93)	.426 (11)
Middle	.176 (1148)	.248 (378)	.308 (312)	.426 (131)	.408 (301)	.510 (118)
Younger	.204 (845)	.361 (412)	.317 (724)	.510 (320)	.503 (407)	.695 (269)
New Generation		.454 (272)		.668 (458)		.821 (488)

The techniques of categorical modeling--as in Tables 2,6, and 8--allow us to state these conclusions more precisely. Table 12 summarizes the results.

Table 12 has no significant interaction effects, but each coefficient is significant, confirming Stouffer's propositions A and B, "the older generation was less tolerant (and) the less educated were less tolerant." But, as Stouffer did not say, there is a significant within-category increase of +.131, an across-the-board increase in tolerance within cohort and education groupings.

Figure 6 presents these results, along with those in Figure 5, as a flow graph model of change in tolerance. By multiplying source and residual values by their appropriate arrow coefficients and summing, we can decompose the modeled change, as shown in Table 13.

The table decomposes change in tolerance into: (a) direct effects of changes in cohort composition, summing to +.05454; (b) indirect effects of cohort changes operating through their impact on education, summing to +.03602; (c) a contribution from the increase in COLLEGE not accounted for by cohort changes, +.00635; and (d) the residual within cohort and educational group increase, +.131. These sum to +.22791, which differs from the raw data change of +.2827 because of interaction effects that were shown to be non-significant.

How do Stouffer's predictions stand up?

He was correct in predicting the +.03602 increase coming from cohort effects on educational levels.

He was wrong in predicting the "period-age" effect to be negative. It is positive and of non-trivial magnitude, +.131.

TABLE 12

PARAMETER ESTIMATES FOR TOLERANCE IN TABLE 11

Difference in Tolerance	Pooled d	Interaction			Significance of d		
		Chi Square[a]	D.F.	P	Chi Square[a]	D.F.	P
Year:							
1972-73 v. 1954	+ .131	7.05	8	> .50	55.3	9	<.001
Cohort:							
OLD v. MIDDLE	- .055	5.35	5	> .30	12.1	6	.10>p>.05
YOUNG v. MIDDLE	+ .055	7.00	5	> .20	16.8	6	<.02
NEW v. MIDDLE	+ .116	1.15	2	> .50	12.4	3	<.01
Education:							
COLLEGE v. HIGH	+ .141	7.1	6	> .30	49.45	7	<.001
GRADE v. HIGH	- .137	4.2	6	> .50	59.25	7	<.001

[a]Chi square has been divided by two to adjust for multistage sampling, as explained in text.

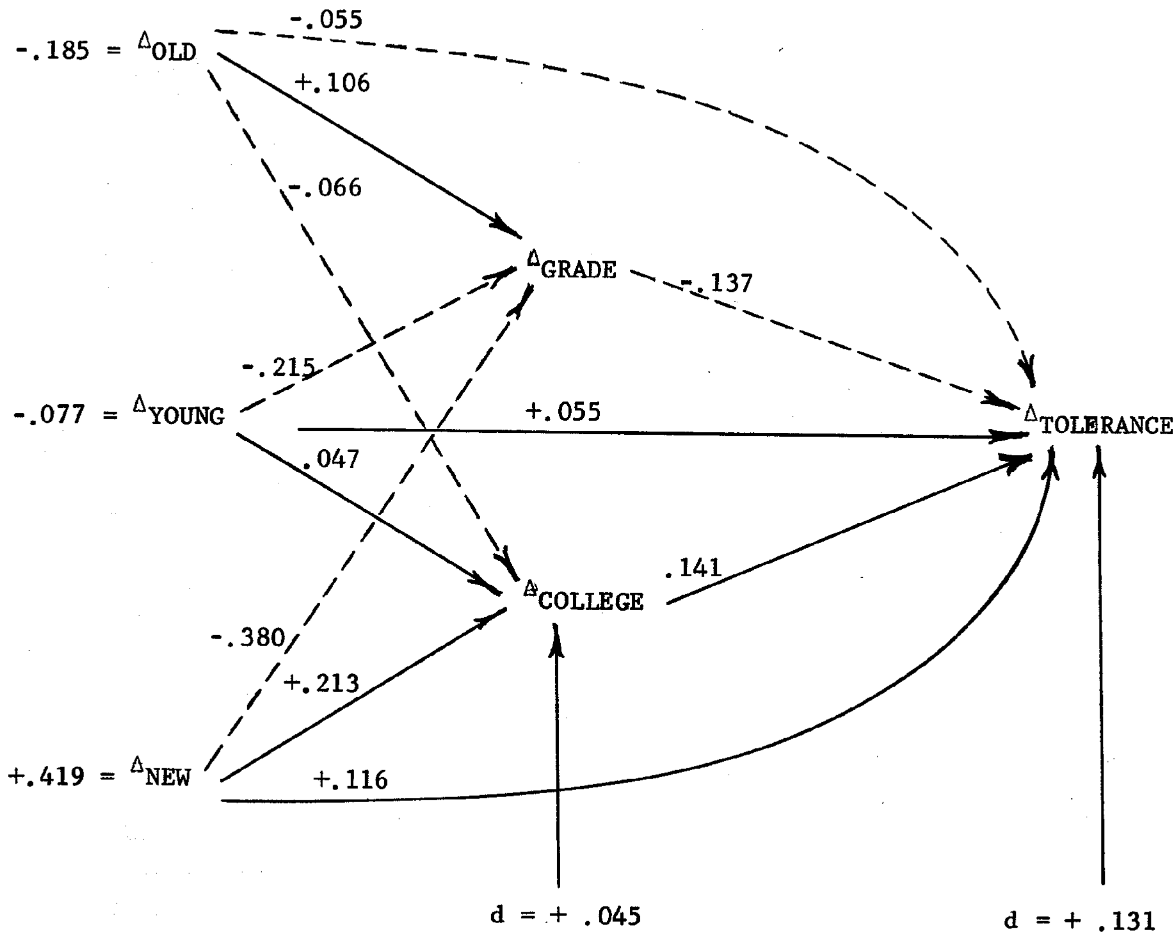

Fig. 6.--Flow Graph Model for Change in Cohort, Education, and Tolerance, 1954 and 1972-73

TABLE 13

DECOMPOSITION OF CHANGE IN TOLERANCE FROM FIGURE 6

Source			Change
Prior (OLD)			
Direct	-.185 * -.055		+.01018
Via Education			
GRADE	-.185 * +.106 * -.137 =		+.00269
COLLEGE	-.185 * -.066 * +.141 =		+.00172
Within MIDDLE			+.131
Later			
Direct			
YOUNG	-.077 * +.055 = -.00424	}	+.04436
NEW	+.419 * +.116 = +.0486		
Via Education			
GRADE	-.077 * -.215 * -.137 = -.00227	}	+.01954
	.419 * -.380 * -.137 = +.02181		
COLLEGE	-.077 * +.047 * +.141 = -.00051	}	+.01207
	.419 * +.213 * +.141 = +.01258		
COLLEGE change not accounted for by Cohort	+.045 * +.141		+.00635
	Total		+.22791
	(raw data		+.2827)

He did not foresee the direct effect of cohort replacement, net of education, of +.05454, nor the mysterious residual increase in COLLEGE and its contribution of +.00635, but neither contradicts his line of reasoning.

In sum, the implicit Stouffer model accounts for about 10 of the 23 units of increase, while the remaining +.13 represents a false prediction. Rather than becoming more conservative as they moved through the 1950's, 1960's, and early 1970's, Americans became more tolerant, regardless of their cohort or education group.

This residual increase is perhaps the most interesting finding in the analysis, but it is difficult to interpret.

Because age and period are necessarily confounded in the design, we cannot say that the data refute the hypothesis that aging induces conservatism. But we can argue that if a "natural" negative effect for age has been offset by a positive period effect, the period effect is really extraordinary!

Could the residual occur because our categories were too coarse? I doubt it. Without going into detail, it is easy to show that collapsing categories produces spurious residual d's only when the subcategory proportions change considerably. Aside from the Old Cohort, I doubt that mortality has been sufficient to change age proportions and year of school proportions much <u>within</u> the broad categories we used.

Why then have Americans become much more tolerant than can be accounted for by changes in cohort and education? It is hard to find non-circular hypotheses, save for our previous negative observation that decline in Cold War tensions seems implausible because the change for Atheists is about the same as the change for Communists. To invoke "the climate of the times," the "effect of media," "shifts in values," and so forth, is to say nothing concrete. Alas, as best we know, there are no national data for the Stouffer items between 1954 and 1972-73, so that it is impossible to tell whether specific events are related to change.

To dig into the problem, it seems that our only choice is to examine trends in other attitude and opinion items to see whether the same patterns turn up in race relations, sex, family matters, and similar General Social Survey items where baseline data are available.

To summarize, I take the liberty of quoting the anonymous referee's comments on the first draft of this paper:

> I would say that there is solid empirical ground for suspecting that the changes observed here were not isolated changes in these particular attitudes, but part of a general movement including all sorts of (issues) of the liberalism-dogmatism variety (not economic liberalism), including civil liberty, racial prejudice, women's rights, tolerance of nudity and sexual experimentation. . . . The attitude institutionalized very strongly in sociology in particular and in the humanities and social sciences generally, has been gaining ground. . . . I would like to see some overall speculation about what is going on in society that might produce such a pattern of several indicators moving in the same direction and in the same pattern. But that goes beyond the available data and might offend much of the profession. Besides, I'll be damned if I know what I think about it myself. But I'm sure glad about it.

APPENDIX

Flow Graphs for Categories: A Brief Introduction

Consider Table A1, a hypothetical fourfold table presented in percentage form. The familiar percentage difference, $d_{yx} = 75 - 50 = 25$, indicates that the percentage "Y" among the X_1's is 25 units higher than the percentage among the X_0's. It is well known that the percentage difference in a fourfold table is analagous to the "slope" in a linear system. If we think of X and Y as variables with only two possible values, 0.0000 and 1.000, the "mean on Y" when X is zero equals .50, the mean on "Y" when X is 1.000 equals .75, and the increase in mean Y for a one-unit increase in X is .25.

Pursuing the analogy we can write a set of equations for the data, shifting from percentages to proportions.

$$X_1 = .615 \qquad \text{(A1)}$$

$$Y = (.250 * X_1) + .500 \qquad \text{(A2)}$$

Equation (A1) says that the mean on $X_1 = .615$, which, in a zero-one system, turns out to be the marginal proportion X_1. Equation (A2) says that the mean on Y (its marginal proportion) equals the coefficient (d_{yx}), times the value of X_1, plus the constant or intercept value (i.e., the mean Y when X = zero).

Substituting: (A1) into (A2):

$$.6538 = (.250 * .615) + .500 \qquad \text{(A3)}$$

In sum, there are three strict analogies between fourfold tables and recursive systems of linear equations:

TABLE A1

HYPOTHETICAL FOURFOLD TABLE

	Per Cent "Y"	Case Base
X_1	75	(800)
X_0	50	(500)
Total	65.38	(1300)

(1) Variable means = marginal proportions

(2) Coefficients = percentage differences = slopes

(3) Constants = (Per Cent in Dependent Category for Category scored 0 on prior variable) = intercept

Any set of equations can be translated into a linear graph according to the following rules: (1) variables = points, (2) coefficients = values associated with one-way arrows connecting points, (3) constants = dummy sources whose arrows have implicit values of 1. Figure A1 presents the graph for our hypothetical system.

The graph has no information not available in Equation (A3), but, with more complicated systems, one can use simple rules to find visual solutions for results that would be tedious with algebra. Examples appear in the substantive text.

To extend the approach beyond dichotomies, let us add a third category to X; Table A2 presents the results.

The "zero-one" analogy breaks down because X has three values, but if we keep X_0 as the "intercept" or "base" category, the following equation is perfectly correct:

$$Y = (d_{y,x_2x_0} * X_2) + (d_{y,x_1x_0} * X_1) + \text{Proportion Y in intercept category of X} \qquad \text{(A4)}$$

Thus,

$$.5588 = (-.250 * .235) + (.250 * .471) + .500 \qquad \text{(A5)}$$

Equation (A4) can be graphed, as in Figure A2.

The approach can be extended to systems with any number of categories in the independent or dependent variable, as illustrated in the substantive text.

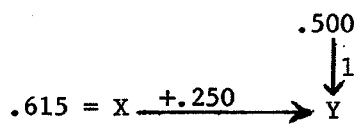

Fig. A1.--Graph of Equation A3

TABLE A2

	Per Cent "Y"	Case Base	d	Case Bases As Proportions
X_2	25	(400)		.235
X_1	75	(800)	+25 -25	.471
X_0	50	(500)		.294
Total	55.88	(1700)		1.000

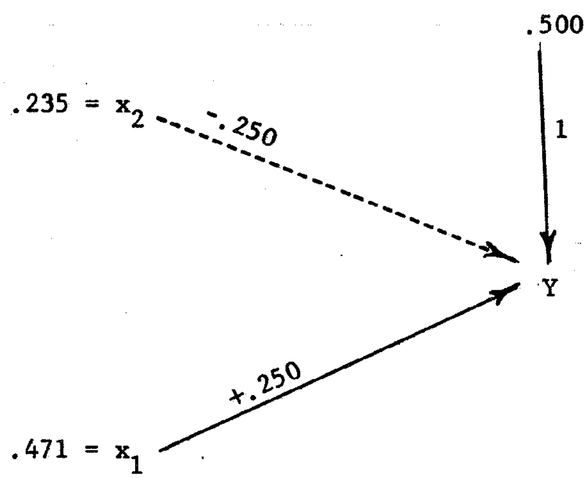

Fig. A2.--Graph of Equations A4 and A5

One may also extend the technique to systems with more than two variables, using "partial d's," provided that: (a) the variables have a strict causal order and (b) there are no interactions such that the value of a conditional d varies with the category of a control (test) variable. (Examples of the procedures used appear in the substantive text.) Data with interactions or ambiguous causal directions may be handled by "block recursive models," as explained in Davis (1975). At first glance, the system may appear identical to dummy variable regression, but it is not. The method of dichotomizing the prior variable is different, and dummy variables cannot be used in flow graphs since they have inevitable, artifical, negative correlations with each other.

The major drawback of the system is the arbitrary character of the intercept or base category. One could model the data in Table A2 using X_0, X_1, or X_2 as the base. Each choice would "add up" perfectly, although the values might be quite different. Unfortunately, the necessity to suppress one category seems fundamental in analyzing categorical data (Fennessey, 1968; Cohen, 1968). Without it, one or more of the parameters estimated would be redundant--that is, there would be more parameters than degrees of freedom.

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SUBJECTIVE SOCIAL CLASS, PARTY IDENTIFICATION, AND PRESIDENTIAL VOTE, 1952-1974

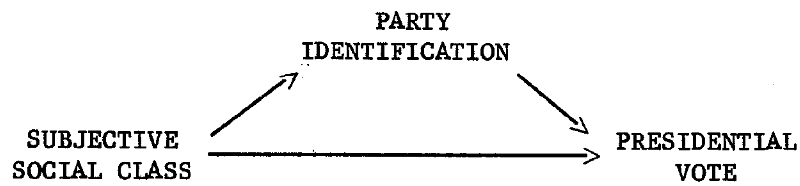
James A. Davis

February 1975

This effort was aided by Gregory Gaertner, who assisted with the tabulations; John Fry and D. Garth Taylor, who developed the computer programs; and Karen Newman Gaertner, who spotted a major error. For all of which, thanks.

Introduction

We here consider the three-variable system:



and its dynamics for the years 1952 to 1972. That is, we will examine change and stability in:

1) subjective Social Class
2) the relationship between Class and Party
3) Party, net of Class
4) the relationship between Class and Vote, net of Party
5) the relationship between Party and Vote, net of Class
6) Vote, net of Class and Party.

There is a considerable literature on these separate topics, but (to our knowledge) no study of all three variables over time.

Beginning with Class, Schreiber and Nygreen (1970) review previous studies and ten data sets from 1945 to 1968 and infer (1970:350) "The main conclusion regarding any trend in choice of the working class label from 1945 to 1968 is that it increased after 1945, reached a peak about 1960, and then declined to a point still above that for 1945." Hamilton (1972:101-102) examines 13 studies from 1945 to 1964, concluding "...the basic fact to be observed is the remarkable stability in the distribution of the responses."

Concerning Class and Party identification, Knoke and Hout (1974: 704) report a "secular decline" in the correlation in an elaborate analysis of Michigan Survey Research Center election studies for 1952 through 1972. I know of no studies of changes in Party Identification controlling for Social Class, but numerous investigators report a zero-order trend toward "independence" during the period (cf. Glenn, 1973: footnote 1).

As for Party and Presidential Vote, I am not aware of any trend study, although the implication of the classic American Voter research (Campbell, et al., 1960) is that such correlations are rather stable.

The classic study of Presidential Vote and Subjective Class (Converse, 1958) infers trendless fluctuations in the relationship. (For the related topic of occupational class and vote, see Glenn, 1973.)

The National Opinion Research Center (NORC) Social Change Project, with its data bank of baseline measures for items in the NORC General Social Survey, allows us to study these variables using 8 to 21 surveys (depending on the variables in question) over a twenty-year time span. Reasonably consistent results emerge which, alas, differ with all of the propositions in the literature.

In addition, the analysis illustrates how d-system modeling (Davis, 1976) can be extended from two times (Davis, 1975) to many. The main principles are presented in an Appendix to the preceding paper (see page 97), with which we shall assume the reader to be familiar.

Subjective Social Class

Table 1 gives the proportion of respondents (minus "no answers" and those who deny the existence of social classes, both relatively infrequent in all these surveys) classifying themselves as "Middle or Upper" for 26 national surveys from 1948 to 1974.

As Schreiber and Nygreen (1970) note, it is important to take into account the response alternatives given to the respondents. In the left and center columns we see the Michigan election series and other studies with "Lower-Working-Middle-Upper"; in the right hand column, four studies adding "Upper Middle" and one (AIPO 412T) substituting "Laboring" for "Working." Each of the five gives higher marginals than any of the 21 in the other columns, sustaining the impression that addition of "Upper Middle" causes 10 per cent or more of "Working" to promote themselves to "Middle".

TABLE 1

SUBJECTIVE SOCIAL CLASS, 1948-1974

(Proportion Classifying Themselves as "Middle or Upper Class")

	LOWER-WORKING-MIDDLE-UPPER		OTHER CATEGORIES*
Year	Michigan Series	Other	
1948		.436 (1580) AIPO 412K	.622 (1549) AIPO 412T
1949		.327 (1261) NORC 163	
		.351 (1283) NORC 166	
		.306 (1232) NORC 168	
1950		.388 (1270) NORC 276	
1952	.378 (1735)	.383 (3051) AIPO 502	
1956	.371 (1694)		
1958	.391 (1758)		
1959			.621 (1505) ICPR 7258
1960	.331 (1126)		
1962	.411 (759)		
1964	.421 (1761)		.598 (1931)NORC SRS760
1965			.531 (1433)NORC SRS870
1966	.408 (1252)	.481 (1436)NORC SRS876	
1968	.447 (1613)		
1969		.451 (1506) AIPO 783	
1970	.449 (1640)		
1972	.450 (2623)	.461 (1604)GENSOC 72	
1973		.485 (748)GENSOC 73	.544 (745)GENSOC 73
1974		.489 (1475)GENSOC 74	

Note: AIPO = Gallup Poll (American Institute for Public Opinion), NORC = National Opinion Research Center, NORC SRS = NORC Survey Research Service, GENSOC = NORC General Social Survey.

*Includes "Upper-Middle" as a choice, except for AIPO 412T which uses "Laboring" instead of "Working".

Limiting our attention to the studies using Lower-Working-Middle-Upper, we see an apparent upward trend. Applying the tests outlined in the Appendix, we conclude that the data show a rough linear trend (Case IIIb). (Table 2 summarizes all the trend tests in this report.) B-C is significant at the .001 level ($r^2 = .632$), but the linear trend does not account for the data, since C is significant at the .001 level. Inspection of the computer output shows four outliers--studies producing chi square values of 5.000 or more for the discrepancy between the observed proportion and that predicted by the weighted regression (Table 3).

Since the chi squares are much larger for 1948 and 1960, we reran the data deleting these two studies. Table 2 shows the trimmed data to be nicely linear. The improvement for fitting the trend line (B-C) is highly significant and the weighted linear estimates fit the data well. (C is not significant.) Figure 1 illustrates.

We can use the (weighted) regression equation to estimate the Social Class parameter in our model:

$$\text{Proportion Middle and Upper} = .10 + .0050 * (\text{Year} - 100) \qquad (1)$$

The equation estimates a steady half per cent a year increase in Middle and Upper class identification, a 1952 value of .365, a 1972 value of .465, and, thus, a 10 per cent increase for the study period, 1952 - 1972.

Class and Party Preference

We located 17 national studies between 1948 and 1974 containing Party Identification and using the Lower-Working-Middle-Upper categories for Subjective Class.

Party Identification was trichotomized as Independent-Republican-Democrat. Where possible, third party adherents and cases coded in some studies as "totally apolitical" were excluded, both groups being infrequent in all files. In the Michigan items, "leaners" within Independents were classified as Independents.

TABLE 2

SUMMARY STATISTICS FOR MODELING SUBJECTIVE CLASS, PARTY, AND VOTE

Parameters	Deleted Outliers	N	Chi Square A	Chi Square B	Chi Square C	Probabilities A	Probabilities B	Probabilities C	Probabilities A-B	Probabilities B-C	r^2	b	Case
Constants													
MIDDLE CLASS		21	11512.4	168.8	62.1	-	.001	.001	-	.001	.632	+.0044	IIIb
MIDDLE CLASS	AIPO 412K MICH 1960	19	10623.1	150.8	23.9	-	.001	.122	-	.001	.848	+.0050	III
REP PARTY		15	1711.0	35.9	37.4	-	.001	.001	-	N.S.	.156	-.0005	IV
DEM PARTY		15	8020.2	82.5	66.3	-	.001	.001	-	.001	.147	-.0032	IIIb
DEM PARTY	NORC 66	14	7321.2	55.9	35.7	-	.001	.001	-	.001	.297	-.0036	IIIb
DEM PARTY	NORC 66 MICH 64	13	6589.7	44.3	23.0	-	.001	.018	-	.001	.396	-.0036	IIIb
DEM PARTY	NORC 66 MICH 64 GENSOC 72	12	6035.4	42.1	13.7	-	.001	.189	-	.001	.613	-.0044	III
REP VOTE		8	513.0	44.7	34.6	-	.001	.001	-	<.01	.274	-.0074	IIIb
REP VOTE	MICH 64	7	496.9	20.0	6.2	-	.003	.285	-	.001	.594	-.0083	III
DEM VOTE		8	353.9	42.7	45.0	-	.001	.001	-	N.S.	.011	-.0046	IV
DEM VOTE	MICH 64	7	265.2	17.3	17.2	-	.008	.004	-	N.S.	.040	-.0036	IV
DEM VOTE	MICH 64 MICH 72	6	218.7	7.0	6.9	-	.220	.141	-	N.S.	.020	+.0013	II
Coefficients													
CLASS by DEM PARTY		15	253.5	10.4	9.0	.001	.731	.772	.001	>.30	-	+.0014	II
CLASS by REP PARTY		15	261.4	26.1	14.1	.001	.025	.365	.001	.001	.297	-.0038	III
CLASS by REP VOTE		8	92.5	5.6	2.4	.001	.584	.880	.001	>.10	-	-.0029	II
CLASS by DEM VOTE		8	10.6	10.1	7.4	.226	.183	.286	>.30	>.10	-	+.0020	I
REP PARTY by DEM VOTE		8	245.0	12.3	12.5	.001	.091	.051	.001	N.S.	-	+.0024	II
REP PARTY by REP VOTE		8	401.6	14.2	11.6	.001	.047	.071	.001	>.10	-	+.0037	IIIa
REP PARTY by REP VOTE	MICH 56	7	381.7	6.2	6.1	.001	.403	.297	.001	>.70	-	+.0008	II
DEM PARTY by DEM VOTE		8	344.7	19.8	14.1	.001	.006	.028	.001	<.02	.155	-.0049	IIIb
DEM PARTY by DEM VOTE	MICH 72	7	307.7	7.1	6.8	.001	.314	.232	.001	>.50	.020	-.0013	II
DEM PARTY by REP VOTE		8	262.4	44.1	22.5	.001	.001	.001	.001	.001	.456	+.0096	IIIb
DEM PARTY by REP VOTE	MICH 64 MICH 68	6	198.8	36.0	9.4	.001	.001	.050	.001	.001	.705	+.0106	III

Note: Tests A, B, and C are defined in the Appendix.

To correct for multistage sampling, all standard deviations (for weights) have been multiplied by 1.414 and all chi squares multiplied by .5.

Test C and the regression coefficient, b, are based on the weighted regression estimates; r^2 is based on the unweighted regression. In all cases, there is no important difference between the weighted and unweighted results.

TABLE 3

OUTLIERS FOR SUBJECTIVE CLASS

Year	Study	Discrepancy	Chi Square
1948	AIPO 412K	+.082	21.702
1960	Michigan	-.075	14.409
1949	NORC 168	-.052	7.898
1966	NORC SRS876	+.048	6.760

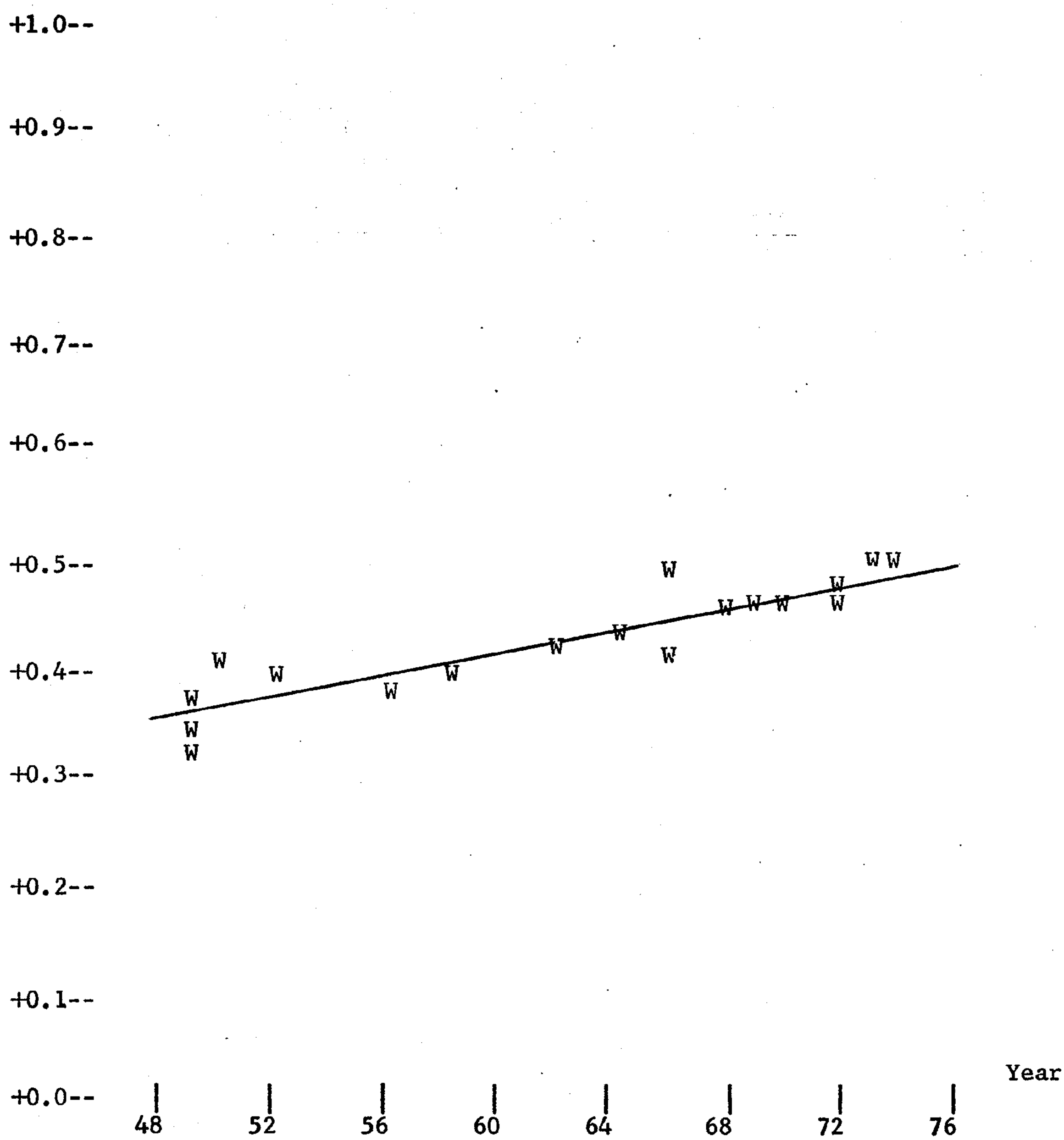


Fig. 1--Proportion Middle and Upper Class, 1949-1974, and Linear Trend Line (AIPO 412K and Election 60 deleted)

Treating the crosstabulation of Class by Party as a d-system (Davis, 1976), we want then to estimate the model shown in Figure 2. Therefore, we must estimate:

1) the d coefficient for Class and Proportion Democratic;
2) the d coefficient for Class and Proportion Republican;
3) the constant for Republican (the proportion Republican among Working and Lower); and
4) the constant for Democratic (the proportion Democratic among Working and Lower).

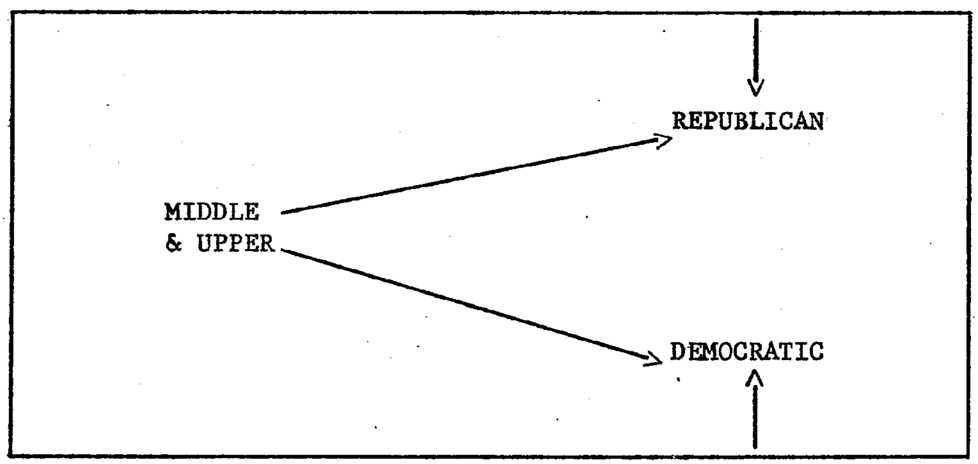
Table 4 illustrates the model and Tables 5 through 8 give the basic data for the 17 studies.

In Tables 5 through 8 we separated the questions that asked Party Identification with the qualifier "generally speaking" from the two Gallup studies that used "as of today". Folklore in the survey world and inspection of the tables suggest that the "today" version gives slightly but consistently different results.

The research literature and common observation predict that Middle-and-Uppers should be more likely than Working-and-Lowers to prefer Republicans and less likely to prefer Democrats. Tables 5 and 6 support this view. In each of the 15 studies, Middle-and-Uppers have a negative d for Democrats and a positive one for Republicans.

Statistical analysis (Table 2) shows the negative d for Class and Democrats to be a constant (Type III). The pooled value, -.146, improves the fit (A-B is significant), but there is no evidence of any trend (B and B-C are not significant). Thus, we infer a constant -.146 (15 per cent) class differential in Democratic preference from 1952 to 1974.

Table 2 shows that the Class-Republican coefficient falls in the linear trend (Type III) group. The weighted regression estimate is significantly better than the pooled constant (B-C is significant) and fits the data satisfactorily (C is not significant), with no



Base = Working & Lower Independent

Fig. 2--Flow Graph Model for Class and Party

TABLE 4

SUBJECTIVE CLASS AND PARTY PREFERENCE IN THE 1966 MICHIGAN ELECTION SURVEY

	Independent	Republican	Democratic	Sum
	A. N's			
Middle and Upper	148	167	178	493
Working and Lower	205	145	372	722
				1215
			Other and NA	37
				1252
	B. Proportions			
Middle and Upper	.300	.339	.361	1.000
Working and Lower	.284	(.201)	(.515)	1.000
	d	+.138	-.154	

C. Flow Graph

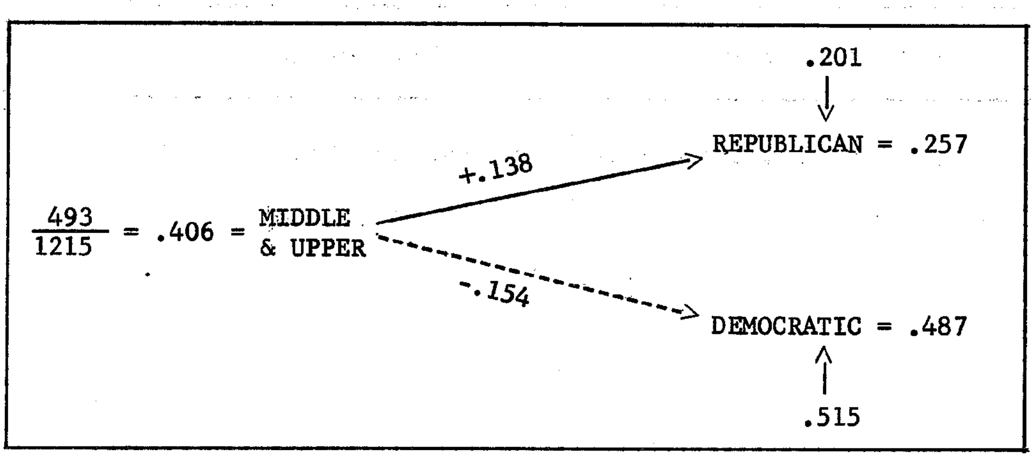


TABLE 5

CLASS AND DEMOCRATIC PREFERENCE, 1948-1974

(d Coefficients)

Year	"Generally" Michigan Series	"Generally" Other	"Today"
1948			-.087 (.025) AIPO 412K
1952	-.187 (.024)	-.159 (.019) AIPO 502*	
1956	-.138 (.025)		
1958	-.162 (.025)		
1960	-.141 (.037)		
1962	-.118 (.038)		
1964	-.180 (.025)		
1966	-.154 (.029)	-.101 (.027) NORC SRS876	
1968	-.155 (.026)		
1969			-.088 (.026) AIPO 783
1970	-.098 (.025)		
1972	-.110 (.019)	-.150 (.025) GENSOC 72	
1973		-.122 (.037) GENSOC 73	
1974		-.199 (.027) GENSOC 74	

Note: Numbers in parentheses are one standard error for the difference in proportions, not corrected for multistage sampling.

* Question uses "normally" rather than "generally."

TABLE 6

CLASS AND REPUBLICAN PREFERENCE, 1948-1974

(d Coefficients)

Year	"Generally" Michigan Series	"Generally" Other	"Today"
1948			+.063 (.024) AIPO 412K
1952	+.171 (.023)	+.209 (.017) AIPO 502 *	
1956	+.121 (.024)		
1958	+.120 (.023)		
1960	+.162 (.036)		
1962	+.087 (.036)		
1964	+.166 (.022)		
1966	+.138 (.026)	+.094 (.025) NORC SRS876	
1968	+.092 (.023)		
1969			+.113 (.024) AIPO 783
1970	+.103 (.021)		
1972	+.074 (.017)	+.097 (.022) GENSOC 72	
1973		+.111 (.032) GENSOC 73	
1974		+.166 (.024) GENSOC 74	

Note: Numbers in parentheses are one standard error for the difference in proportions, not corrected for multistage sampling.

* Question uses "normally" rather than "generally."

TABLE 7

CLASS AND REPUBLICAN CONSTANT (PROPORTION REPUBLICAN IN LOWER AND WORKING) 1948-1974

Year	"Generally" Michigan Series	Other	"Today"
1948			.321 (.016) AIPO 412K
1952	.217 (.013)	.171 (.009) AIPO 502 *	
1956	.252 (.014)		
1958	.239 (.013)		
1960	.254 (.019)		
1962	.263 (.021)		
1964	.166 (.012)		
1966	.201 (.015)	.237 (.016) NORC SRS876	
1968	.211 (.014)		
1969			.237 (.015) AIPO 783
1970	.185 (.013)		
1972	.205 (.011)	.187 (.014) GENSOC 72	
1973		.182 (.020) GENSOC 73	
1974		.175 (.014) GENSOC 74	

Note: Numbers in parentheses are one standard error for the difference in proportions, not corrected for multistage sampling.

* Question uses "normally" rather than "generally."

TABLE 8

CLASS AND DEMOCRATIC CONSTANT (PROPORTION DEMOCRATIC IN LOWER AND WORKING) 1948-1974

Year	"Generally" Michigan Series	"Generally" Other	"Today"
1948			.461 (.017) AIPO 412K
1952	.558 (.015)	.593 (.012) AIPO 502*	
1956	.509 (.016)		
1958	.580 (.016)		
1960	.512 (.022)		
1962	.541 (.024)		
1964	.612 (.016)		
1966	.515 (.019)	.673 (.018) NORC SRS876	
1968	.540 (.017)		
1969			.449 (.018) AIPO 783
1970	.499 (.017)		
1972	.460 (.013)	.566 (.017) GENSOC 72	
1973		.486 (.026) GENSOC 73	
1974		.489 (.019) GENSOC 74	

Note: Numbers in parentheses are one standard error for the difference in proportions, not corrected for multistage sampling.

* Question uses "normally" rather than "generally."

outliers generating chi square values of 5.0 or more. The relationship is not strong ($r^2 = .297$), but the regression estimate gives a 1952 value of +.174 and a 1972 value of +.098, a decline .076 over 22 years. Figure 2 shows the trend. Here is the equation:

$$d_{\substack{\text{Middle-and-Upper} \\ \text{x Republican}}} = .37 - .0038 * (\text{Year} - 100) \qquad (2)$$

The implications of all of this will be discussed later.

Next, we consider the constants--that is, the proportion Republican and Democratic among Working-and-Lowers. The Republican constant (see Table 2) shows a nonlinear trend (Case IV), the B test being significant but the C model no improvement at all. Thus, lower status preference for the GOP fluctuates significantly from 1952 to 1974, but shows no general trend upward or downward.

To estimate the various values, we first pooled the three cases with two estimates a year, obtaining .186 ($\sigma = .008$) for 1952, .218 ($\sigma = .011$) for 1966, and .198 ($\sigma = .009$) for 1972. (1972 and 1966 are quite homogeneous, with p values of .518 and .244; the 1952 estimates are significantly different, p = .037. We have, however, no clue as to which is the better estimate, so we pooled these as well.) Next, we reran the data, with the results shown in Table 9.

Table 9 makes sense in the light of United States political history. In most years from 1952 to 1972 the Republican proportion is close to .203, but it is significantly higher (since the test has K-1 degrees of freedom, each year has almost one d.f. where the .05 critical value is 3.841) in 1956, 1958, and 1962, and significantly lower in 1964, with 1960 of borderline significance. Remembering that the 1952 survey was conducted in the last two months of 20 years of Democratic hegemony, the suggestion is that Eisenhower's incumbency increased Republican allegiance among the Working-and-Lowers, that Kennedy was unable to reverse this pull, but that Goldwater managed to do so. The much-touted lower status shift to the GOP under Nixon is not visible in Table 9, the deviations in 1970 and after being negative and insignificant.

TABLE 9

ESTIMATES OF REPUBLICAN CONSTANT

Year	Proportion	Not Significant	Significant	Chi Square
1952	.186	-.017		2.3
1956	.252		+.049	6.1
1958	.239		+.036	3.8
1960	.254		(+.051)	3.6
1962	.263		+.060	4.0
1964	.166		-.037	4.8
1966	.218	+.015		0.9
1968	.211	+.008		0.2
1970	.185	-.018		1.0
1972	.198	-.005		0.2
1973	.182	-.021		0.6
1974	.175	-.028		2.0

Note: Vs. Pool = .203

Turning to the vicissitudes of the Democrats, Table 2 indicates a rough linear trend (Case IIIb) with steadily decreasing Democratic choice among the Working-and-Lowers. The computer printout gives one clear outlier, the 1966 NORC study, with a chi square of 28.575. When it is removed, the 1966 Michigan study stands out (chi square = 11.999). When both are removed, the 1972 General Social Survey departs from the linear prediction in the amount of 7.902. Finally, when all three outliers are removed, the data give a nice linear trend with an r^2 of .613 (see Table 2 for details). Figure 3 illustrates.

The weighted regression, after the removal of the three outliers, gives the following equation:

$$\text{Proportion Democratic Among Lower-and-Working} = .80 - .0044 * (\text{Year} - 100) \qquad (3)$$

The equation gives estimates of .575 for 1952, .486 for 1972, and, thus, a decline of .089 for the study period.

We have now estimated the five parameters necessary to model Subjective Class and Party Preference. Figure 4 summarizes.

Figure 4 pulls together the main findings so far:

1) There has been a half per cent a year linear increase in the proportion Middle and Upper.
2) The association between Class and Democratic preference has been a constant -.146 throughout the study period.
3) The positive association between Class and Republican has declined steadily.
4) The proportion Democratic among Working-and-Lowers has declined steadily.
5) The proportion Republican among Working-and-Lowers has fluctuated up and down without any general trend.

To analyze the system's dynamics it is useful to examine the state and change graphs from 1952 to 1972. For simplicity, we present only the presidential year figures for 1952, 1956, 1960, 1964, 1968, and 1972 in Figure 5.

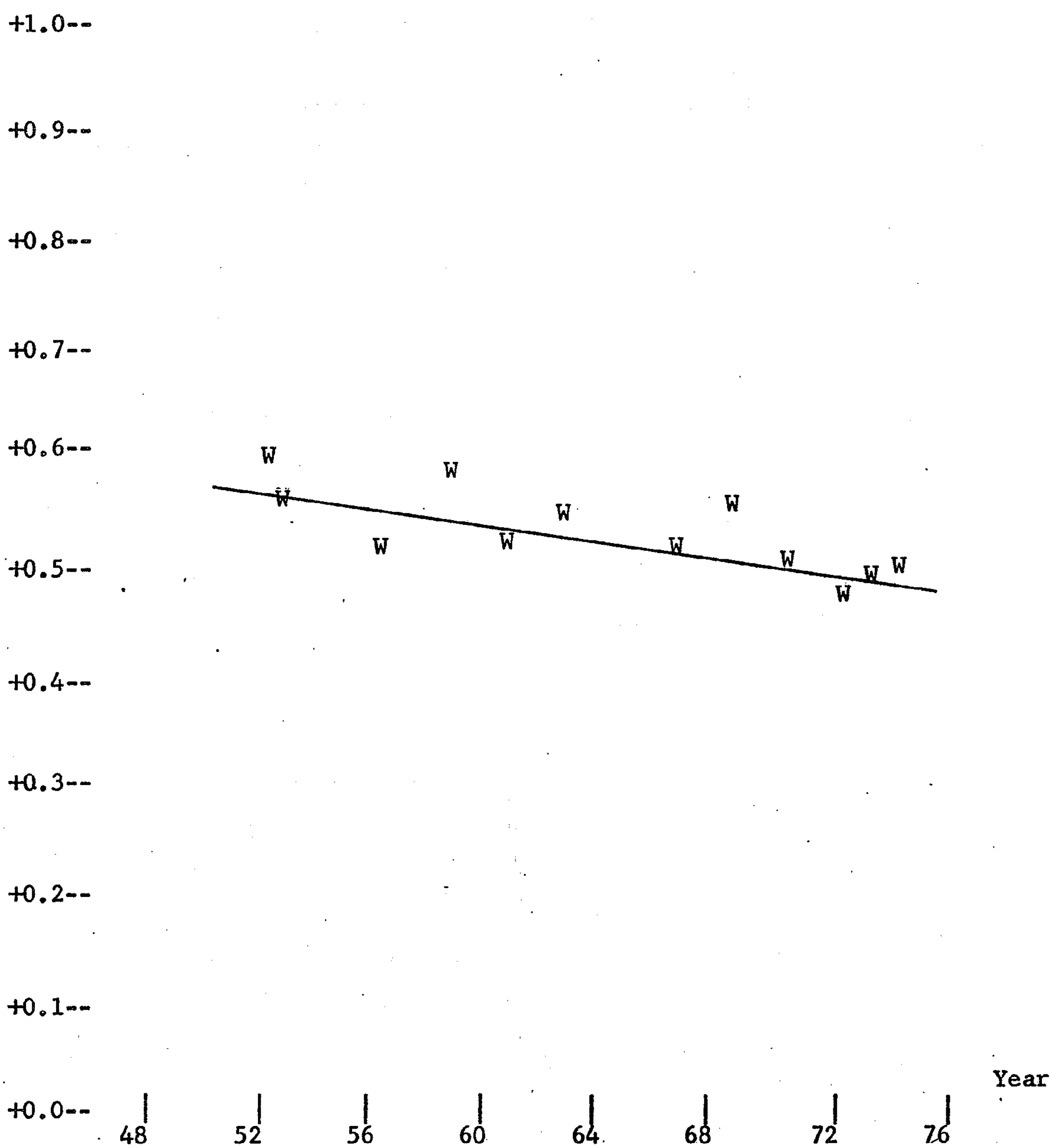


Fig. 3--Proportion Democratic Among Working-and-Lowers
1952-1974 (3 outliers deleted)

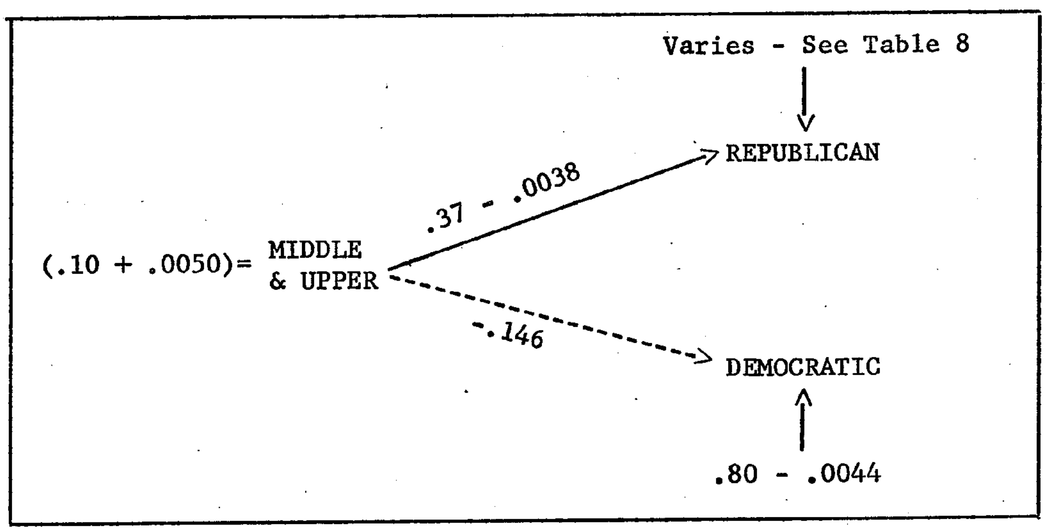


Fig. 4--Flow Graph for Class and Party Preference, 1952-1972

(1952)

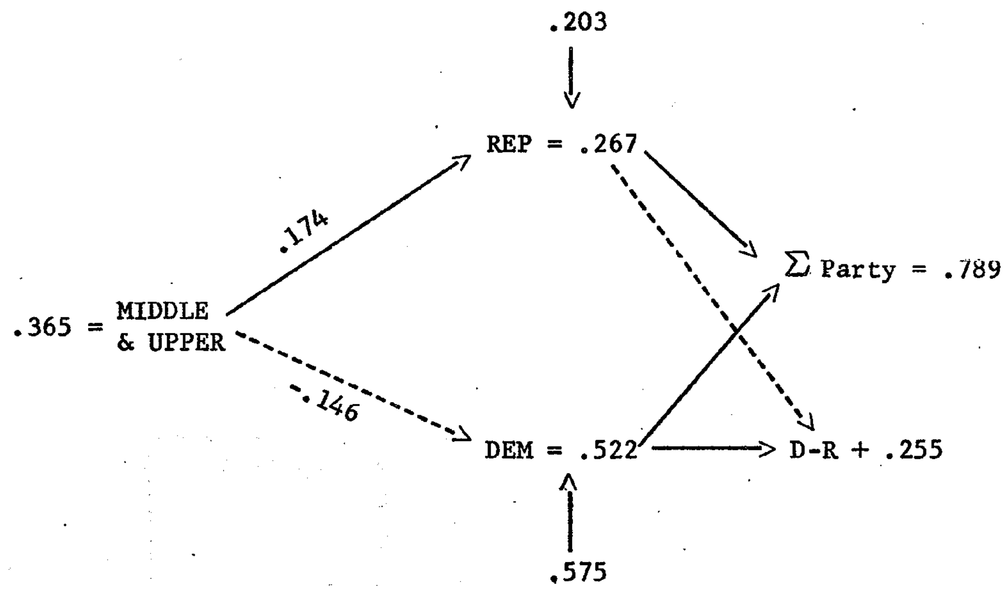
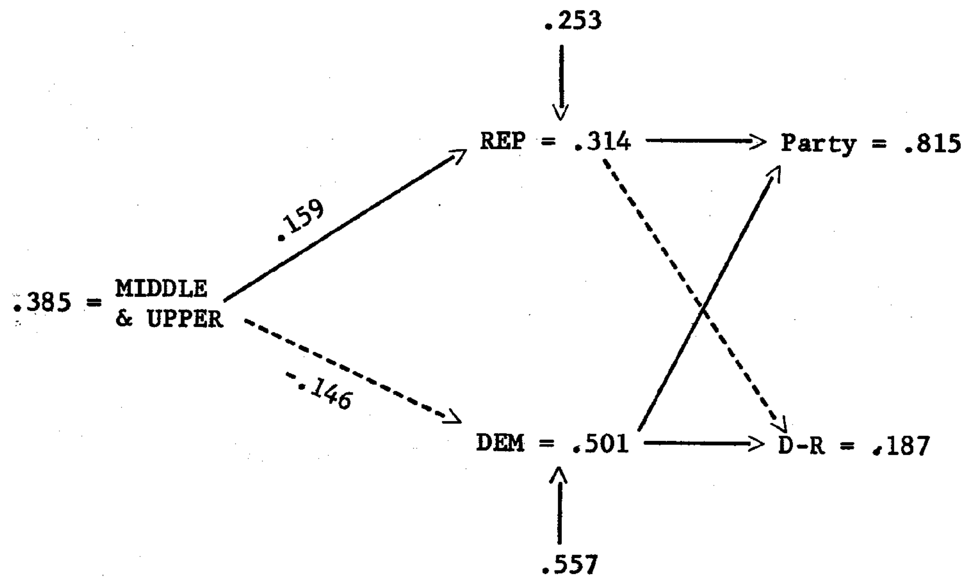


Fig. 5--Flow Graphs and Change Graphs, 1952-1972
(modeled parameters)

Note: Since the value of the Republican and Democratic nodes is their proportions, we can add two useful dummy nodes: (1) the sum, Republican + Democratic, is the total with a major party preference; and (2) the difference, Democratic - Republican, is the Democratic plurality for party preference.

Since the Class-Republican coefficient changes, we must add an extra branch in the change graphs (see Davis, 1975) for the $Time_2$ value of Class and the change in coefficient.

(1956)



(Change 1952-1956)

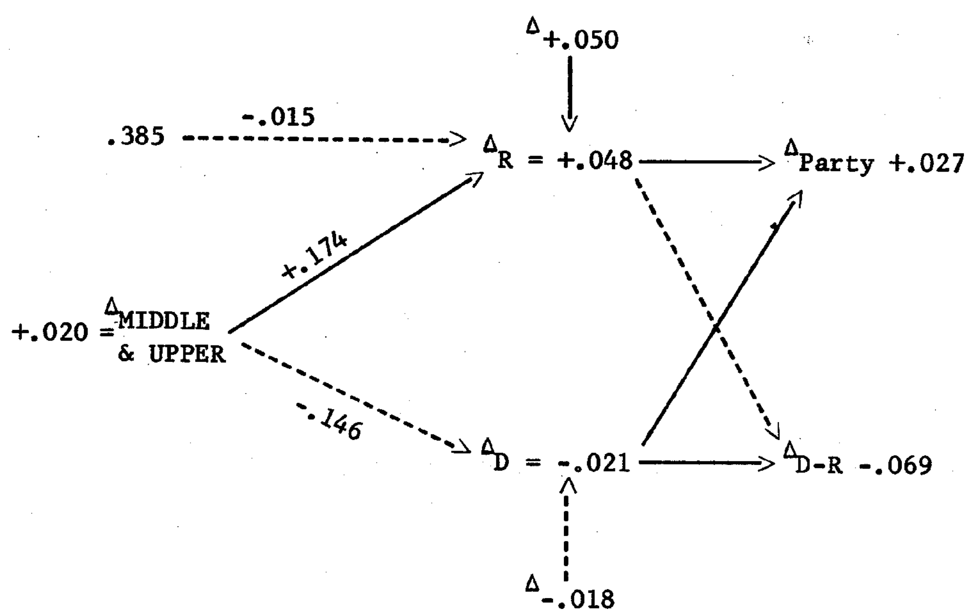
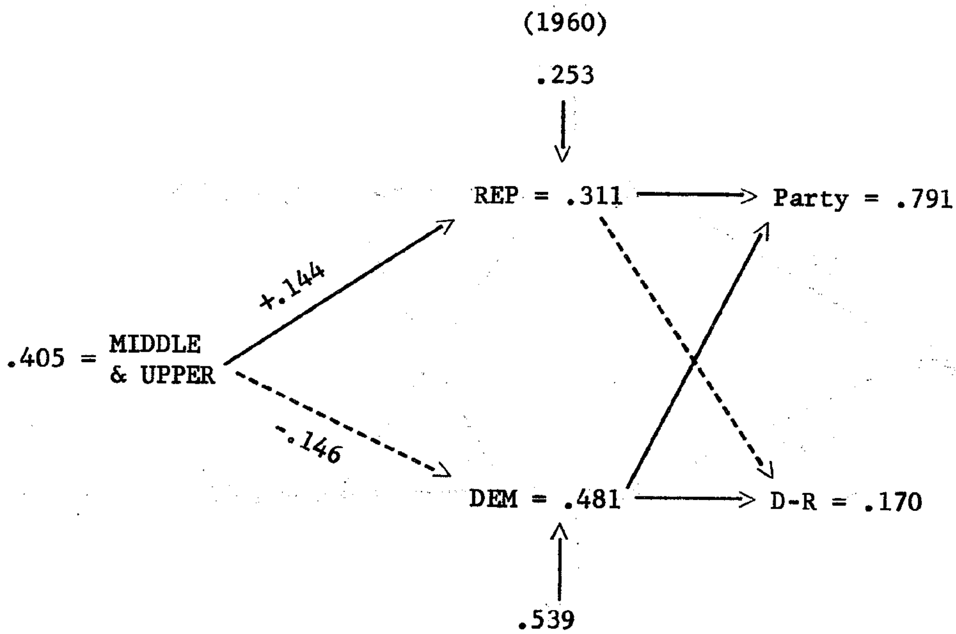


Fig. 5--Continued



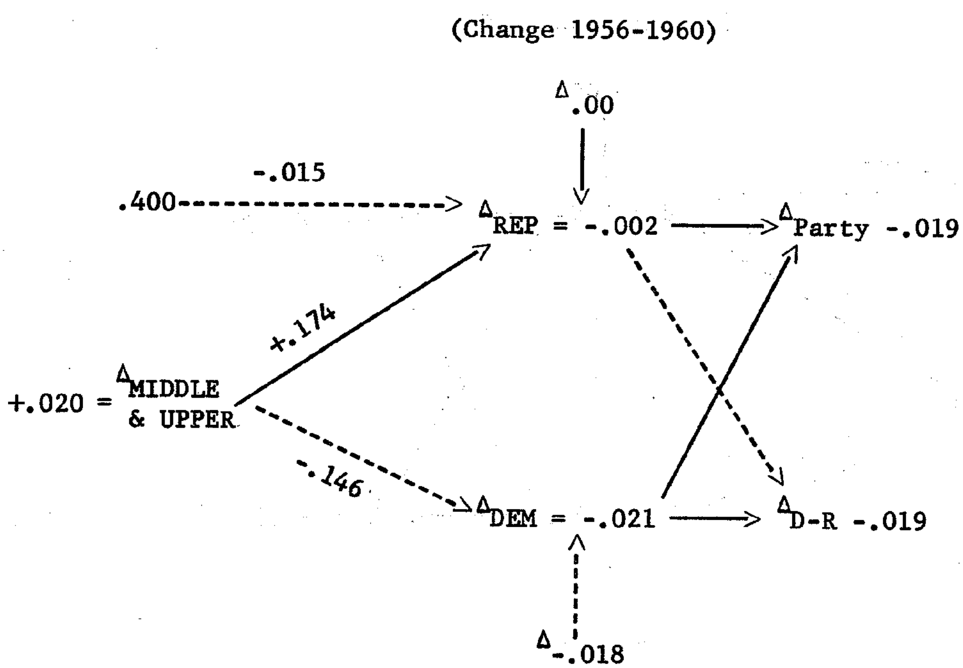
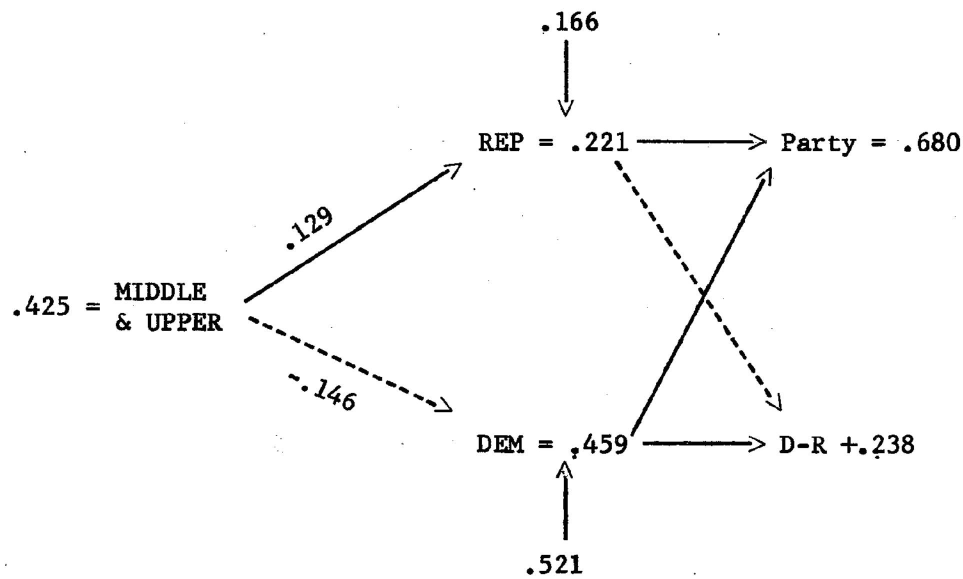


Fig. 5--Continued

(1964)



(Change 1960-1964)

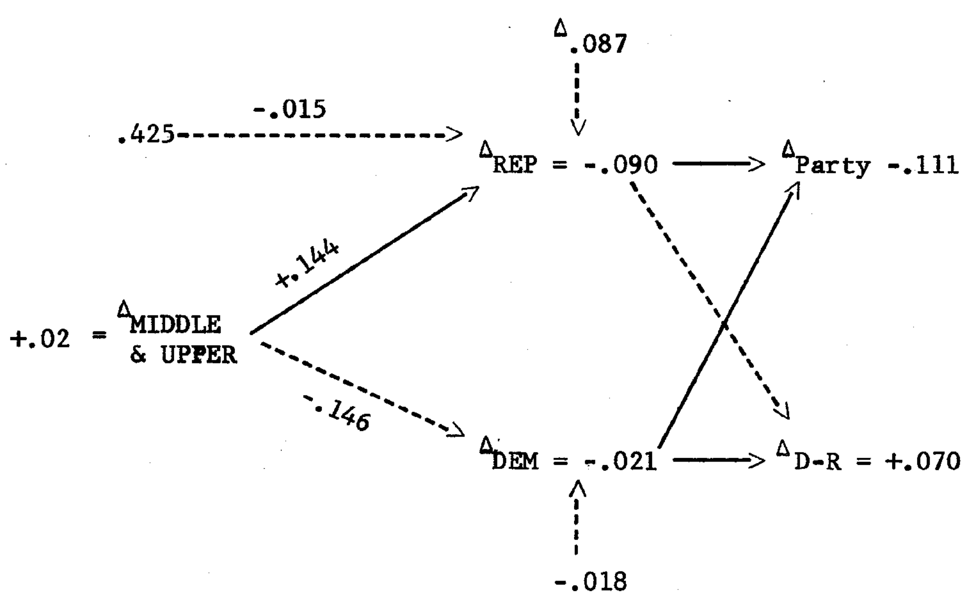
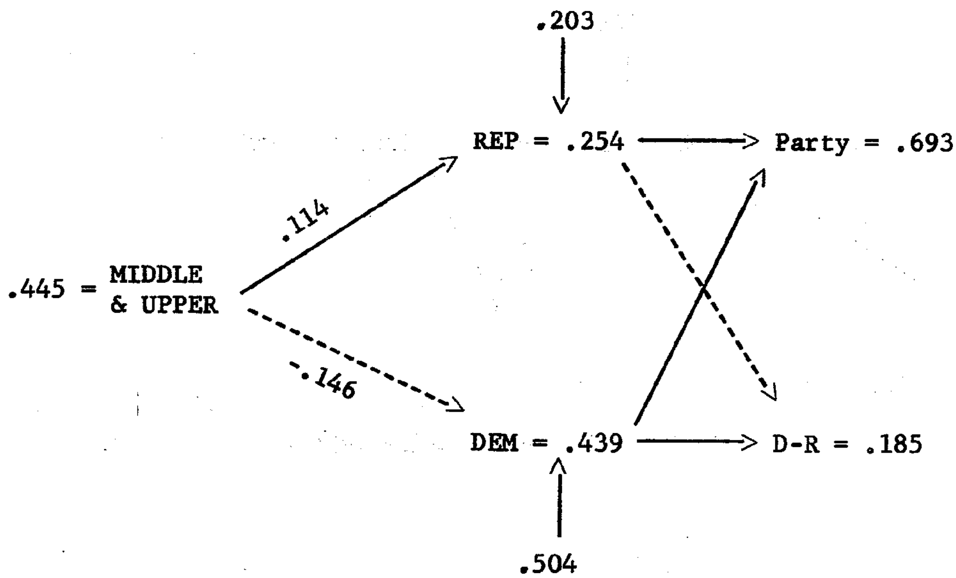


Fig. 5--Continued

(1968)



(Change 1964-1968)

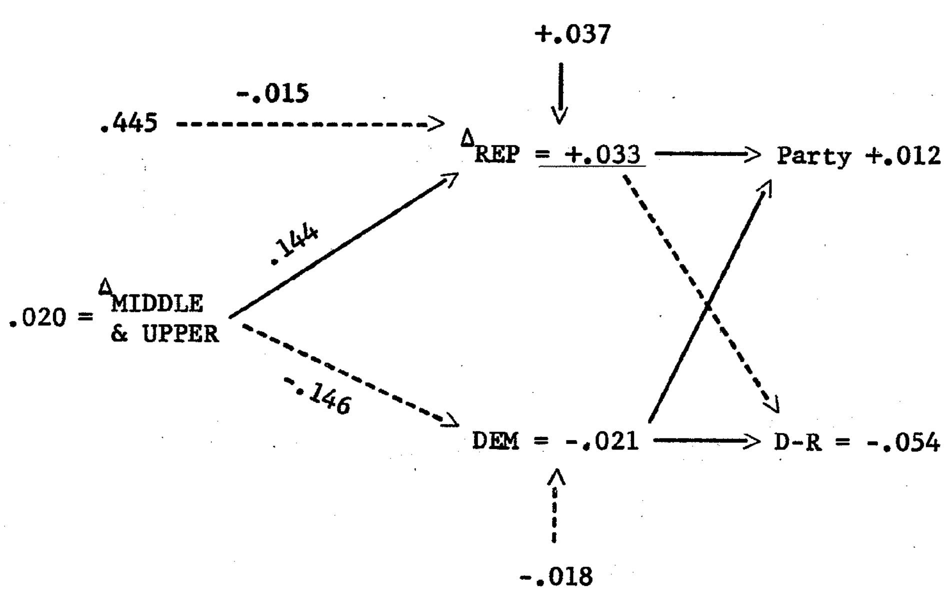
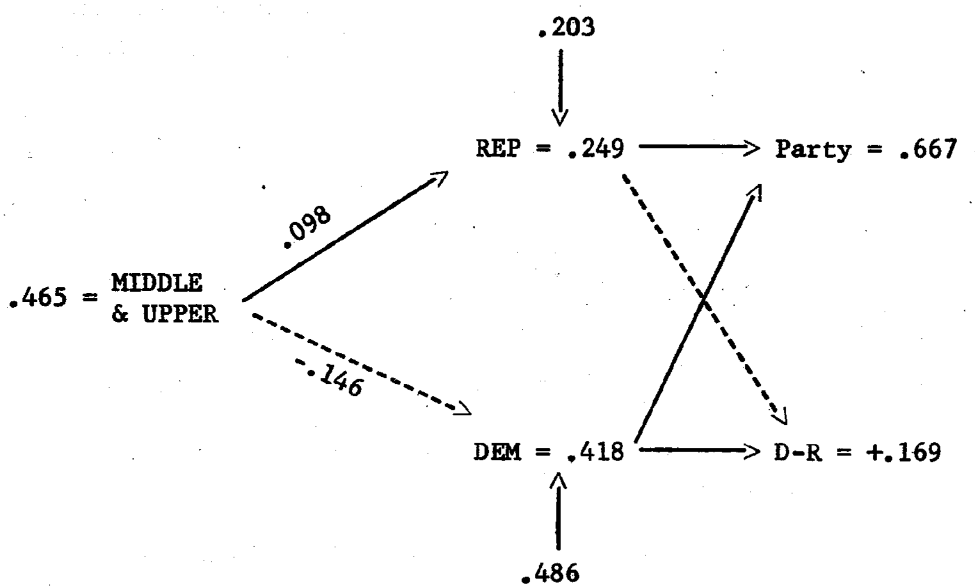


Fig. 5--Continued

(1972)



(Change 1968-1972)

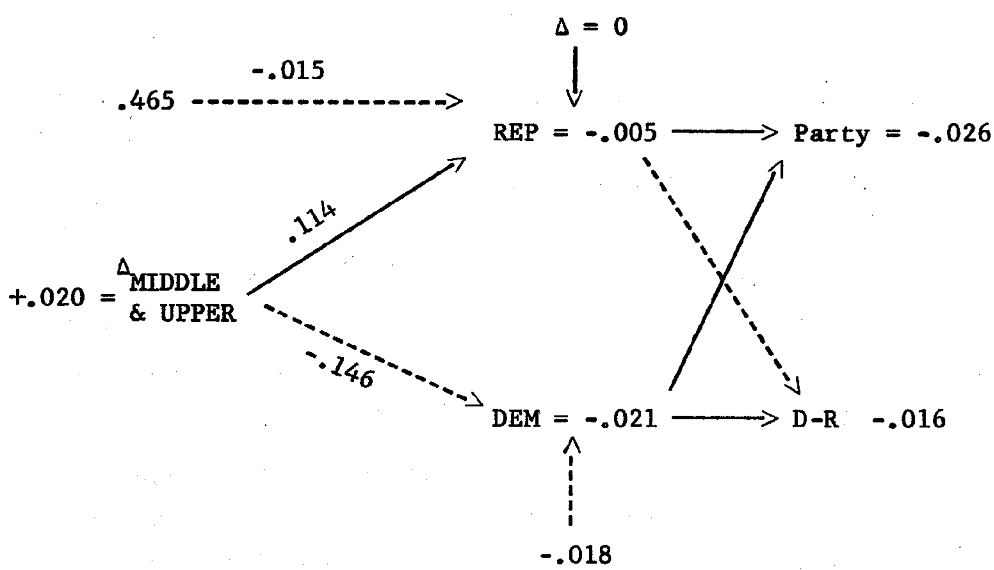


Fig. 5--Continued

Let us start in 1952, just prior to Eisenhower's first election. The state graph shows the following proportions: .365 Middle and Upper, .267 Republican, .522 Democratic, .789 Major Party (see note to figure for 1952), and a +.255 Democratic plurality. Four years later in 1956:

1) the proportion Middle Class increased +.020;
2) Republican preference among the Working-and-Lowers increased +.050 (we will use this figure for all of the positive deviations in Table 8);
3) the Class-Republican coefficient declined .015; and
4) Democratic preference among Working-and-Lowers declined .018.

What were the consequences?

The proportion Democratic declined .021, .018 coming from the secular trend against Democrats in the Working-and-Lowers, .0029 = (+.020 * -.146) coming from the decline in the proportion Working-and-Lower. This loss, -.021, will appear in each new election as a secular erosion of the Democrats' class base and in their ability to command the loyalty of the Working-and-Lowers. (These models do not <u>require</u> that any voters change their minds--the differences found here could come entirely from cohort replacement. However, we shall discuss the effects as changes for simplicity in explanation.)

For Republicans, the situation is a bit more complicated. They gain +.050 in their constant--possibly from the charisma of the first Eisenhower administration--and gain +.0035 = (.020 * $\pm$.174) from the increased proportion Middle and Upper. This, however, is offset -.0058 (.385 * -.015) by the declining coefficient. The sum of the two class effects, -.0023, is a slight net <u>loss</u> for the Republicans, who added to their constituency but slipped in its relative affections. These three effects give a net change of +.048 for Republicans.

These two changes in Party yield a slight increase in Major Party Preference (+.027) and a drop (-.069) in Democratic plurality, the sum of the secular trend against the Democrats and the Republican upswing.

Although John Kennedy moved into the White House in 1960 (in a very tight election), the model shows little dramatic change from 1956 to 1960: the Democrats add -.021 to their secular decline and the Republicans show no additional increase or decrease among the Working-and-Lowers. The two Class effects are +.0035 and -.0060, giving a total of -.0025. The result of this is virtually no change in Republicanism (-.002), a trivial decline in Major Party (-.019), and a trivial decline in the Democratic plurality (-.019). (How the Democrats won the election will be considered in the next section where we include Presidential vote.)

The Johnson-Goldwater election in 1964, however, produces some activity. Republicans drop -.090, of which -.087 comes from the significant drop in Republican preference among the Working-and-Lowers, and (-.0064 + .0029 =) -.0035 from the two Class effects. The Republican setback combined with the steady -.021 Democratic decay, gives a -.111 drop in Major Party and a +.070 recovery in Democratic plurality.

1968 saw a recovery among the Republicans, or more exactly a +.037 rebound from Goldwater among the Working-and-Lowers, and a (+.0029 - .0067 =) -.0038 Social Class effect, giving a total shift of +.033. The result is a slight increase in Major Party and a -.054 deterioration in the Democratic plurality.

Finally, in 1972, as in 1960, there is little change in Party Preference. The Republicans lose .005 from Class effects, and the Democrats lose their usual -.021, giving a -.026 drop in Major Party, and a -.016 dip in Democratic plurality.

We can attempt to pull all this together by considering the four party nodes, in turn.

1) Democrats suffer a steady attrition from 1952 to 1974, losing adherents at a steady -.021 a year. Of this, -.018 is a secular decline and -.0029 comes from erosion of their Working-and-Lower base.

2) Republican trends are more complex. Despite recent claims from Republican strategists, the socioeconomic upgrading of the

American nation has not strengthened the GOP. The increasing proportion Middle class does help Republicans (in the third decimal each four years), but this is offset by the secular decline in the correlation between Class and Party. The major effect on Republican proportions has been in the constant term--a definite boost during the Eisenhower era, cancelled out by the Goldwater election in 1964. The upshot: Republicans in 1974 were just about where they were when Truman was finishing his term, the model giving .249 Republican in 1972 versus .267 in 1952, compared with a high of .314 in 1956.

3) The main trend in Major Party has been down. The Democratic decline subtracted .021 every four years and a total of -.105 for 1952 to 1974. The Republican surge in 1956 to 1960 cancelled out this loss, but with the "return to normal" of Republicanism, the proportion Major Party is down to .667 in 1974, in comparison with highs of almost .800 for 1952 to 1960.

4) Since it is a function of a number of complex effects, the Democratic plurality shows no distinct trend. It has highs of +.255 in 1952 and +.238 in 1964 and values close to .180 in the other years. The Democrats no longer have the edge they presumably had under Truman and Roosevelt, but the inability of the Republicans to hold their Eisenhower gains leaves a substantial deficit in popular appeal for the GOP.

Table 10 summarizes all of these figures.

Returning to the original question regarding Subjective Social Class and Party Preference, the model offers a bit of a paradox. The unambiguous social upgrading in the United States since World War II has hurt both parties. The Democrats have suffered a slight but steady loss amounting to ((.465 - .365 = 1.00) * (-.146) =) -.0146 from 1952 to 1972, but the Republicans were unable to gain because the correlation between Class and Republicanism declined steadily and outweighed the contribution of an increasing middle class.

TABLE 10

SUMMARY OF PARTY VALUES, 1952-1972

(Model Parameters)

Year	Node			
	Republican	Democratic	Major Party	Democratic Plurality
1952	.267	.522	.789	+.255
1956	.314	.501	.815	+.187
1960	.311	.481	.792	+.170
1964	.221	.459	.680	+.238
1968	.254	.439	.693	+.185
1972	.249	.418	.667	+.169
1952-56	+.048	-.021	+.027	-.069
1956-60	-.002	-.021	-.019	-.019
1960-64	-.090	-.021	-.111	+.070
1964-68	+.033	-.021	+.012	-.054
1968-72	-.005	-.021	-.026	-.016

Subjective Class, Party Preference, and Presidential Vote

We are now ready to add the sink variable, Presidential Vote. Preliminary inspection of a number of studies suggests it is best to use only surveys collected within 12 months of an election, since retrospective presidential preference seems to shift toward the winner after a year or two. Therefore, we are down to eight surveys: the Michigan election studies for 1952, 1956, 1960, 1964, 1968, and 1972; AIPO 783 (July, 1969); and the 1973 NORC General Social Survey (March, 1973).

In each election, Presidential Vote was grouped under three headings: Republican, Democratic and Other, and No Vote, the latter being defined when possible as "eligible to vote but did not do so."

Each of the eight 18-cell cross classifications of Class, Party, and Vote was run on "CATFIT," the NORC interactive computer program for estimating d-systems. None of the six coefficients showed significant (.05, corrected for multistage sampling) interactions in any of the eight studies, so it is proper to work with pooled estimates (see Davis, 1976).

Table 11 gives the parameters and their standard errors before multistage correction. As with Party, we used Republican and Democratic-Other as nodes, assigning the base category (see Davis, 1976) to No Vote.

Taking the findings in order of complexity and referring to Table 2:

1) There is a constant association (pooled d = +.103) between Class and Republican Vote. In each election, Middle-and-Uppers are more likely to vote Republican, regardless of their party preference. A-B is significant, but B and C are not.

2) The partial association between Class and Democratic Vote is generally zero (Case I). Test A is not significant so we cannot reject the null hypothesis that all d's are sampled from a constant universe value of zero.

TABLE 11

PARAMETER ESTIMATES FOR PRESIDENTIAL VOTE, 1952-1972

Parameter	Study							
	1952	1956	1960	1964	1968	1968a	1972	1972a
Constants								
REP VOTE	.437	.515	.345	.153	.381	.300	.301	.340
sigma	(.034)	(.033)	(.044)	(.027)	(.036)	(.030)	(.021)	(.033)
DEM VOTE	.282	.196	.294	.506	.287	.325	.164	.225
sigma	(.031)	(.026)	(.042)	(.038)	(.034)	(.030)	(.017)	(.029)
Coefficients								
CLASS by REP VOTE	.145	.114	.137	.109	.076	.098	.064	.117
sigma	(.023)	(.022)	(.032)	(.019)	(.023)	(.022)	(.018)	(.024)
CLASS by DEM VOTE	-.037	.025	-.026	-.018	.018	-.011	.039	.009
sigma	(.015)	(.014)	(.024)	(.025)	(.022)	(.021)	(.013)	(.018)
REP PARTY by REP VOTE	.306	.202	.354	.357	.291	.423	.342	.295
sigma	(.033)	(.032)	(.047)	(.036)	(.035)	(.031)	(.025)	(.033)
REP PARTY by DEM VOTE	-.218	-.166	-.264	-.210	-.195	-.257	-.134	-.189
sigma	(.025)	(.021)	(.039)	(.037)	(.029)	(.027)	(.016)	(.023)
DEM PARTY by REP VOTE	-.288	-.365	-.242	-.134	-.288	-.191	-.085	-.196
sigma	(.030)	(.029)	(.041)	(.025)	(.029)	(.027)	(.021)	(.029)
DEM PARTY by DEM VOTE	.261	.358	.282	.225	.333	.266	.172	.271
sigma	(.030)	(.027)	(.044)	(.033)	(.031)	(.031)	(.020)	(.029)

Note: Studies are from the Michigan election series, save for 1968a, which is AIPO 783, and 1972a, which is the NORC 1973 General Social Survey.

Combining (1) and (2), we may say that, net of party preference, Middle-and-Uppers are consistently more likely to turn out for the Republican candidate, less likely to be a No Vote, and neither more nor less likely to vote Democratic, when compared with Working-and-Lowers. The Republican party has been consistently able to attract Upper-and-Middle votes even among Independents and Democrats, but the Democrats attract Working-and-Lower votes only to the extent that Class determines Party Preference. Turning to Party, regardless of their Class identification:

3) Self-declared Republicans are less likely (than Independents, the base category) to vote Democratic (pooled d = -.185). A-B is significant, but B is not (Case II).

4) Conversely, Republicans are consistently more likely than Independents to vote Republican. On the first run, the relationship fell into the borderline linear trend classification (Case IIIa) since the B test was significant (p = .047) and C was not. When, however, the 1956 Michigan elections study with an outlier chi square of 7.0 is removed, B is no longer significant and B-A is significant at the .001 level (Case II). The pooled value after deleting the 1956 study is .339. (Prior to the deletion, the pooled value was .322.)

5) Self-declared Democrats show a constant tendency to cast Democratic ballots more often than Independents. On the first run, B was quite significant, and a linear trend seemed possible. However, when the 1972 Michigan study (a 9.5 outlier in the B estimates and a 4.4 outlier in the C's) is deleted, the constant model fits quite nicely with a pooled value of +.289.

6) The association between Democratic party and Republican ballot is negative, as one would expect, but the results are complex. The complete set of eight studies shows a rough negative linear trend (Case IIIb) that becomes a negative trend when the 1964 and 1968 Michigan studies (chi squares for deviations from the C estimates = 6.4 and 6.3) are deleted. The weighted regression equations show the

relationship declining from -.348 in 1952 to -.136 in 1972. The weighted equation is as follows:

$$d_{\substack{\text{DEM PARTY by} \\ \text{REP VOTE}}} = -.90 + .0106 * (\text{Year} - 100) \qquad (4)$$

Figure 6 illustrates.

These six results generally support the main theme of The American Voter. Party adherents show a stable and fairly strong tendency to turn out for their candidate and to abstain from the standard bearer of the other party when compared with Independents in the same Class. Party preference, furthermore, explains the tendency for Working-and-Lowers to vote Democratic, though not the persistent Republican votes of the Middle-and-Uppers.

Finding (6), however, is an exception. While Democrats do turn out consistently for Democratic candidates, they have gradually become less distinguished from Independents with regard to Republicans. Since Republican plus Democratic plus No Vote must add up to 100 per cent, another way to put this is: Democrats who are not going to vote for their own party increasingly tend to vote for Republicans instead of staying home.

Finally, the Presidential Vote constants--the proportions voting Republican or Democratic among the base group, Working-and-Lower Independents (see Davis, 1966):

7) The Republican value shows a negative trend, after deletion of the 1964 Michigan election study, which had a healthy 25.7 outlier chi square on the first run. The weighted regression estimates drop from .473 in 1952 to .308 in 1972, according to the equation:

$$\substack{\text{Republican} \\ \text{Constant}} = .90 - .0083 * (\text{Year} - 100) \qquad (5)$$

Figure 7 illustrates.

8) Finally, Table 2 tells us that the Democratic Vote is a constant (.260), although fit is obtained only after deletion of the 1964 and 1972 Michigan studies. Figure 8 gives the complete system model.

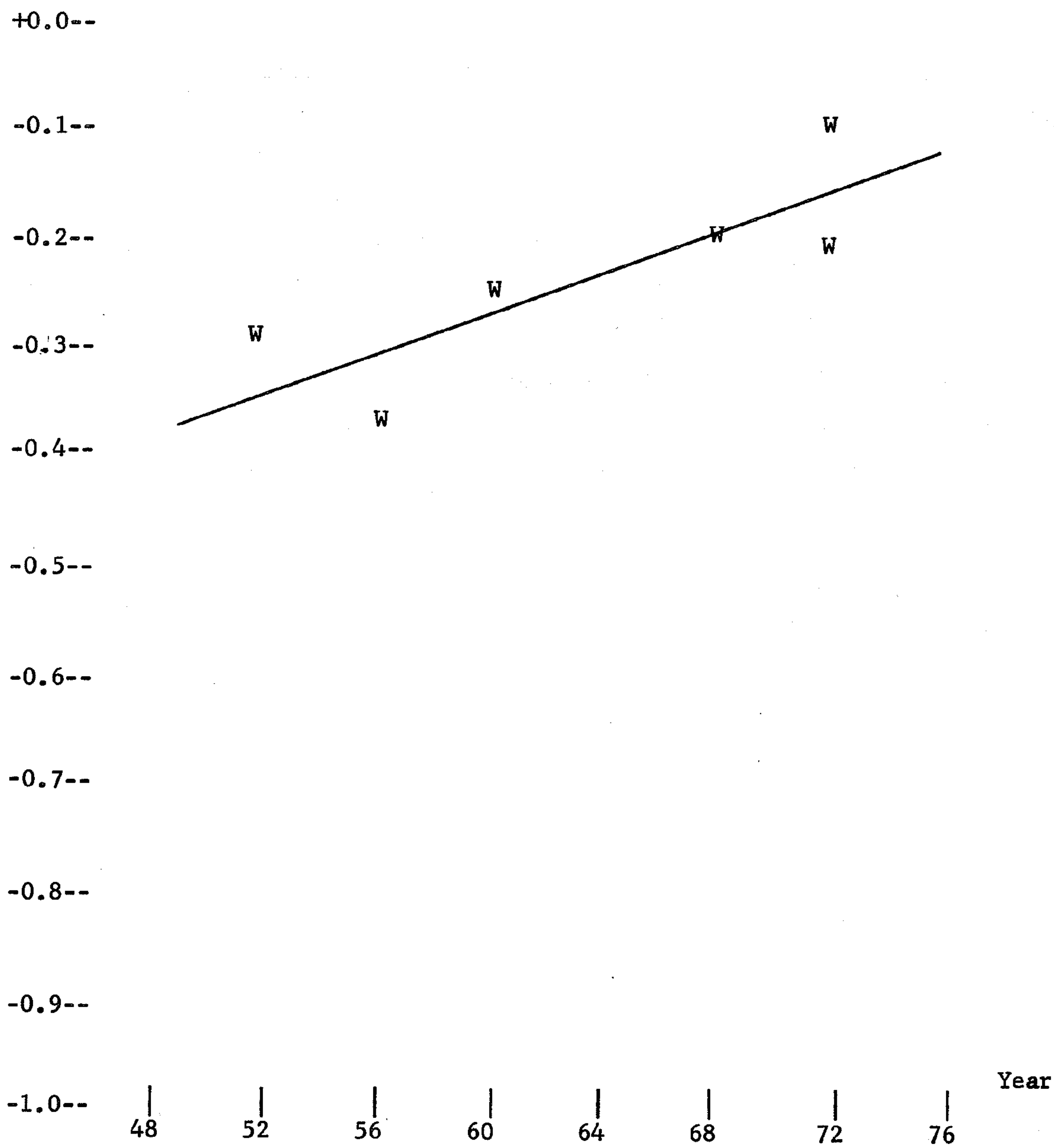


Fig. 6--Democratic Party by Republican Vote, 1952-1972

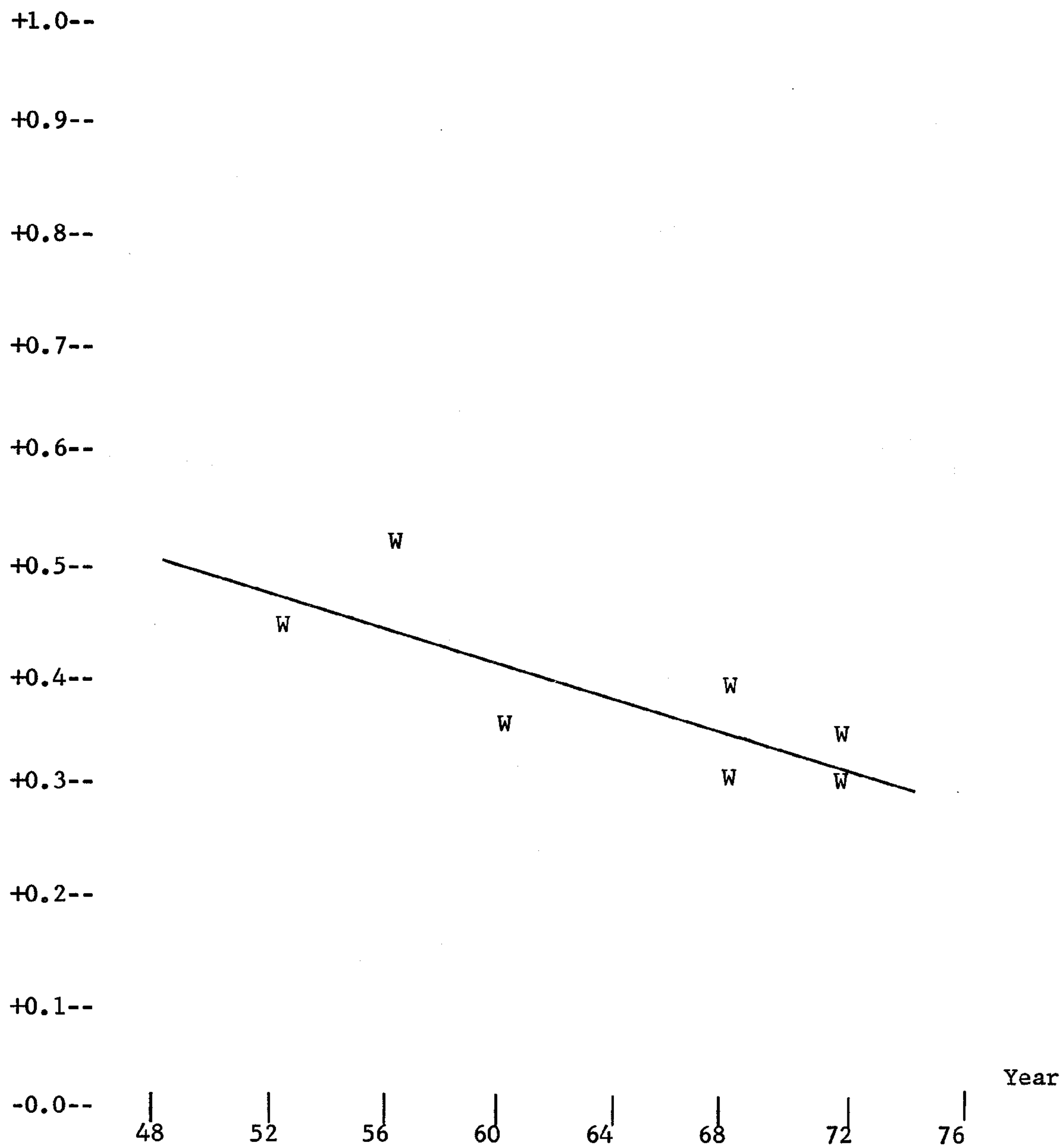


Fig. 7--Republican Vote Constant, 1952-1972
(Michigan 1964 Deleted)

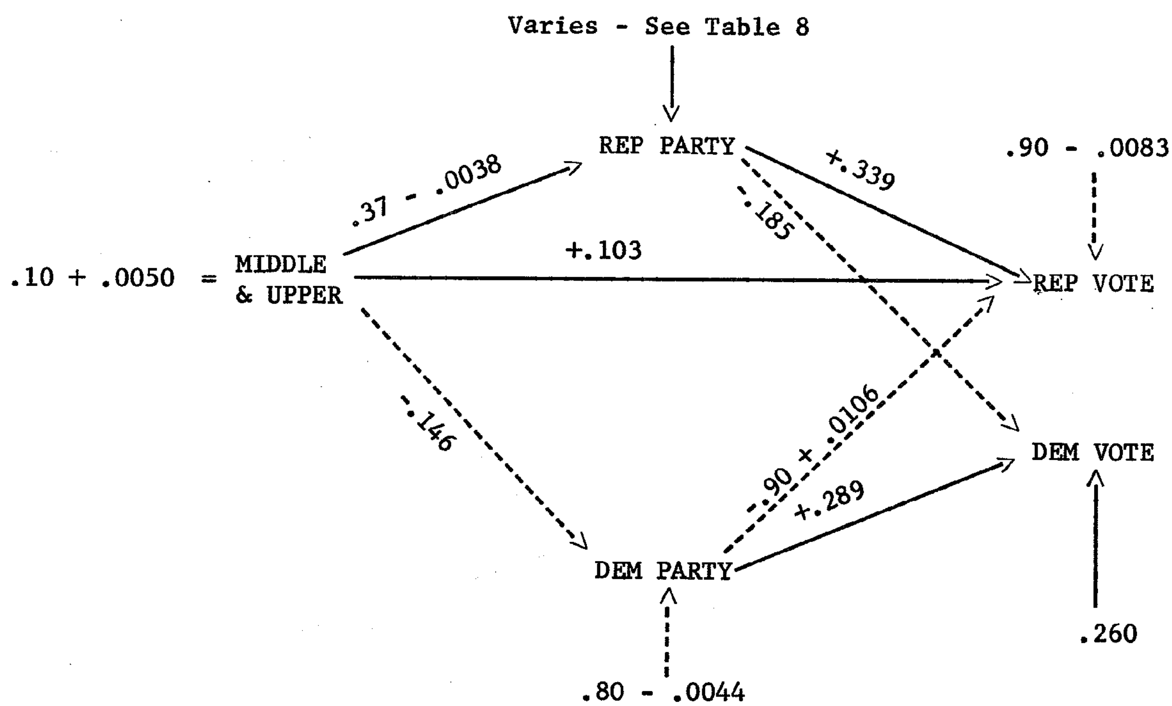


Fig. 8--Flow Graph for Subjective Class, Party Preference, and Presidential Vote, 1952-1972

The broad themes to be drawn from Figure 8 seem to be these:

1) Throughout the period 1952 to 1972, Party Preference was a strong and persistent predictor of Presidential Vote.

2) Social class operated as expected. Middle-and-Uppers voted disproportionately for Republicans and against Democrats, although in the case of Democrats, the effect is mediated entirely through Party Preference.

3) The steady increase in Middle Class identification added a bit to Republican votes (+.020 * .103 = + .002 each four years, and thus +.01 over the twenty years), but this was offset each time by the declining association between Middle-and-Uppers and the Republican Party.

4) The system as a whole tended to deteriorate during the period. The parameters that showed secular trends (Class by Republican Party, Democratic Party constant, Democratic Party by Republican Vote, Republican Vote constant) all moved toward zero.

Figure 9 gives reduced form graphs for each presidential election from 1952 to 1972.

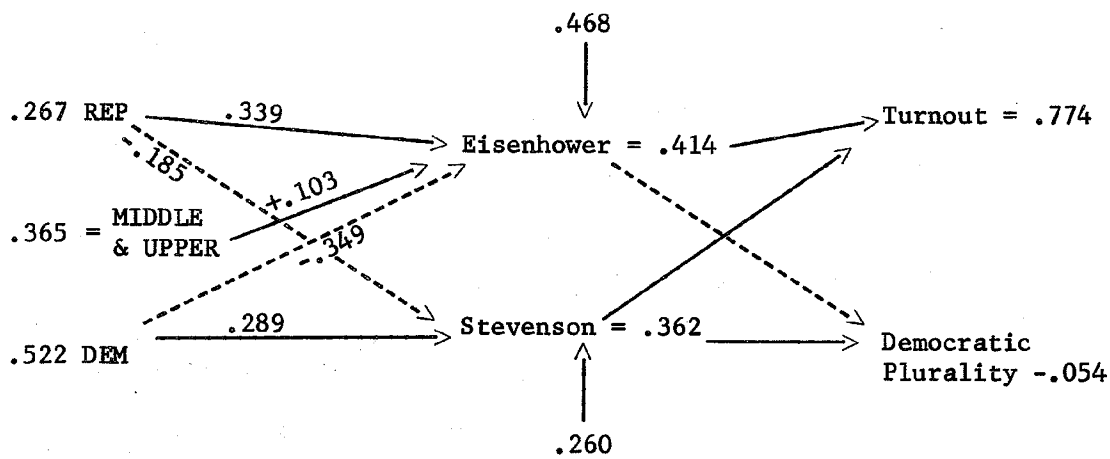
Here, rather than interpreting each as we did in Figure 5, we will look at the performance of the model as a whole. Table 12 gives the information.

The table indicates that the model is a terrible predictor of elections. It awards the White House to the Republicans in each election save 1964, where it calls a tie! Panels (b) and (c) are a bit more optimistic: they show very rough rank agreement between the model and official figures for the Democratic margins and shifts in the margins from election to election. However, the same panels show that the raw marginals from the surveys display better agreement than the models. Why?

First, as is well known, the surveys, and thus the model, strongly underestimate the proportion of non-voters.

Second, we have to consider the precision required. To

(1952)



(1956)

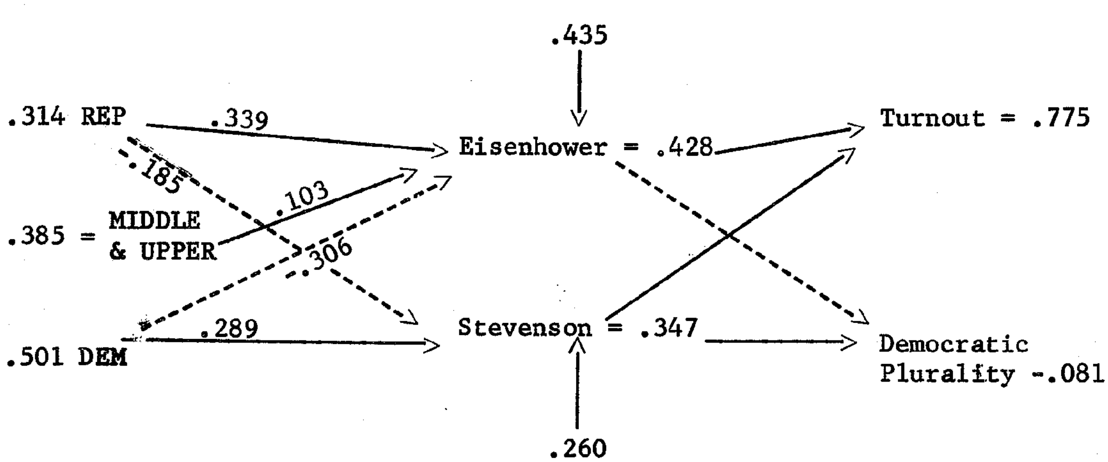
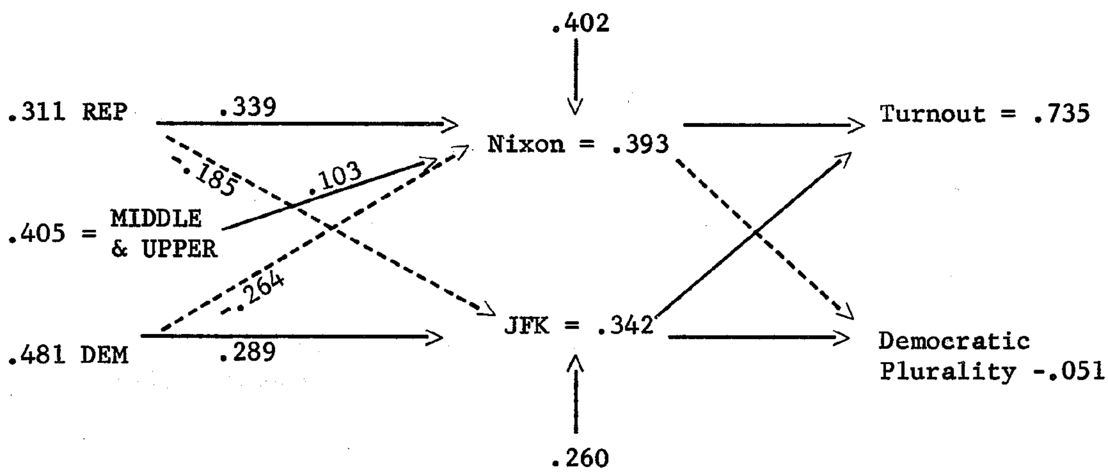


Fig. 9--Flow Graphs for Presidential Years

(1960)



(1964)

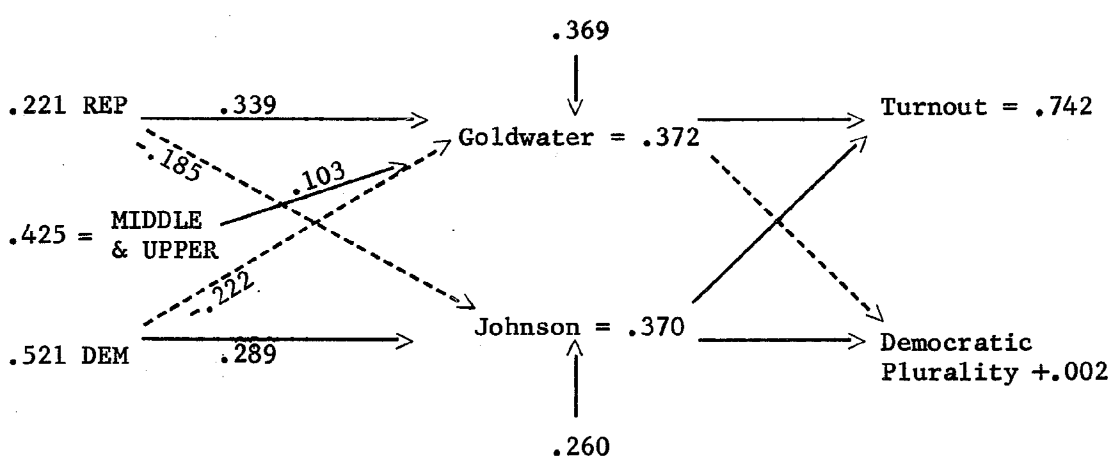
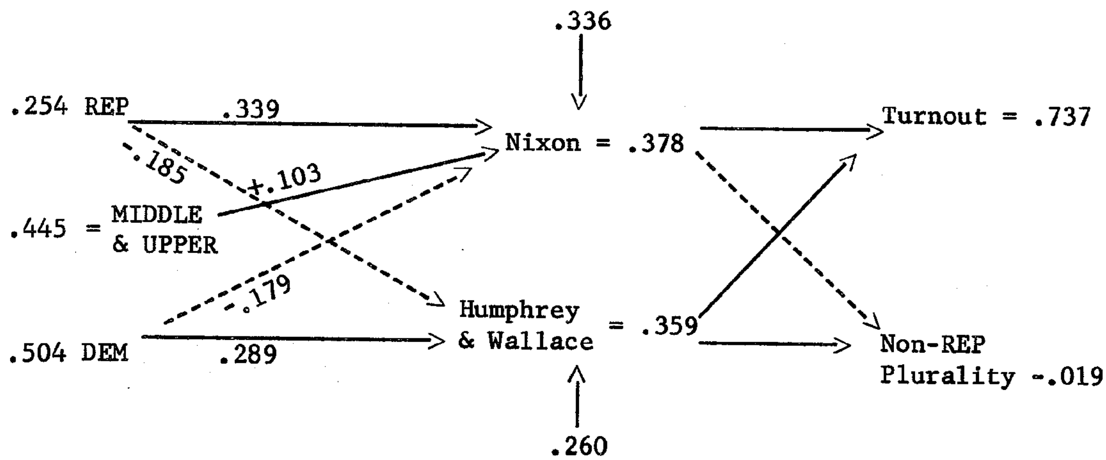


Fig. 9--Continued

(1968)



(1972)

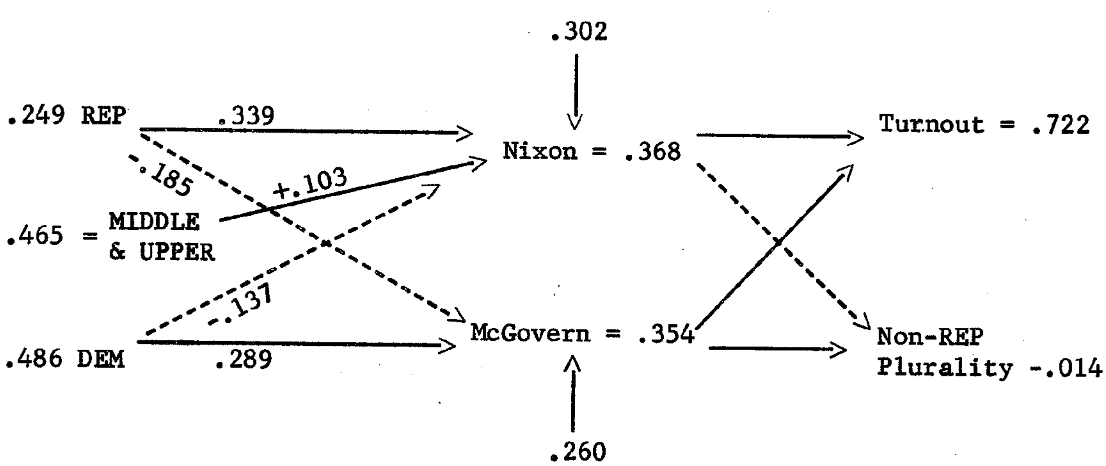


Fig. 9--Continued

TABLE 12

VOTING PROPORTIONS, 1952-1972

(a) Node Values

	Source											
	Official Figures*				Model				Surveys Used in Model			
Year	REP VOTE	DEM VOTE	R+D	D-R	REP VOTE	DEM VOTE	R+D	D-R	REP VOTE	DEM VOTE	R+D	D-R
1952	.34	.28	.62	-.06	.41	.36	.77	-.04	.44	.32	.76	-.12
1956	.34	.25	.59	-.09	.43	.35	.78	-.08	.44	.31	.75	-.13
1960	.31	.32	.63	+.01	.39	.34	.73	-.05	.37	.37	.74	.00
1964	.24	.38	.62	+.14	.37	.37	.74	.00	.25	.54	.79	+.29
1968 * **	.26	.35	.61	+.09	.38	.36	.74	-.02	.38*	.38*	.76*	.00*
1972	.34	.22	.56	-.12	.37	.35	.72	-.02	.41*	.26*	.67*	-.15*
1952-56	.00	-.03	-.03	-.03	+.02	-.01	+.01	-.04	.00	-.01	-.01	-.01
1956-60	-.03	+.07	+.04	+.10	-.04	-.01	-.05	+.03	-.07	+.06	-.01	+.13
1960-64	-.07	+.06	-.01	+.13	-.02	+.03	+.01	+.05	-.12	+.24	+.05	+.29
1964-68	+.02	-.03	-.01	-.05	+.01	-.01	.00	-.02	+.13	-.16	-.03	-.29
1968-72	+.08	-.13	-.05	-.21	-.01	-.01	-.02	.00	+.03	-.12	-.09	-.15

* Bureau of the Census, Pocket Data Book, USA 1973, pp. 97 and 103.

** 1968 and 1972 surveys are averaged.

(b) D-R Ranked

Year	Official	Model	Surveys	Model II	Model IIa
1964	+.14	.00	+.29	+.369	+.369
1968	+.09	-.02	.00	+.010	+.082
1960	+.01	-.05	.00	-.037	-.034
1952	-.06	-.04	-.12	-.076	-.052
1956	-.09	-.08	-.13	-.138	-.112
1972	-.12	-.02	-.15	-.219	-.179

(c) Changes in D-R Ranked

Year	Official	Model	Surveys	Model II	Model IIa
1960-64	+.13	+.05	+.29	+.406	+.403
1956-60	+.10	+.03	+.13	+.101	+.078
1952-56	-.03	-.04	-.01	-.062	-.060
1964-68	-.05	-.02	-.29	-.359	-.082
1968-72	-.21	.00	-.15	-.209	-.097

estimate elections and electoral shifts in this period requires considerable exactitude. The range in the proportion Republican from 1952 to 1972 is only 10 points, and the mean absolute shift in D-R from election to election is 10 points. Since we are working with a predictor using 14 parameters, each of which has a standard error in the neighborhood of .05, it is impossible to obtain fine precision.

Third, it is possible that outliers play an important substantive role in actual elections. Eleven outliers were detected in Table 2. These were pretty well spread around the various surveys, except that three came from 1972 and three from 1964, two elections the model handles poorly. No other year had more than one outlier. It is possible that unique events, departing from the long-term patterns in the model, affected the decisions in these two elections.

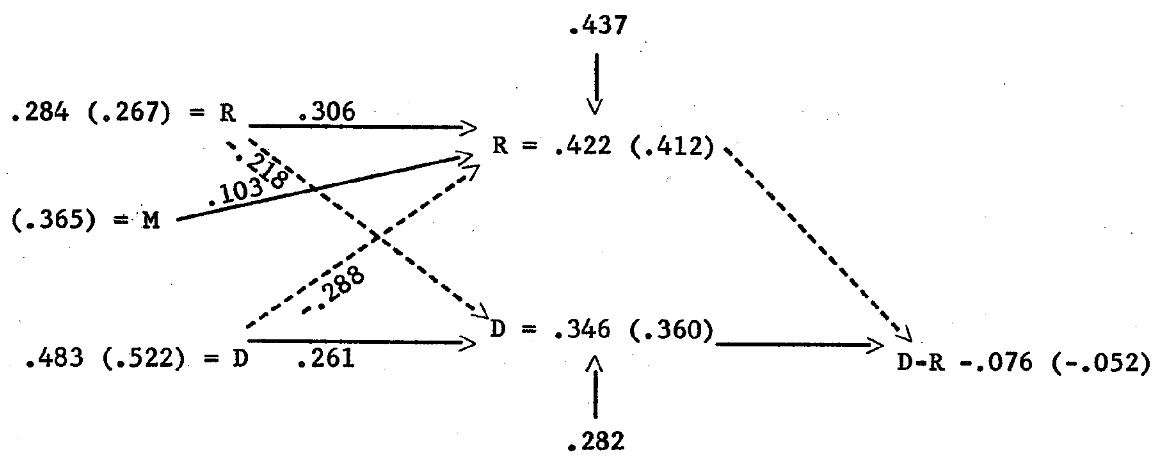
Fourth, the model was applied to an era when it was steadily declining in parameter magnitudes. In a period when a set of variables is tending to "lose its pizazz," one should not expect crisp predictions of small changes.

In sum, the model, while quite satisfactory from the viewpoint of statistical fit, is far from precise. What it does do, however, is to give systematic insight into the relative magnitude of the effects in the system, and a simple yet revealing picture of their broad trends during the study period.

Although the pooled estimate models do not predict elections well, this does not mean that the surveys are inaccurate or that the model methodology is faulty. To show this, we created a second set of models using the specific parameters in Table 11 for the Michigan election series. For each, we used the modeled values for Party and also the raw data Party marginals, the former appearing in parentheses in each model. Figure 10 presents the results. The pooled value for Class was used in all models.

The results from these models appear in Panels (b) and (c) in

(1952)



(1956)

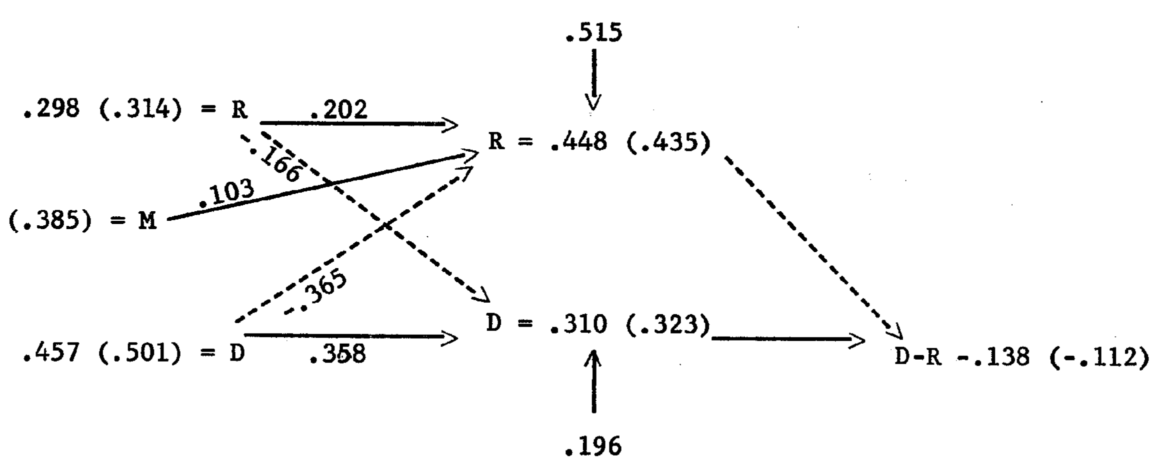
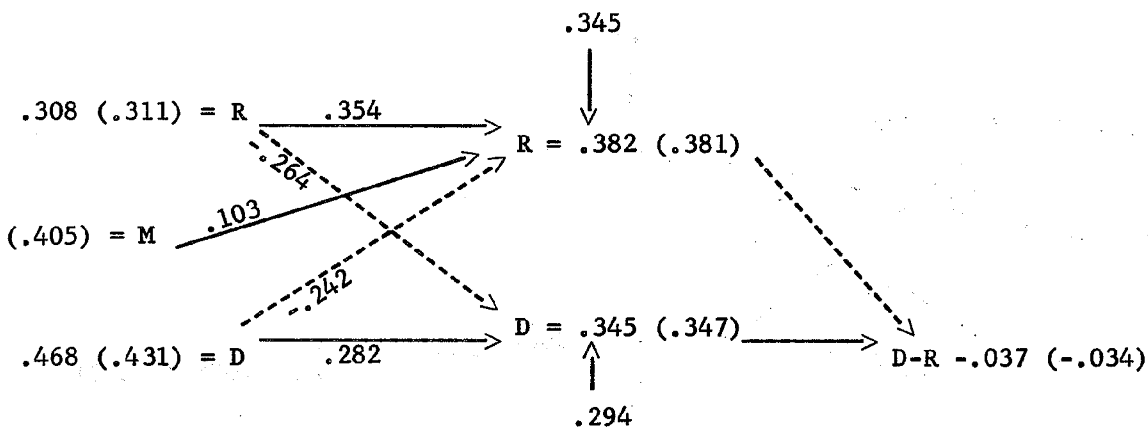


Fig. 10--Models II and IIa

(1960)



(1964)

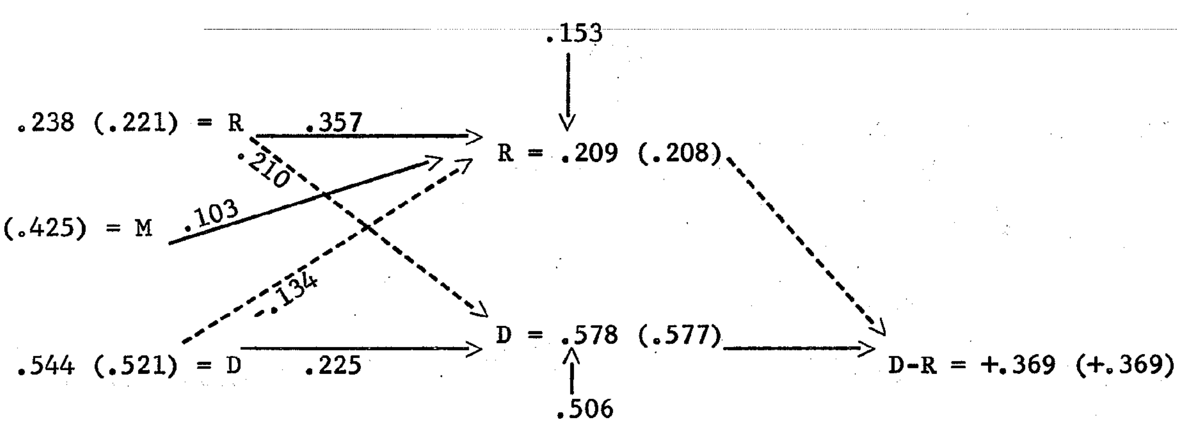
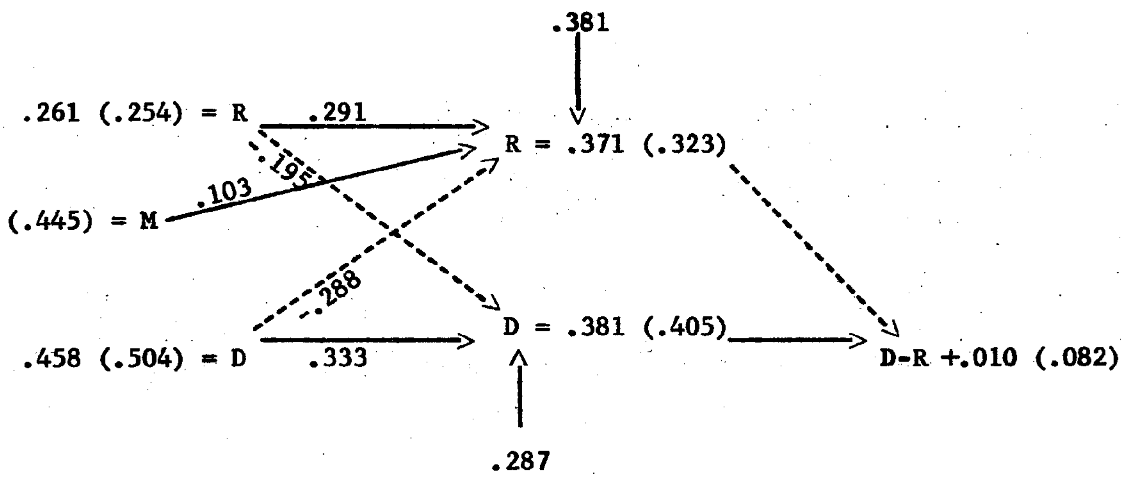


Fig. 10--Continued

(1968)



(1972)

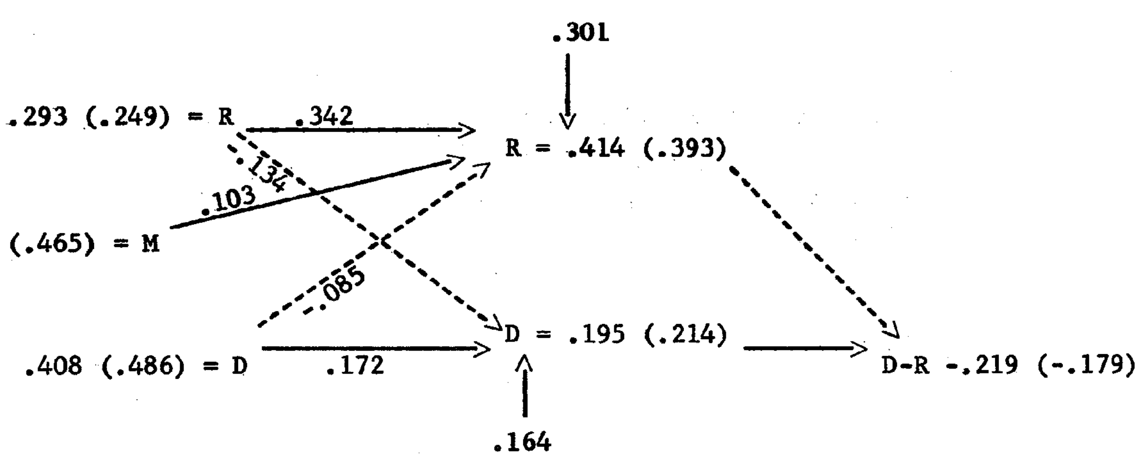


Fig. 10--Continued

Table 12, the raw data results as "Model II" and the partially pooled as "Model IIa." These figures are much closer to the known facts. Although, as in all surveys, the total number of non-voters is under-estimated, the pluralities and election-to-election trends are well estimated.

Returning to the alibis at the end of the previous section, these results give support to the outlier hypothesis. The suggestion is that the outlying values are not "bad studies," but short term historical changes in the variables. Thus, it appears that the general model is "true" as a description of long-term trends in the system of variables, but that specific elections are usually tipped one way or another by "blips" in the system--factors associated with particular candidates or unique historical configurations.

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THE INTERGENERATIONAL TRANSMISSION OF JOB COMPLEXITY IN HORIZONTAL DIVISIONS OF THE OCCUPATIONAL STRUCTURE

Gregory Gaertner

June 1975

The help of Karen Newman Gaertner in formulating and preparing this paper was invaluable, as were James A. Davis's encouragement and support. Thanks also go to Lloyd Temme of the Bureau of Social Research, Washington, D.C., for providing the conversion scheme used here; and to Peter V. Marsden and Edward O. Laumann for statistical and theoretical suggestions.

Introduction

It no longer seems exceptional to call for examination of "horizontal" partitions of the occupational structure in examining occupational mobility, psychological effects of occupational incumbency and labor force participation, or changes in labor force characteristics.[1]

However, little research has been done in this area. We suspect that there are essentially two reasons. First, because there is no reliable or well-grounded theory about the communalities among occupational positions that become differentiated as a result of extended division of labor, most non-ranked partitions of the labor force tend to be unsatisfactorily ad hoc. In the main, the best classifications satisfy only the requirement that the categories created are not socially ranked on some important criterion variable. Second, writers in the area have been vague about the benefits such horizontal partitions might provide and in which problematic areas of occupational research these benefits might accrue. While the former defect has been ameliorated to some extent, the latter remains an obstacle to intelligent use of situs distinctions (non-ranked partitions of the labor force). Although we shall have some occasion to comment on the former problem--the generation of meaningful non-ranked divisions of occupations--this paper is devoted to the specification of certain effects of situs in the intergenerational transmission of forms of job complexity.

The literature on non-ranked divisions of the occupational structure generally refers to these as "situses." This term, coined by Benoit-Smullyan more than 30 years ago, meant "an aggregation of persons socially

[1] See, for example, on mobility, Hatt 1961, Morris and Murphy 1959, and Lane 1972; on psychological effects, Super 1957, and Roe 1956; and on changes in characteristics, Stinchcombe 1965.

distinguished by any common characteristic except status or locus" (1944: 152). Later work expanded this definition to include social positions not judgmentally compared. In the course of this paper we will briefly review the available literature on situs classifications, suggesting modifications and common elements. We will then suggest measures and models appropriate to the examination of intergenerational mobility processes using situs classes as contexts that are differentially conducive to the transmission of job characteristics. Finally, we will present and discuss the results of research using the foregoing schemes.

Theory

As noted above, the concept of situs used here originates with Benoit-Smullyan. He begins with the unexceptional proposition that inherent in the ranking of social positions is the social differentiation of those positions. Thus, social ranking may be viewed as a special case of the more general and logically prior process of social differentiation.[2] Following this observation, we may distinguish situses: partitions of the universe of social positions into socially recognized groupings. A situs, then, is an aggregation of positions that are socially identified but not ordered in terms of desirability, power, perquisites, prestige, and the like. Status groups arise as a special case of situs groups, being aggregations ordered according to social evaluation.

Treatments of situs in later literature seem to follow one of two forms. In the first, the presence of situs groupings is inferred from irregularities in observed phenomena (e.g., Hatt 1961, Stinchcombe, 1965); in the second, the partitions of the occupational structure used to define situses are constructed on theoretical grounds. We discuss each of these approaches in turn.

Hatt (1961) typifies the first approach. He examines the plausibility of situs classifications to explain the apparent non-unidimensionality of the North-Hatt prestige scale. He notes that although the scale scores serve to differentiate occupations on the bases of prestige, "the presence of similar scores for such dissimilar occupations as 'airline pilot,' 'artist who paints pictures,' 'owner of a factory employing

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[2] We examine this issue more thoroughly below, but it is useful at this point to note that the presumption of consistent social rankings of positions among the differentiated segments is a strong model indeed.

about 100 people,' and 'sociologist' raises the problems of whether or not the continuum holds together" (1961: 250). Analyses using Guttman scaling techniques indicated that of three samples (with 25, 16, and 12 occupations) none yielded even a quasi-scale. Thus, the hypothesis that respondents consistently rated the prestige of occupations across the whole range of occupations presented them could not be supported. Hatt then divided the set of occupations into situses and within situses into families whose scalability was much higher (see Table 1).

> The data of this study seem to indicate the presence of at least eight situses . . . . At this point one may only speculate about the nature of the situses, if they exist. Some clearly represent steps in prestige, such as the agricultural situs, which includes "farm tenant," "farm owner," "farmhand," and "sharecropper." Other situses, however, appear to embrace similar functions, as in the case of those that are professional or political. From the data at hand, the only known characteristic is that each situs does include only jobs and occupations that can be compared consistently by most people (1961: 253-54).

Hatt suggests that the finding of plausible situs classes implies two types of vertical mobility, intragenerationally: movement between and movement across situses. Greater costs can be associated with the latter movement, as Hatt notes, since different skills and resources may be relevant in a new situs. Though these inferences are not strictly justified by Hatt's data, the observation that different situses may be characteristic by different skills and investments plays a crucial part in our analysis of intragenerational skill transmission. For, if, as Hatt suggests, inter-situs movement is characterized by increased risk, the advantage of the skills of the father to the son or daughter may differ with the offspring's eventual situs choice. Although Hatt notes that his remarks on the intragenerational movement apply equally to intergenerational movement, appropriate modification is left for later research. We must, however, note that Hatt's work is limited as to both number of occupations and to the criterion variable, prestige. The second limitation is the more significant; there is no reason to suppose that other criterion variables will yield the same situs classes. As we shall see, however, his classification is corroborated by the conspicuous resemblance of other forms we shall consider below.

Morris and Murphy (1959) exemplify the second approach, the attempt to draw the situs classification from a theoretical argument. In

TABLE 1

HATT'S DIVISION OF OCCUPATIONS INTO SITUSES AND FAMILIES

Situs and Family	*Number of Occupations Scaled*	*Number of Responses Scaled*	*Reproducibility*	*Minimum Marginal Reproducibility*
1. Political	7	14	84	67
National	4	8	89	70
Local	3	6	90	59
2. Professional	8	16	77	60
Free professions	4	8	88	60
Pure sciences	6	12	86	60
Applied sciences	4	8	88	66
Community professionals	5	10	85	63
3. Business	4	11	78	55
Big business	3	6	87	61
Small business	4	8	91	70
Labor organization	2	10	85	38
White-collar employees	7	14	87	58
4. Recreation and aesthetics	6	12	80	67
High arts	3	6	86	66
Journalism and radio	3	6	86	63
Recreation	2	4	90	51
5. Agriculture	4	8	87	58
Farming	2	4	93	61
Employed on farms	2	4	92	62
6. Manual work	6	14	84	59
Skilled mechanics	4	8	87	67
Construction trades	3	9	90	55
Outdoor work	4	8	86	61
Factory work	4	8	90	68
Unskilled labor	3	6	88	73
7. Military*	—	—	—	—
Army	2	6	84	50
Navy	—	—	—	—
Marine Corps	—	—	—	—
Coast Guard	—	—	—	—
8. Service	4	8	89	55
"Official community"	4	8	88	60
"Unofficial community"	3	6	98	72
Personal	3	6	86	70

* Only one family was represented in the original data. Thus the existence of the others is merely speculation; it may well be that they do not exist in fact.

Source: Hatt, 1961: 254; Table IX-1--The Scalability by the Cornell Technique of Occupational Situses and Families reviewing the literature on situs differentiation, they note that previous work suffered either from restriction in the range of the socially valued criterion (they cite Hatt as an example), or from logical problems of exclusiveness and exhaustiveness (see Roe, 1956). A classification not encumbered by these errors, they argue, can be constructed on the basis of the nature of the societal functions that occupations fulfill. Their classification is presented below.

Definition of Civilian Occupational Situses

1. Legal Authority--All occupations primarily concerned with the formulation, arbitration, interpretation, or enforcement of the law, including those primarily concerned with the custody of law-breakers.

2. Finance and Records--All occupations primarily concerned with the handling of monetary affirs or the processing of records, accounts, or correspondence.

3. Manufacturing--All occupations primarily concerned with the fabrication or articles or the processing of raw materials on a production-line basis.

4. Transportation--All occupations primarily concerned with the movement of persons or goods from one location to another.

5. Extraction--All occupations primarily concerned with the extraction, procurement, or production of raw materials.

6. Building and Maintenance--All occupations primarily concerned with the construction of buildings or other non-massproduced units, or the installation, maintenance, or repair of equipment, property or facilities.

7. Commerce--All occupations primarily concerned with the buying, selling, exchange, or marketing of goods or persons.

8. Arts and Entertainment--All occupations primarily concerned with the creation of art forms or with the provision of entertainment, recreation, information, or aesthetic satisfaction for the public.

9. Education and Research--All occupations primarily concerned with formal instruction or training or with the acquisition of knowledge as an end in itself.

10. Health and Welfare--All occupations primarily concerned with the detection, prevention, or alleviation of illness, hazard, or distress.

The criterion that the situses be, in some sense, socially recognizable was tentatively examined by these authors in this way: Forty occupations in alphabetical order were presented to 200 undergraduates at UCLA. "The respondents were asked to classify these occupations according to situs, each of which was defined . . . [as in the above list], and to give each occupation a prestige rating, according to the North-Hatt format" (1959: 237). Although no detailed results are presented on the degree of consensus evidenced by the respondents in placing occupations in situses, only nine of the occupations rated were not placed in the situs predicted by the authors by more than 25 per cent of the respondents. Thus, as a socially recognizable classification, the situs grouping presented, has at least prima facie validity.

Comparing Table 1 and the list presented on the preceding page, we note great similarities between Hatt's results and Morris and Murphy's classification. Manual work in Hatt is expanded by Morris and Murphy's classification providing lower status elements of manufacturing, transportation, extraction, and building and maintenance; presumably, business is similarly expanded to provide higher prestige elements of the Morris and Murphy situses. Hatt's military situs is dropped by Morris and Murphy. Other modifications are comparatively minor. An important advance of the Morris and Murphy classification, logically, should be apparent: by breaking the manual work occupations into different situses, differences among the constituent occupations may be observed. However, with respect to consistent rankings of prestige by individuals, it seems clear that such differentiation was not required.

We employ a collapsed version of the Morris-Murphy situs classification in this analysis, but should not be blind to several problems of their analysis. First, a classification by societal function presumes a more developed theory of societal function than we currently possess. Any classification based on such an undeveloped body of literature may be less than useful; that is, may fail to isolate the characteristics that a better informed theory would suggest. Second, the requirement that a classification not be ranked on the basis of a single criterion is unduly restrictive. Positions are ratable, and are rated, on the basis of multiple criteria, which, while correlated, are not totally mutually dependent. The use of a single criterion, as, for example, prestige, serves to mask the fact that prestige may flow from multiple sources. (We suggest several such sources below.) These bases of social esteem may be differentially distributed among the situses and may be differentially transmissible from father to child among situses. Following Hatt, we suggest that the different occupations may be characterized by different levels and sets of skills that are learned by incumbents therein. Further, these skills are of advantage to the children of incumbents to extents differing with the situs of the offspring. For example, the children of a physicist, an occupation characterized by complex manipulation of information, might, through childhood training, instilled motivation, or by more direct means, be similarly advantaged if their occupations were in the sciences; however, if they choose occupations in the building trades, the informational complexity of their father's job might have little influence on their own job's informational complexity. Thus, "investments" of the father may be of differential advantage to children depending on the context of the child's eventual occupation. Such questions as differential transmissibility among situses are at least partly independent of questions of prestige; the child may work in an occupation having prestige similar to his father's in spite of a very different profile of required skills depending in part on the child's situs.

Data

One set of multiple sources of prestige is provided by the Dictionary of Occupational Titles (DOT). Levels of complexity requisite to the successful discharge of job-related duties in each of three central areas of occupational activity are rated for occupations in the Dictionary. These three areas are the handling of information, relationships with people, and the use of tools and physical objects. The levels of complexity in each of these areas and the titles associated with each situs are presented in Table 2. (We will use the terms "data" and "informational complexity" to describe the first; "people" and "interpersonal complexity" for the second; and "things" and "object and tool complexity" for the third.") The ratings on each of the three areas are based on interviews and observations by highly trained occupational specialists.[3]

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[3]For further information on the classification, see Fine (1968), Dictionary of Occupational Titles (USDL, 1965), and Handbook for Analyzing Jobs (USDL, 1972).

TABLE 2

COMPLEXITY LEVELS FOR WORKER TRAITS

Data (Informational Complexity)	People (Interpersonal Complexity)	Things (Object and Tool Complexity)
0 Synthesizing	0 Mentoring	0 Setting-Up
1 Coordinating	1 Negotiating	1 Precision Working
2 Analyzing	2 Instructing	2 Operating-Controlling
3 Compiling	3 Supervising	3 Driving-Operating
4 Computing	4 Diverting	4 Manipulating
5 Copying	5 Persuading	5 Tending
6 Comparing	6 Speaking-Signaling	6 Feeding-Offbearing
7 No significant relationship	7 Serving	7 Handling
	8 No significant relationship	8 No significant relationship

Source: Dictionary of Occupational Titles, V. II, Appendix A.

For the purposes of this study, the three worker-trait complexity scores were coded for all respondents in the experienced civilian labor force and the respondent's father in four studies: The Election Studies of 1966, 1968, and 1970 from the University of Michigan Survey Research Center, and the General Social Survey of 1974 from the National Opinion Research Center (NORC). In 1966, occupation was asked of head of household only, so the 1966 sample is of heads of households. The complexity scores were obtained by matching occupations from the DOT to the reported Census occupational category for each respondent and his or her father. The match of DOT occupation to Census occupation is, in general, acceptable. A measure of the match's acceptability can be created as follows. If it were true that there were one and only one assigned score (on any given trait) for each Census group, either because only one DOT occupation was assigned to each Census occupation or because all DOT occupations assigned to a Census occupation had equal scores on that trait, then an analyses of the variance of that trait across Census categories would reveal a zero within-groups sum of squares and an eta coefficient of 1.000. (Eta is the ratio of the between-groups sum of squares to the total sum of squares.) As DOT occupations with heterogeneous scores were assigned to the same Census occupation, the within-group sum of squares will increase corresponding to a decrease in the "goodness" of the match. Therefore, we may use eta^2 as a measure of the acceptability of fit of the match. When multiple DOT classes fell within a single Census class, a weighted average of each of the three worker-trait scores for the included DOT categories was taken as the score for the Census class, the weights being determined by the proportion of the workers in the Census class found in each DOT class. The worker proportions were taken from the April 1971 Current Population Survey. The eta^2 for the matches using the Census classifications of 1960 and 1970 were between .78 and .8. (For details of the conversion scheme, see Temme 1974.) In order to make the questions from each survey comparable, our analysis is restricted to the experienced civilian labor force. The respondent provides father's occupation for the time when the respondent was 16.

For comparisons among surveys taken at different times, we assume that the complexities of a given occupation are constant through the period under study. Thus, changes in the mean complexity level for some aggregate on some tract reflect the fact that members of the aggregate have moved into occupations rated as more (or less) complex with respect to that trait, rather than indicating a change in the complexity of the occupations themselves.

Trait Compexity as a Basis for Prestige

We argued that the complexity of an occupation with respect to the three areas--data, people, and things--provided three sources of prestige for the occupation. We are now in a position to document this claim using data from the 1974 NORC General Social Survey. If we take the three worker-trait complexity scores and the Duncan prestige score as interval measures, in regressing the Duncan prestige score on the traits we would expect, first, a reasonably large proportion of the variance in the former explained by the latter, and second, non-trivial partial slopes for each of the complexity scores. The results are presented in Table 3. (The results in Table 3 are presented first for the entire sample and then for male respondents only. This procedure will be followed throughout.) We see, in broad outline, that for the general population 59 per cent of the variance in respondent's prestige is explained by data, people, and things complexity; for the fathers of respondents in the total sample, 64 per cent of the variance is explained by the same three areas. Furthermore, for male respondents, nearly 68 per cent of the variance in their prestige is accounted for by the three worker traits. We suspect that the higher R^2's for the fathers in comparison with the general population is mainly a result of their maleness; note that the R^2 for male respondents is higher than for their fathers. It seems clear, therefore, that the worker-trait components isolate important bases of occupational prestige. We note also, however, that each is not equally important for the sample as a whole; the partial b for the things complexity score is an insignificant -.172.[4] Here, data and people complexity seem to be more important predictors of prestige (-4.164 and -2.418, respectively). For fathers, however, things complexity is a significant basis of prestige (b=-.289, $p < .05$), and data and people continue to be so (-3.684 and -2.317, respectively). For male respondents, the predictors seem more equally important: the partial slope for things rises to a significant -.579. While inferences on social change from inter-generational data are dubious (Duncan 1966), the pattern of the coefficients here leads us to suspect that (1) the importance of complex manipulation of objects as a basis for prestige has increased for men

[4]The scale for complexity runs inversely to prestige; thus, a low score on the things complexity trait (meaning high complexity) is associated with a high prestige score (meaning high prestige). This inversion in coding is true for all the worker traits in Table 3, and throughout this paper.

TABLE 3

REGRESSIONS OF PRESTIGE ON WORKER TRAIT SCORES (FOR FATHERS AND RESPONDENTS, FOR THE GENERAL POPULATION AND FOR MALES ONLY)

	General Population			Male Respondents		
	b	Sig.	R^2	b	Sig.	R^2
Father's Prestige		<.001	.637		<.001	.649
Informational Complexity	-3.684	≤.001		-3.689	<.001	
Interpersonal Complexity	-2.317	<.001		-2.175	<.001	
Object and Tool Complexity	- .289	.025<p<.05		- .330	.025<p<.05	
Respondent's Prestige		<.001	.592		<.001	.679
Informational Complexity	-4.164	<.001		-3.896	<.001	
Interpersonal Complexity	-2.418	<.001		-2.860	<.001	
Object and Tool Complexity	- .172	N.S.		- .579	<.005	

(-.330 versus -.574) while it has decreased for the general population (-.289 versus -.172), and therefore for women; and (2) the prestige of occupations is less predictable by the worker traits for the general population than for males (R^2 = .592 versus .679) for the general population. Thus, prestige of occupation for females seems to rest, to some extent, more than for males on sources other than the worker traits used here. Overall, however, we are well warranted in suggesting that prestige is a function of these worker traits to a large extent, and that use of the single indicator, prestige, in occupational mobility may serve to mask more complex processes of mobility in these constituent traits. This finding does not refute, but rather is supported by, Duncan's use of aggregate measures of income and education to predict prestige (Duncan 1961). Since two predictors were required to adequately estimate prestige, our argument for multiple sources of prestige is supported.[5]

Methods

Before we turn to the major portion of the analysis, some discussion of our procedures and the classes of results we might expect is in order. As above, we take the data, people, and things worker traits to be interval measures, scaled from zero for high complexity, to 7 for data and to 8 for people and things for low complexity. We then regress each worker trait on the corresponding worker trait for father to determine the relative advantage for the respondent of the father's complexity score. These regressions are then run in each situs and analyses of covariance are performed to determine significant differences in the influence of father's trait complexity on respondent's complexity among the various situses. Our situs classification was based on the industry of the respondent along the guidelines set up by Morris and Murphy (1959). (We combined certain situses to insure adequate members in each situs.) Specifically, the situses are as in Table 4.

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[5]For analysis of the relative efficacy of the two sets of sources in predicting prestige, see Temme (forthcoming: Chapter 4).

TABLE 4

SITUS CLASSIFICATIONS

Situs Classes	Included Census Subclasses	Included Census Codes (1970)	Corresponding Morris and Murphy Situs
Extractive	Agriculture, Forestry, Fisheries, Mining	017-057	Extraction
Manufacturing and Transportation	Manufacturing, Durable Goods, Nondurable Goods, Transportation	107-429	Manufacturing, Transportation
Commerce	Wholesale and Retail Trade Personal Services	507-698 769-798	Commerce
Legal Authority and Financial Services	Finance, Insurance and Real Estate, Public Administration	707-718 907-937	Legal Authority Finance and Records
Construction and Building Maintenance	Construction, Business and Repair Services, and Utilities and Sanitary Services	067-077 727-759 467-479	Building and Maintenance
Professional and Kindred	Communications, Entertainment and Recreation Services, Professional and Related Services	447-449 807-809 828-897	Aesthetics and Entertainment, Education and Research, Health and Welfare

We note that with six situses, the model described is equivalent to

$$\hat{X}_{Rj} = A + BX_{Fj} + C_1 S_{1j} + \ldots + C_6 S_{6j} + D_1 X_{Fj} S_{1j} + \ldots + D_6 X_{Fj} S_{6j} \quad (1)$$

where $S_{ij} = \begin{cases} 1 \text{ if respondent j is in situs i} \\ 0 \text{ otherwise} \end{cases}$

$\hat{X}_{Rj}$ = estimate of respondent j's score on trait X

X_{Fj} = respondent j's father's score on trait X

The C_i and D_i $(i = 1,2,\ldots,6)$, then, are the effects associated with the covariate in a classical analysis of covariance design. The C_i are the coefficients associated with the direct additive effects of situs, and the D_i are associated with the interactions of situs and father's complexity on respondent's complexity. Equation (1) is, of course, indeterminate (one of the situses must be used as a "base" or "reference" situs for solutions to be determinate in practice). For a respondent in situs k the terms associated with situses S; k ≠ i become zero, leaving

$$\hat{X}_{RjESk} = A + BX_{FjESk} + C_k S_k + D_k X_{Fj} S_k \quad (2)$$

which in turn implies

$$\hat{X}_{RjESk} = (A + C_k) + (B + D_k) X_{Fj} \quad (3)$$

From Equation (2) we note that if we express X_{Fj} and X_{Rj} in terms of deviations from their respective grand means, in actuality Equation (2) states

$$\overline{X}_R + (X_{Rj} - \overline{X}_R) = (a + c_k) + (b + d_k) [X_{Fj} - \overline{X}_F] + (b + d_k) [\overline{X}_F] + e_j$$

where a, b, c_k and d_k are maximum likelihood estimates for A, B, D_k and C_k, respectively. The subscript ES_k in X_{RjESk} is dropped to improve clarity.

So,

$$X_{Rj} = \overline{X}_R + [-\overline{X}_R + c_k + a (b + d_k) \overline{X}_F \quad] + (b + d_k) (X_{Fj} - \overline{X}_F) + e_j \quad (4)$$

If $d_k = 0$, then (4) becomes

$$X_{Rj} = \overline{X}_R + [-\overline{X}_R + c_k + a + b\overline{X}_F] + b(X_{Fj} - \overline{X}_F) + e_j$$

But since $a + b\overline{X}_F = \overline{X}_R$, by the logic of the regression, we have

$$X_{Rj} - b(X_{Fj} - \overline{X}_F) = \overline{X}_R + c_k + e_j \quad (5)$$

Equation (5) says that we can predict the respondent's score on trait X using only the mean score for all respondents on trait X and the direct effect of situs k on complexity, after subtracting $b(X_{Fj} - \bar{X}_F)$, when $d_k = 0$.

If we rewrite Equation (4) reflecting the fact that $\bar{X}_R = a + b\bar{X}_F$, we see that

$$X_{Rj} = \bar{X}_R + [c_k + d_k\bar{X}_F] + (b + d_k)\ (X_F - \bar{X}_F) + e_j$$

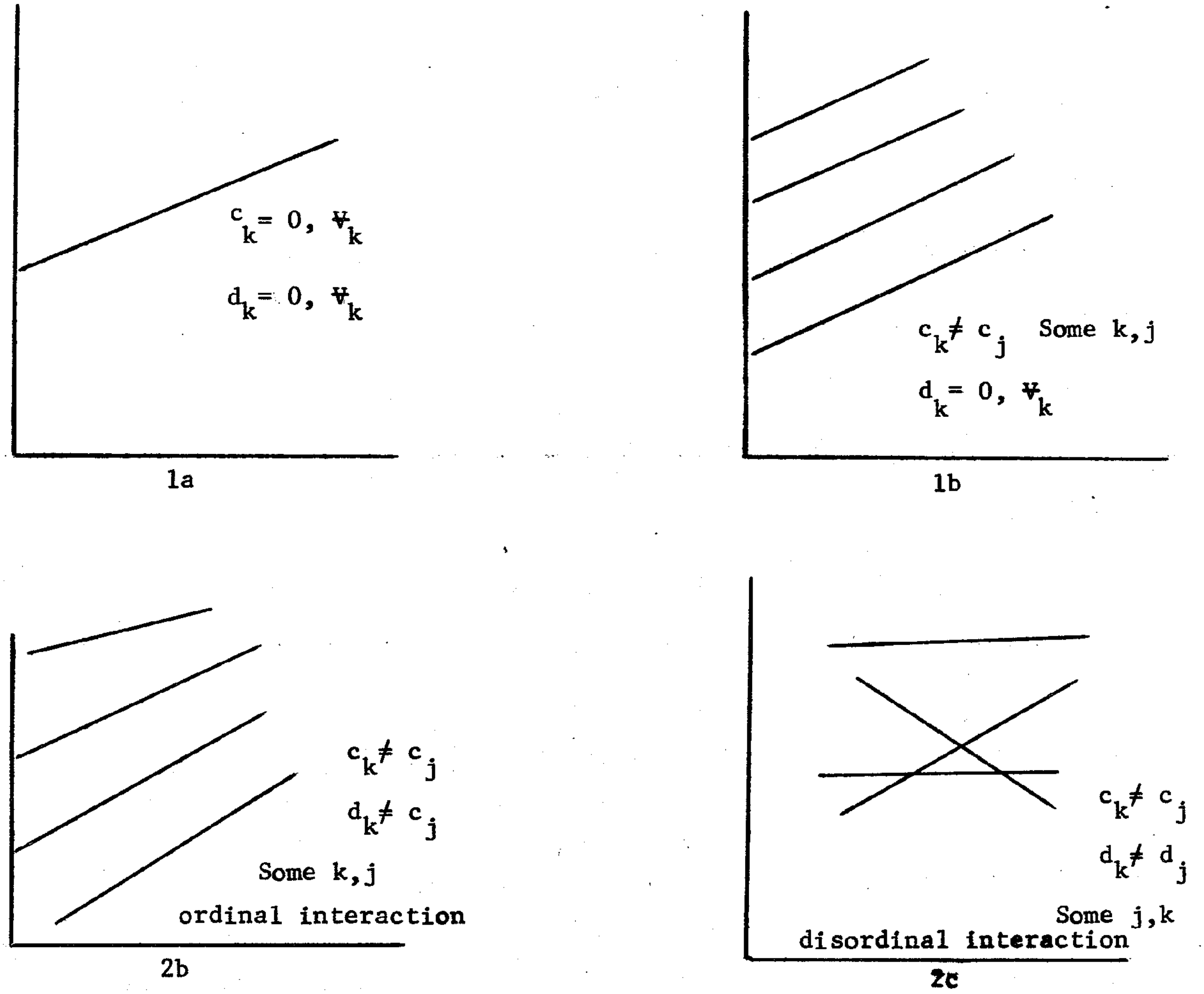
$$= \bar{X}_R + [c_k + bX_{Fj} - b\bar{X}_F + d_kX_{Rj}] + e_j$$

which implies,

$$X_{Rj} - b(X_{Fj} - \bar{X}_F) = \bar{X}_R + c_k + dX_{Rj} + e_j \qquad (6)$$

Thus, after the adjustment of $X_{Rj} - b(X_{Fj} - \bar{X}_F)$, the respondent's score can be expressed as the sum of the grand mean, a direct effect of situs, and the coefficient associated with the interaction $(d_k{*}X_{Rj})$. Recall from Equation (3) that the c and d are the extent to which the effect and slope differ from the overall line, not from zero. Now it is clear that for the effects of situs, if $\bar{X}_F$, $\bar{X}_R$ and b can be taken as unproblematic, the working parts for differences from the overall line are c and d. We can combine them as shown in the legend of Figure 1. The cells in the legend refer to the segments of Figure 1, which graphically depicts the resulting state of affairs (assume $a, b \neq 0$, which is, as we shall see, not an unwarranted assumption).

The model in cell 1a, graphed in Figure 1, allows neither direct nor interaction effects for the situs classification, whereas 1b allows the direct effect of situs. That is, independent of father's complexity on trait X, we find that situs serves to raise or lower respondent's complexity. The two graphs that depict the cell in which c_j and d_j are not zero reflect two possible forms of the interaction. Cell 2b depicts an ordinal interaction (Kerlinger and Pedazur, 1973:246), in which the rank order of the prediction from each situs is constant. Cell 2c presents a disordinal interaction; the estimate of the respondent's score may be greater in situs i than in situs k for respondents with fathers at, say, a high level of complexity, but less for respondents whose fathers are at low levels of



KEY

d_k for all k

c_k for all k	= 0	≠ 0
= 0	1a	
≠ 0	1b	2b, 2c

Fig. 1--Graphs of Postulated Statistical Effects

complexity. The cell in which $d \neq 0$ but $c = 0$ is of no practical import here since our decomposition of the variance is hierarchical. That is, if the interaction is present, we do not test for direct effects.

It can be seen that models similar to 2b will tend to confirm our expectations of the transmissability of complexity intergenerationally, and differentially by situs. Model 1b would confirm that differences in complexity by situs are not simple functions of parental background; it does not, however, support the hypothesis that the differential parental advantage to the respondent is a function of situs as well.

Hypotheses and Results

While many more sophisticated hypotheses might be entertained,[6] for our purposes we will suggest that the slope relating respondent's to father's complexity will vary as a function of the complexity level in that situs. That is, the higher the mean complexity at a given trait, the more advantage will accrue to the respondent as a function of his father's complexity level on that trait (and conversely, of course, the less complexity for the father, the greater the disadvantage for the son). This hypothesis rests on the assumption that traits that have a high mean complexity in a given situs will tend to be focal areas of skills and activities for that situs. Thus, for example, in manufacturing and transportation, or construction and maintenance--situses that tend to be highly complex with regard to manipulation of tools and physical objects, and less in terms of information handled--the investments of the respondent's father in mastery of and access to the former will be highly beneficial to the respondent's tool and object complexity in that situs. For complexity of information handling, in situses like construction and manufacturing, we suspect father's trait complexity will provide lesser advantages to the respondent, since such activities would not be focal in the situs. While the hypothesis is admittedly crude, we note a certain prima facie plausibility.

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[6]More sophisticated hypotheses might involve the slope varying as a function of the proportion self-employed, the proportion clerical, the presence or absence of restricted access to the situs resulting from unionization or required educational credentials. These more sophisticated models await further research.

Mean Trait Levels Over Time, Intergenerationally and by Sex

In Table 5, Parts A and B, we present the means for each trait within each situs for each of our studies, first for the general population, and then for males only. In Table 6, Parts A and B we present the means for father's traits using the same format. Figures 2A and 2B graphically present the means for each worker trait, for each situs; 2A for the general population, 2B for males only. First, we examine the means overall for each trait and over time. These may be compared with the grand means for the fathers of the respondents over time. We will also compare the general population with the male subset over time. Then, for each situs, analogous comparisons will be made.

For the sample as a whole, while no trend seems in evidence for data complexity, we note that interpersonal trait complexity seems to be increasing slightly (6.521 in 1966 versus 6.266 in 1974) while complexity in the use of tools and objects seems to be decreasing somewhat (4.899 in 1966 versus 5.730 in 1974). Compared with their fathers, the respondents' occupations seem to be considerably less informationally complex, though the difference appears to be decreasing over time (.533 in 1966 and .261 in 1974). Respondents' occupations appear to be more complex than their fathers' occupations with respect to relations with people, this difference remaining largely constant over time. We note, however, that fathers appear to have more complex occupations than respondents in terms of object and tool manipulations, and this difference has remained largely constant over time (averaging 1.583 units over the period). That fathers have more and not less complex jobs than their children in terms of information and object manipulation are somewhat surprising results, in view of the prevailing beliefs that the occupational world is becoming more and more complex. We shall return to this problem later.

It should be understood that in comparisons between males and the general population, we are actually comparing, indirectly, males with females. This comparison is complicated, however, by the fact that the general population includes all the males in our samples. The mode of interpretation is similar to that employed in multiple classification analysis, comparing a category mean to the grand mean. This cumbersome mode of exposition was forced on us by exigencies of time and budget; the resultant trends, however, are still clear. The mean trait scores for males are plotted against the means for the general population in Figure 3 for each situs [See Key for interpretation].

TABLE 5

MEAN WORKER TRAIT SCORES FOR EACH YEAR AND EACH SITUS

	PART A--GENERAL POPULATION												PART B--MALES ONLY											
	ELEC66			ELEC68			ELEC70			GSS74			ELEC66			ELEC68			ELEC70			GSS74		
	Mean	Rank	N	Mean	Rank	N	Mean	Rank	N	Mean	Rank	N	Mean	Rank	N	Mean	Rank	N	Mean	Rank	N	Mean	Rank	N
Informational Complexity																								
Extractive	2.786	2	113	3.393	3	80	2.852	2	78	3.333	3	43	2.631	2	59	3.210	4	65	2.601	3	70	3.379	4	40
Commerce	3.299	4	168	3.783	5	180	3.487	4	182	3.647	4	138	2.666	3	67	2.693	2	80	2.824	4	80	3.243	3	66
Legal and Financial	2.838	3	94	2.984	2	91	2.731	1	116	2.631	1	89	2.730	4	53	2.864	3	57	2.592	2	62	2.553	2	59
Construction and Maintenance	3.734	5	115	3.425	4	109	3.675	5	91	3.967	5	86	3.728	5	52	3.432	5	99	3.554	5	79	4.046	6	81
Professional and Kindred	2.645	1	131	2.723	1	198	3.087	3	231	2.890	2	196	2.382	1	48	1.959	1	74	2.373	1	80	2.532	1	83
Manufacturing and Transportation	4.327	6	263	4.166	6	264	4.514	6	306	4.039	6	243	4.413	6	131	3.810	6	188	4.200	6	220	3.912	5	184
Overall	3.450		884	3.514		922	3.588		1004	3.484		795	3.329		410	3.176		563	3.324		591	3.426		513
Interpersonal Complexity																								
Extractive	7.675	6	113	7.689	6	80	7.530	6	78	7.504	6	43	7.573	6	59	7.796	6	65	7.496	6	70	7.577	6	40
Commerce	5.910	2	168	6.121	2	180	6.052	2	182	6.436	3	138	5.618	2	67	5.587	2	80	5.713	2	80	6.211	3	66
Legal and Financial	6.298	3	94	6.393	3	91	6.165	3	116	6.033	2	89	6.231	3	53	6.241	3	57	6.211	3	62	6.069	2	59
Construction and Maintenance	7.115	4	115	6.909	4	109	7.253	4	91	7.556	5	86	7.051	4	52	6.954	4	99	7.276	5	79	7.534	5	81
Professional and Kindred	4.563	1	131	4.707	1	198	5.278	1	231	4.585	1	196	3.952	1	48	4.344	1	74	5.101	1	80	4.234	1	83
Manufacturing and Transportation	7.210	5	263	7.118	5	264	7.281	5	306	6.934	4	243	7.304	5	131	6.978	5	188	7.184	4	220	6.876	4	184
Overall	6.521		884	6.356		922	6.486		1004	6.266		795	6.504		410	6.448		563	6.651		591	6.429		513
Object and Tool Complexity																								
Extractive	2.378	1	113	3.072	1	80	2.956	1	78	3.720	2	43	2.458	1	59	2.767	1	65	2.701	1	70	3.424	2	40
Commerce	6.399	4	168	6.926	6	180	6.657	4	182	6.655	1	138	6.728	5	67	6.645	6	80	6.451	6	80	6.391	4	66
Legal and Financial	6.508	5	94	6.642	4	91	6.997	6	116	7.220	6	89	6.641	4	53	6.256	5	57	6.400	5	62	6.948	6	59
Construction and Maintenance	3.843	2	115	4.043	2	109	3.960	2	91	3.362	1	86	3.839	2	52	3.791	2	99	3.472	2	79	3.161	1	81
Professional and Kindred	6.512	6	131	6.774	5	198	6.802	5	231	7.087	5	196	6.752	6	48	6.231	4	74	5.797	4	80	6.460	5	83
Manufacturing and Transportation	4.108	3	263	4.481	3	264	4.130	3	306	4.758	3	243	3.868	3	131	4.201	3	188	3.902	3	220	4.451	3	184
Overall	4.899		884	5.496		922	5.425		1004	5.730		795	4.825		410	4.787		563	4.564		591	5.029		513

TABLE 6

MEAN WORKER TRAIT SCORES FOR EACH YEAR AND EACH SITUS

	PART A--FATHERS OF GENERAL POPULATION								PART B--FATHERS OF MALES ONLY							
	ELEC66		ELEC68		ELEC70		GSS74		ELEC66		ELEC68		ELEC70		GSS74	
	Mean	Rank	Mean	Rank	Mean	Rank	Mean	Rank	Mean	Rank	Mean	Rank	Mean	Rank	Mean	Rank
Informational Complexity																
Extractive	2.622	2	2.303	1	2.481	1	3.380	4	2.435	1	2.174	1	2.405	1	3.255	3
Commerce	2.920	4	3.137	5	3.030	4	3.606	6	3.128	5	2.948	4	2.969	4	3.445	6
Legal and Financial	2.757	3	3.012	4	2.949	3	2.874	2	2.509	2	2.922	3	2.832	2	3.039	1
Construction and Maintenance	2.607	1	2.887	3	3.180	5	3.371	3	2.766	4	2.882	2	3.284	5	3.440	5
Professional and Kindred	2.927	5	2.720	2	2.778	2	2.812	1	2.636	3	2.974	5	2.863	3	3.045	2
Manufacturing and Transportation	3.230	6	3.144	6	3.340	6	3.384	5	3.362	6	3.208	6	3.295	6	3.427	4
Overall	2.917		2.944		3.028		3.223		2.919		2.941		3.038		3.311	
Interpersonal Complexity																
Extractive	7.793	6	7.676	6	7.832	6	7.599	6	7.840	6	7.675	6	7.819	6	7.617	6
Commerce	7.001	3	7.071	7	6.790	3	7.116	4	6.828	3	6.816	3	6.481	2	7.007	3
Legal and Financial	6.765	2	6.525	2	6.503	1	6.571	1	6.367	2	6.456	1	6.306	1	6.900	2
Construction and Maintenance	7.040	4	7.209	5	7.411	5	7.519	5	7.308	5	7.374	5	7.447	5	7.539	5
Professional and Kindred	6.310	1	6.319	1	6.650	2	6.574	2	6.100	1	6.613	2	6.693	3	6.726	1
Manufacturing and Transportation	7.307	5	7.070	3	7.294	4	7.084	3	7.210	4	7.066	4	7.289	4	7.108	4
Overall	7.071		6.925		7.016		6.981		7.012		7.035		7.080		7.117	
Object and Tool Complexity																
Extractive	2.287	1	2.394	1	2.083	1	3.086	1	2.188	1	2.338	1	2.108	1	2.941	1
Commerce	3.656	4	3.574	3	4.015	4	4.209	4	4.181	5	3.742	3	4.374	5	4.233	5
Legal and Financial	3.954	5	4.397	5	4.669	6	4.533	5	4.162	4	4.425	5	5.050	6	4.029	3
Construction and Maintenance	3.403	3	3.063	2	3.136	2	3.266	2	4.927	6	2.736	2	3.188	2	3.247	2
Professional and Kindred	4.752	6	4.928	6	4.068	5	4.638	6	3.174	2	4.856	6	4.239	4	4.728	6
Manufacturing and Transportation	3.390	2	3.746	4	3.340	3	4.124	3	3.562	3	3.780	4	3.405	3	4.098	4
Overall	3.546		3.835		3.667		4.162		3.654		3.632		3.638		3.985	

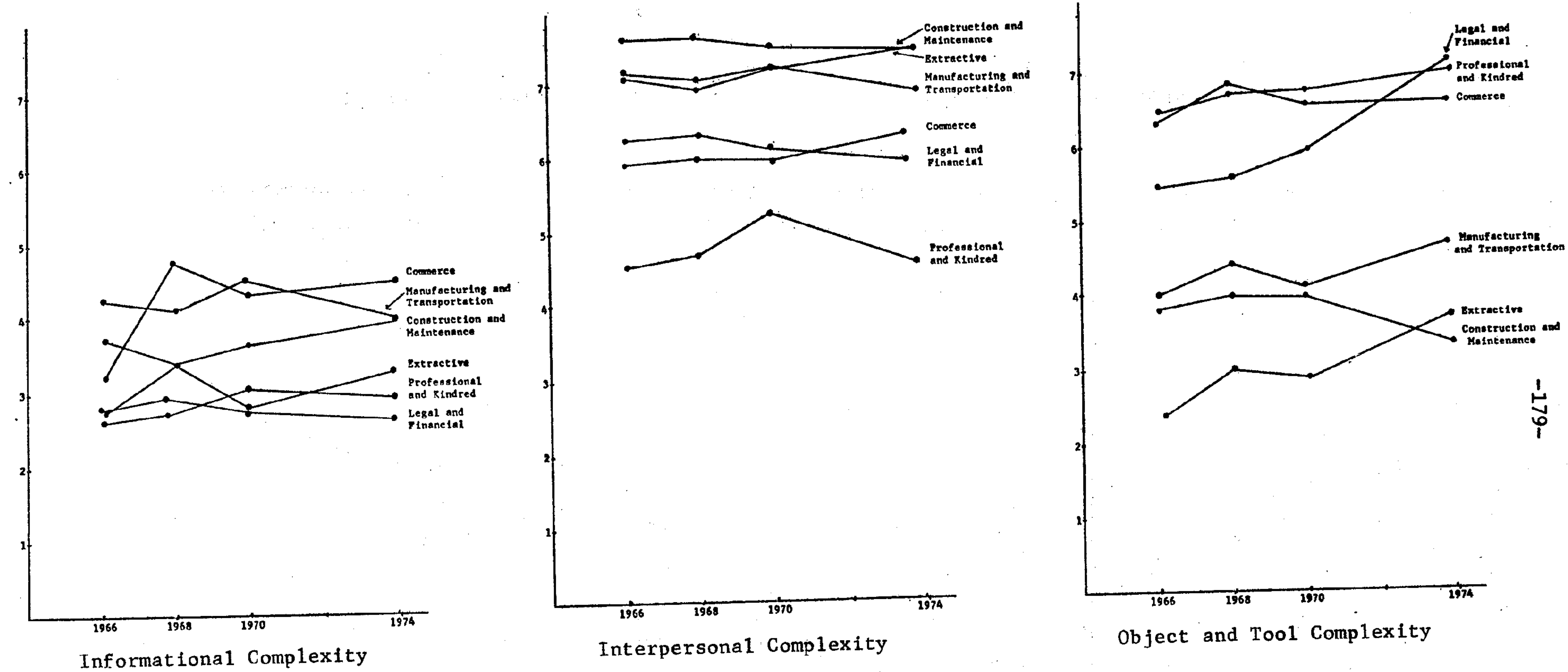


Fig. 2A--Mean Worker-Trait Scores Over Time for Each Situs: General Population

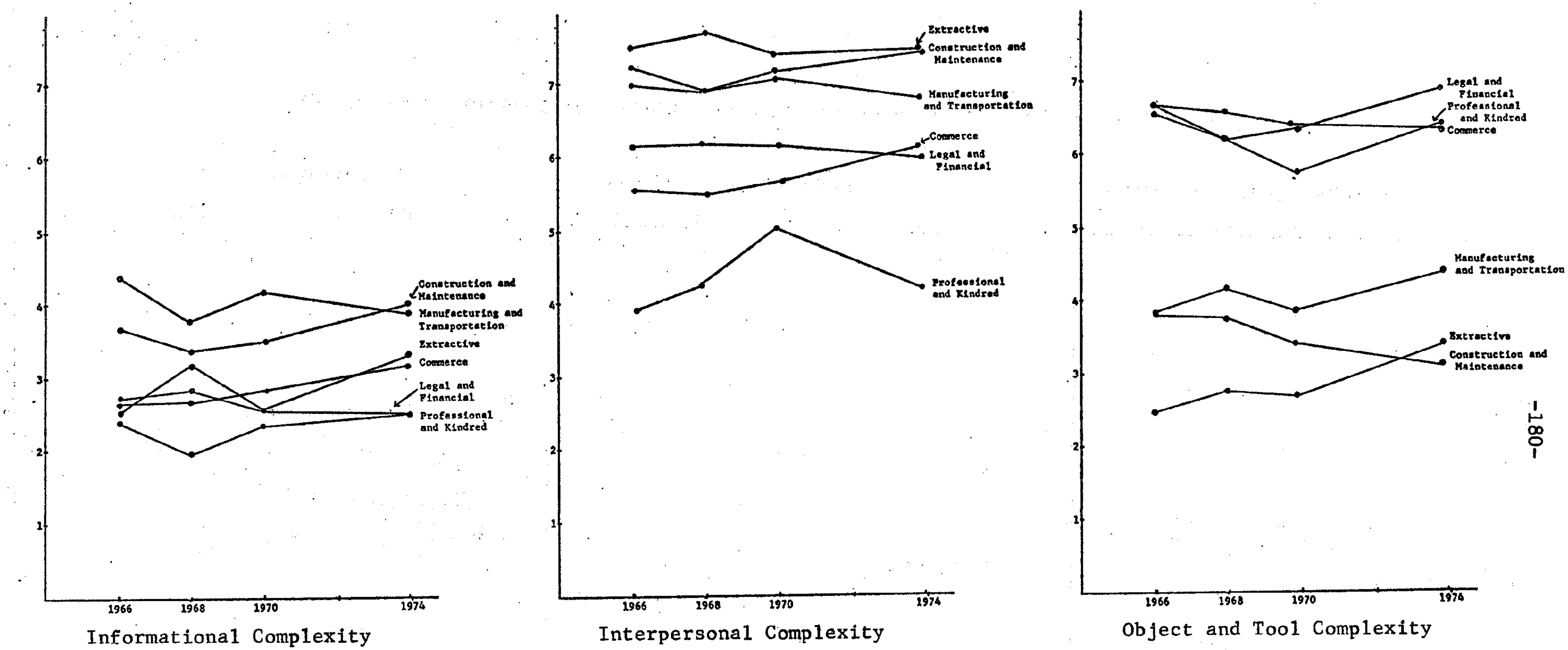
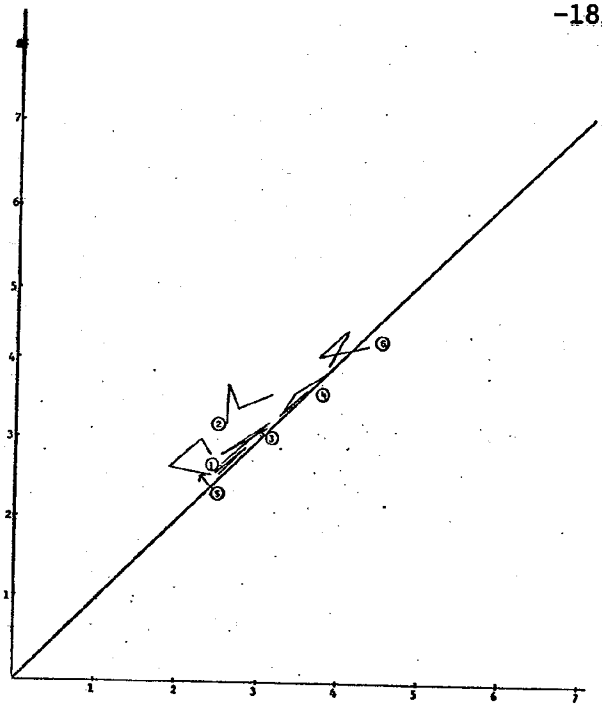


Fig. 2B--Mean Worker-Trait Scores Over Time for Each Situs: Males Only



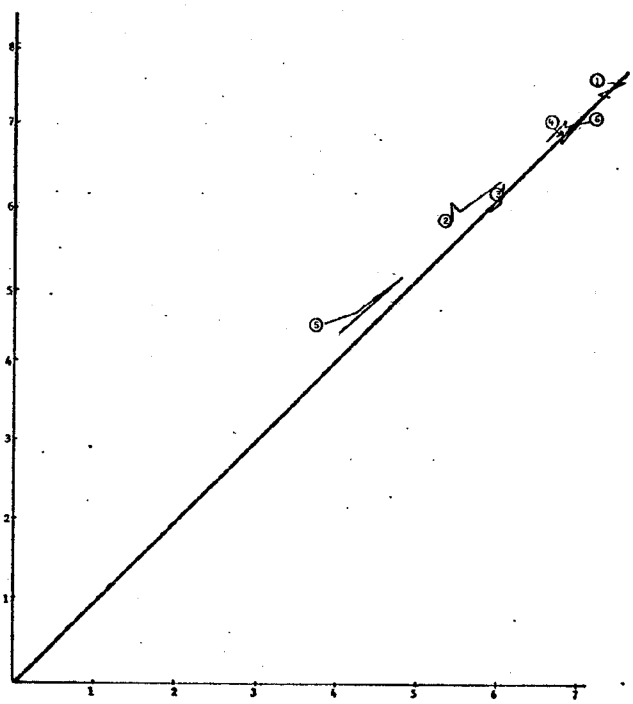
Informational Complexity

Legend

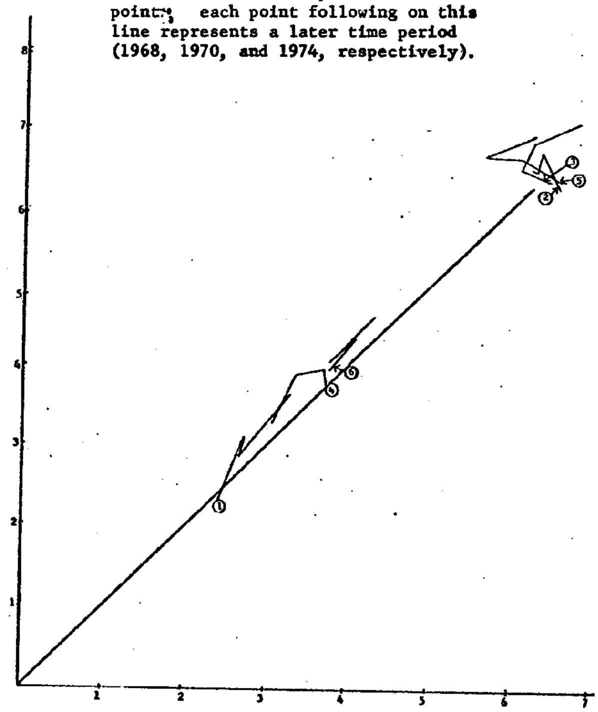
1--Extractive
2--Commerce
3--Legal and Financial
4--Construction and Maintenance
5--Professional and Kindred
6--Manufacturing and Transportation

KEY

Mean scores for males in a situs are measured along the x-axis; mean scores for the general population are scored along the y-axis. Points above the diagonal representing the equation x = y indicate higher scores (and therefore lower complexity) for the general population than for the male subset. The situs labels correspon- ding to circled numbers can be found in the legend above; the point nearest the circled number represents the 1966 point; each point following on this line represents a later time period (1968, 1970, and 1974, respectively).



Interpersonal Complexity



Object and Tool Complexity

Fig. 3--Mean Worker Trait Scores for Each Situs (Male by General Population) Over time

Men seem, in general, to have more complex jobs with respect to data manipulation than women, although this difference appears to be decreasing, if slightly, over time (.121 in 1966, and only .058 in 1974; the intermediate differences, however, are closer to the 1966 than the 1974 mark). With respect to interpersonal complexity, males seem to have less complex occupations, and the difference seems to be increasing. (Males are advantaged in 1966 by .017, but they are less advantaged compared to the total sample in 1974, the difference in means being .16 for that year). As might be expected, males exhibit considerably more complexity of objects manipulated than the general population; the difference, averaging .586, seems constant over the period. Probably a major part of the advantage of men in the latter trait, and their disadvantage in interpersonal complexity, stems from their disproportionate presence in situses emphasizing manual rather than interpersonal complexity. This can be observed in Table 7, which presents percentage distributions across the various situses for males and for the general population. We note that males are over-represented in the situses of manufacturing and transportation and construction and building maintenance, both of which are object-focused. (Manufacturing and transportation ranks, on the average, third in complexity of object manipulation among the situses, but only fifth and sixth for interpersonal and informational complexity, respectively; construction and maintenance averages second in object complexity but fourth and fifth in interpersonal and informational complexity, respectively.) Further, women are over-represented in wholesale and retail trade, a situs characterized by higher interpersonal and lower object complexity (ranking second and fourth, on the average, respectively). It might be argued that, within situses, differential mean skills levels obtain for males versus the total population. Thus, some residual effects of sex, beyond distribution in situses, seem to affect overall skill level; that is, overall skill levels would be slightly different even if males and females were identically distributed among the situses. For example, in 1974, if men were distributed exactly as is the general population across the situses, their overall mean, expressed as a weighted average of the conditional means, would have been: for informational complexity 3.348 (versus the observed 3.484); for interpersonal complexity, 6.271 (versus 6.266); and for object and tool complexity, 5.722 (versus 5.730). Obviously, in 1974, however, most difference between situses is explained by differential situs distribution.

TABLE 7

PERCENTAGE DISTRIBUTION OF RESPONDENTS OVER SITUSES (FOR GENERAL POPULATION AND FOR MALES ONLY) IN EACH YEAR

	ELEC66		ELEC68		ELEC70		GSS74	
	Per cent of Population	Per cent of Males Only	Per cent of Population	Per cent of Males Only	Per cent of Population	Per cent of Males Only	Per cent of Population	Per cent of Males Only
Extractive	12.8	14.4	8.5	11.5	7.8	11.8	5.4	7.8
Commerce	19.0	16.3	19.5	14.1	18.1	13.5	17.4	12.9
Legal and Financial	10.6	12.9	9.9	10.1	11.5	10.4	11.2	11.5
Construction and Maintenance	13.0	12.7	11.8	17.6	9.1	13.3	10.8	15.8
Professional and Kindred	14.8	11.7	21.5	13.2	23.0	13.5	24.7	16.2
Manufacturing and Transportation	29.7	31.9	28.6	33.4	30.5	37.4	30.6	35.9
N	884	410	922	563	1004	591	795	513

Differences in Mean Trait Levels by Situs Over Time, Intergenerationally and by Sex

Comparing the situses with respect to mean level of complexity for each trait reveals substantial and patterned differences at any point, but few trends. For information complexity, the legal and financial situs has increased both relatively and absolutely in complexity (2.838 in 1966 versus 2.631 in 1974), becoming the situs characterized by the highest mean informational complexity. This increase is accompanied by a decrease in the professional and kindred occupations, which have declined in informational complexity both relatively and absolutely. The extractive, retail and wholesale trade, and manufacturing and transportation situses form a relatively stable hierarchy of decreasing complexity. For interpersonal complexity, there is rather impressive relative stability in overall increasing complexity. Professional and kindred occupations seem most complex, followed by commerce, legal and financial, construction and building maintenance, manufacturing and transportation, and the extractive situses, in that order. In complexity of tool and object manipulation, we note a less extreme but still impressive relative stability, this time in the overall decline in complexity. Although the extractive industries are characterized by the highest level of complexity over the period, they decline rather steeply in the period (from 2.378 to 3.720, a net decrease of 1.342), while construction and maintenance increases in complexity from 3.843 to 3.362, a net increase of .481 in the period. Manufacturing and transportation and then commerce rank next, both showing some overall decrease, with professional and kindred improving relatively while declineing absolutely (.575, net decrease over the period). The legal and financial situs worsens both relatively and absolutely, a fairly thumb-fingered situs (decreasing from 6.508 in 1966 to 7.220 in 1974, a net of .712).

We note also that the decline in complexity in physical operations is not simply a function of the changing distribution of employment among the situses. Had the 1974 sample been distributed as the 1966 sample in this respect, its average complexity in tool and object manipulation would have increased to 5.405 (from 5.730) but would still be considerably less than the 1966 average (4.899). It is possible, as we shall discuss more fully below, that cohort succession may play some part here.

Our treatments of the comparisons of respondents to fathers and men to women with regard to differences among situses will be slightly more cursory, but should be adequate considering our earlier more fully developed discussion. We note, first, that the rankings of situs with reference to mean trait complexity are not as stable as those for the respondent, particularly for informational complexity. For the situs characterized by the highest complexity in information in the general population, the legal and financial occupations, the respondents begin the period with, on the average, less complex occupations than their fathers (difference is .081); by the end of the period, respondents have a higher average complexity (difference is .243). By contrast, the respondents' advantage in 1966 evaporates in 1974 in the professional and kindred situses (difference in 1966 is .282 favoring the respondents; in 1974 this difference has declined to a slight edge for the fathers, .078). Differences for the extractive, commerce, construction and maintenance, and manufacturing and transportation situses, reflecting higher father's complexity, seem to decrease over the period.

With respect to interpersonal complexity we observe both high stability of fathers' scores and, in line with the stability of respondents' scores mentioned above, fairly stable differences over time. There appears to have been a strong and across-the-board increase in interpersonal complexity for respondents over fathers. These differences in means are most pronounced for situses characterized by the highest complexity on that trait for the respondents: professional and kindred (average difference over the period is 1.68) and commerce (average difference is .878).

The case seems to reverse for object and tool complexity. As for respondents, complexity of object manipulation overall for fathers seems to decline over the period, although at a less pronounced rate. These similar rates of decline are reflected in across-the-board and fairly constant differences in each situs, to the advantage of fathers. It should be noted that the differences are substantial. For professional and kindred occupations, the average difference in means is 2.197 in the period. Nor are the differences simply efforts by respondents to upgrade their fathers' status in any obvious way: in 1974 (the only year for which we have relevant data), the fathers' mean Duncan prestige is lower than the respondents' (39.275 versus 41.189 respectively, a difference of 1.914). Whether the respondent selectively reports his father's occupation to overestimate tool and operations complexity is a question beyond the scope of this paper; however, the magnitude of the differences resists any simple explanation in terms of respondent bias.

This average difference cannot be called a function of differential distribution among situses. Had the fathers been distributed among the situses as are their children for 1974, their average informational complexity would have been 3.225 (a trivial decrease from 3.223), still higher than the mean for respondents, 3.484. Similarly, for object and tool complexity, had fathers been distributed across situses as their children, complexity would have decreased from 4.162 to 4.341, again still substantially higher than respondents at 5.73. It might be argued that since fathers are always male, the appropriate comparison is with the male respondents, using the distribution of male respondents in 1974 as the baseline. We find, using this distribution, that the overall mean informational complexity for fathers would have been 3.262 (again, versus 3.223), still higher than the male respondents' mean 3.426. Similarly, for object and tool complexity, the mean complexity for fathers, using the sons' situs distribution, would have been 4.053, a higher level than the 4.162 for sons.

Comparing males with the general population, we find the overall pattern of results in the general population, with some departures. Males seem to be concentrated in the more informationally complex levels of retail and wholesale trade, raising the complexity of this situs both absolutely, compared with the general population, and relatively, compared with the male means for the other situses. However, for males the decline in the informational complexity in that situs seems more pronounced (from 2.66 in 1966 to 3.243 in 1974, a net decrease of .574). Also, the decline of the relative position of professional and kindred occupations in the general population is not reflected in the male sample, suggesting that women are occupying less complex positions in this most complex situs increasingly over time. As before, interpersonal complexity is distributed with remarkable stability and diversity across the situses, in this case both for men and in general. It would appear that the female advantage in interpersonal complexity through this period is largely a function of their participation in jobs of greater complexity in the building and maintenance occupations, since in other situses females occupy less complex positions.

With respect to object and tool complexity, women seem to be concentrated overall in less complex positions and in each situs, this situation is reflected with only minor variations between situses.

Because considerations of space force curtailment of the discussion of variation in types and levels of complexity by sex and situs, and over time, it is apparent that we have only scratched the surface. More detailed analysis might focus on the distribution of complexity within situs. For example, are women or men concentrated at various points in the distribution of complexity? Also, the effects of exogenous variables, such as the history of a particular situs (see Stinchcombe 1965), proportion clerical, and growth of industry might have considerable effect on differences in and mean levels of complexity across and within aggregates. As we shall see, many of these suggestions apply equally well to our analysis of the mobility of complexity, which follows.

Intergenerational Transmission of Trait Complexity by Situs

Parts A and B of Table 8 present slopes, intercepts, and R^2's for the regression of respondent's complexity on father's complexity, in each situs and for each trait. Part A presents the results for the sample as a whole, Part B for the male subset of the sample. Figures 4a and 4b present these results graphically, for each sex and year. Figures 5A and 5B show the regression coefficients over time.

Table 9 presents the results for analyses of covariance, testing the significance of the contribution to the fit of the model by allowing differences in the slopes. A significant F-ratio for the interaction implies that the model allowing the slopes to differ fits significantly better than one that merely allows the direct effects of situs.

In all cases, the direct effects of situs are significant. In terms of our discussion of outcome regions, a significant F-ratio for the interaction forces us to choose model 2b or 2c over 1b, implying that we must reject the null hypothesis that $D_k=0$ for all k. Scanning Table 9 we note that the null hypothesis that $C_k=0$ for all k is rejected throughout, so we shall have no need to consider model 1a.

TABLE 8--PART A

REGRESSION EQUATIONS (RESPONDENT'S ON FATHER'S WORKER TRAIT SCORES) FOR EACH SITUS AND YEAR: GENERAL POPULATION

	ELEC66 (N = 884)			ELEC68 (N = 922)			ELEC70 (N = 1004)			GSS74 (N = 795)		
	Slope	Intercept	R^2	Slope	Intercept	R^2	Slope	Intercept	R^2	Slope	Intercept	R^2
Informational Complexity												
Extractive	.341	1.892	.094	.653	1.888	.228	.649	1.241	.293	.338	2.190	.138
Commerce	.244	2.587	.050	.029	3.691	.001	.225	2.806	.046	.259	2.712	.072
Legal and Financial	.311	1.980	.118	.203	2.374	.065	.068	2.531	.009	.066	2.440	.085
Construction and Maintenance	.192	3.232	.026	.262	2.669	.067	-.009	3.705	.000	.188	3.332	.037
Professional and Kindred	.179	2.122	.034	.119	2.400	.015	.152	2.664	.028	.326	1.972	.112
Manufacturing and Transportation	.115	3.957	.012	.047	4.027	.002	.043	4.372	.002	.167	3.473	.025
Overall	.228	2.786	.043	.157	3.051	.023	.165	3.089	.027	.254	2.666	.064
R^2	.127			.104			.136			.127		
Interpersonal Complexity												
Extractive	.523	3.599	.085	.298	5.402	.098	-.104	8.348	.003	.255	5.563	.098
Commerce	.152	4.843	.034	.235	4.461	.086	.121	5.232	.029	.126	5.539	.025
Legal and Financial	.080	5.759	.017	.086	5.829	.013	.024	6.007	.001	.030	5.839	.001
Construction and Maintenance	.251	5.348	.251	.185	5.579	.091	-.067	7.746	.005	.021	7.395	.001
Professional and Kindred	.168	3.504	.017	.257	3.083	.045	.244	3.653	.044	.181	3.392	.018
Manufacturing and Transportation	.069	6.709	.005	.198	5.726	.053	-.020	7.430	.001	.283	4.927	.079
Overall	.273	4.580	.058	.307	4.233	.078	.198	5.099	.035	.281	4.303	.052
R^2	.295			.285			.229			.292		
Object and Tool Complexity												
Extractive	.304	1.681	.106	.328	2.288	.104	.140	2.665	.011	.769	1.347	.422
Commerce	.004	6.386	.000	.027	6.830	.001	.031	6.533	.002	-.106	7.100	.017
Legal and Financial	.036	6.364	.002	.090	6.247	.012	-.021	7.087	.001	.066	6.920	.011
Construction and Maintenance	.328	2.727	.103	.220	3.369	.036	-.081	4.215	.005	-.082	3.628	.007
Professional and Kindred	.035	6.344	.002	.109	6.237	.020	.068	6.527	.008	.041	6.896	.003
Manufacturing and Transportation	.005	4.091	.000	.199	3.738	.048	-.048	4.290	.003	.198	3.940	.047
Overall	.191	4.220	.035	.234	4.599	.056	.138	4.917	.020	.159	5.069	.027
R^2	.331			.301			.328			.329		

TABLE 8--PART B

REGRESSION EQUATIONS (SONS ON FATHER'S WORKER TRAIT SCORES)
FOR EACH SITUS AND YEAR: MALES ONLY

	ELEC66 (N = 410)			ELEC68 (N = 563)			ELEC70 (N = 591)			GSS74 (N = 513)		
	Slope	Intercept	R^2	Slope	Intercept	R^2	Slope	Intercept	R^2	Slope	Intercept	R^2
Informational Complexity												
Extractive	.290	1.925	.065	.639	1.822	.200	.605	1.147	.277	.408	2.048	.180
Commerce	.303	1.718	.118	-.032	2.786	.001	.196	2.243	.048	.292	2.236	.091
Legal and Financial	.459	1.580	.201	.269	2.078	.082	.111	2.276	.018	.140	2.128	.028
Construction and Maintenance	.265	2.996	.053	.202	2.849	.038	-.001	3.557	.000	.159	3.498	.026
Professional and Kindred	.091	2.141	.007	-.123	2.325	.027	.137	1.981	.025	.339	1.497	.126
Manufacturing and Transportation	.144	3.928	.020	.086	3.533	.008	.074	3.956	.005	.198	3.233	.033
Overall	.282	2.506	.066	.133	2.789	.017	.176	2.790	.029	.264	2.552	.065
R^2		.192			.131			.156			.142	
Interpersonal Complexity												
Extractive	-.152	8.764	.004	.183	6.393	.063	-.118	8.416	.004	.291	5.361	.141
Commerce	.077	5.088	.013	.142	4.621	.040	.119	4.944	.034	.110	5.440	.017
Legal and Financial	.131	5.395	.064	.138	5.350	.025	.043	5.936	.044	.092	5.432	.007
Construction and Maintenance	.474	3.586	.224	.134	5.964	.016	-.077	7.851	.005	.028	7.324	.001
Professional and Kindred	.093	3.386	.006	.111	3.610	.005	.293	3.136	.040	.113	3.471	.005
Manufacturing and Transportation	-.041	7.597	.002	.242	5.278	.071	-.034	7.433	.001	.318	4.610	.084
Overall	.248	4.762	.054	.262	4.605	.050	.187	6.325	.030	.285	4.400	.046
R^2		.374			.285			.228			.299	
Object and Tool Complexity												
Extractive	.296	1.811	.086	.262	2.154	.084	.164	2.358	.018	.727	1.284	.404
Commerce	.002	6.719	.000	-.011	6.686	.000	.119	5.930	.025	-.038	6.553	.002
Legal and Financial	.089	6.269	.013	.070	5.948	.006	.002	6.388	.000	.082	6.619	.012
Construction and Maintenance	.426	2.487	.172	.128	3.441	.010	-.109	3.821	.010	-.131	3.586	.020
Professional and Kindred	.071	6.403	.011	.163	5.440	.033	.177	5.045	.040	-.059	6.743	.004
Manufacturing and Transportation	-.057	4.073	.004	.195	3.464	.043	-.099	4.239	.012	.208	3.597	.054
Overall	.232	3.978	.054	.246	3.890	.056	.165	3.965	.027	.163	4.380	.026
R^2		.399			.259			.277			.308	

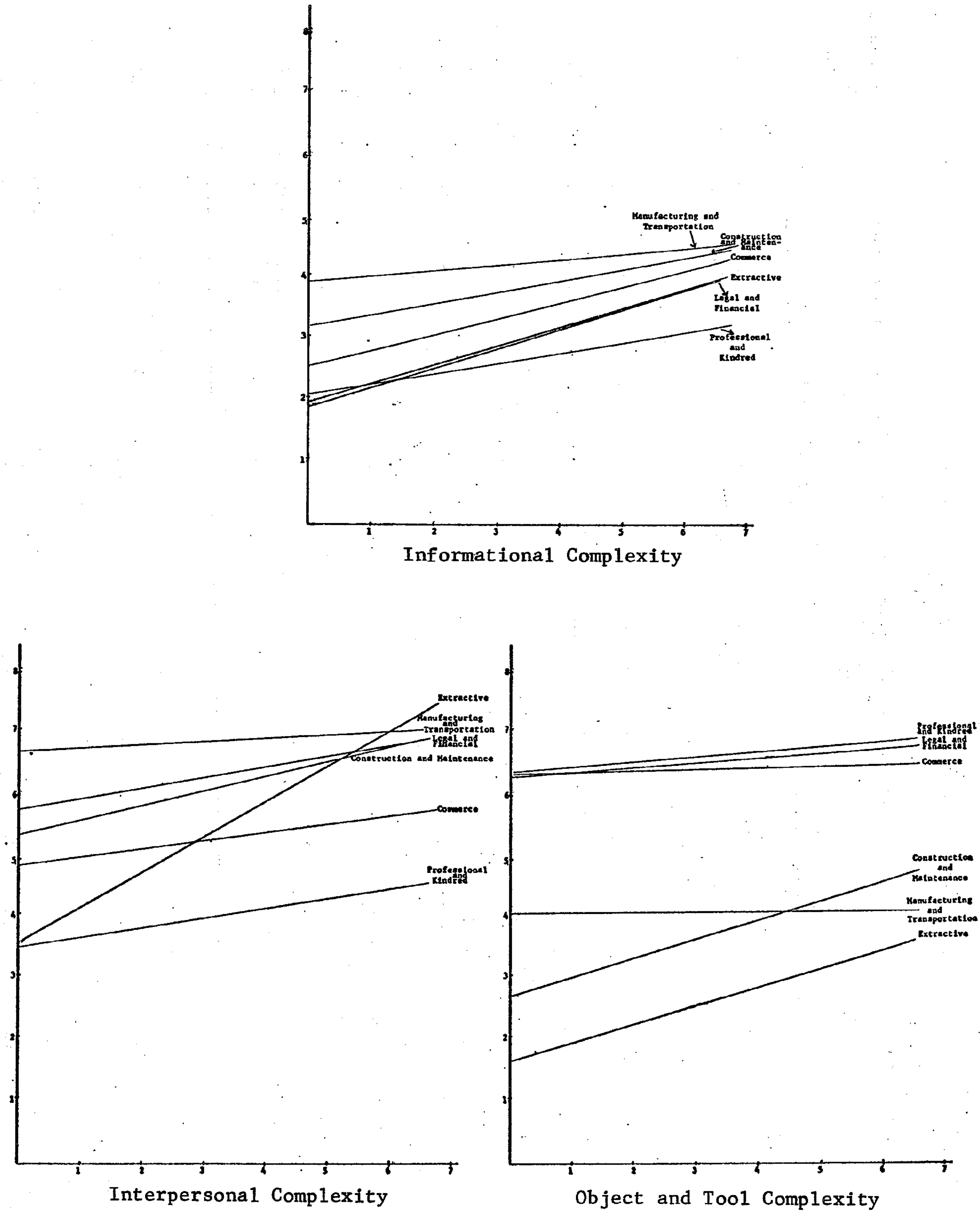
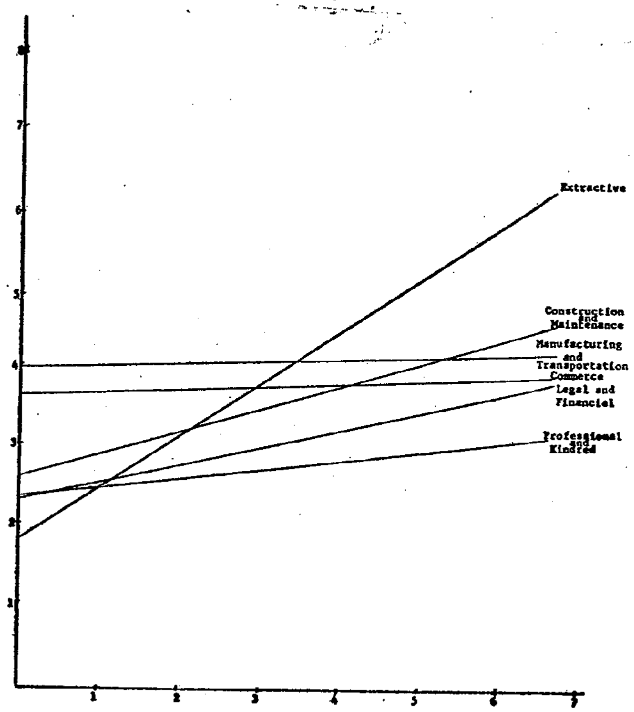
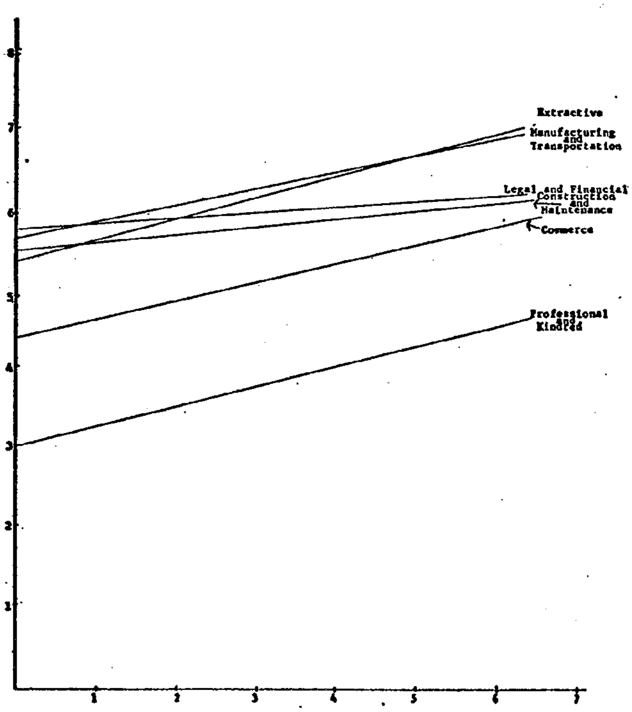


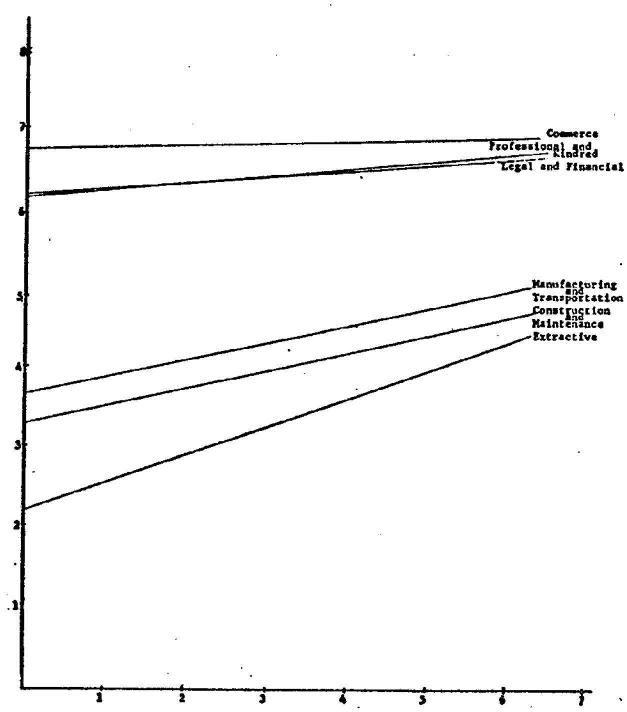
Fig. 4A.--Respondent's Worker-Trait Score Regressed on Father's Score for Each Year for Each Situs: General Population. ELEC66



Informational Complexity



Interpersonal Complexity



Object and Tool Complexity

Fig. 4A--Continued: ELEC68

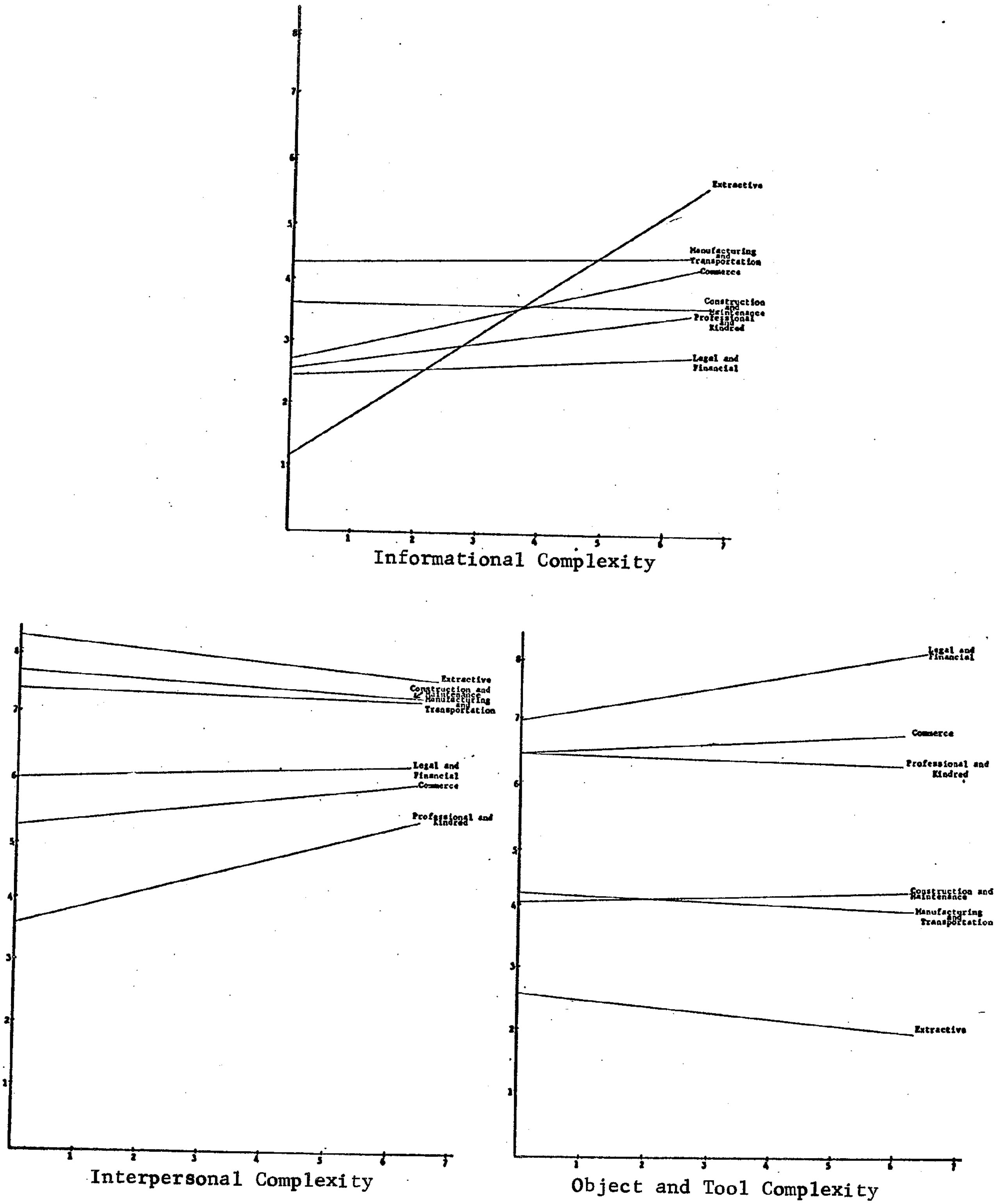
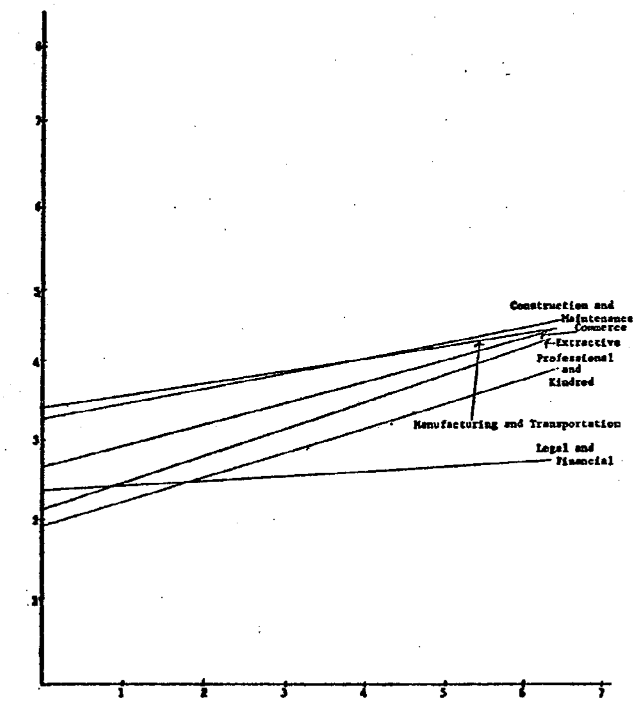


Fig. 4A--Continued: ELEC70



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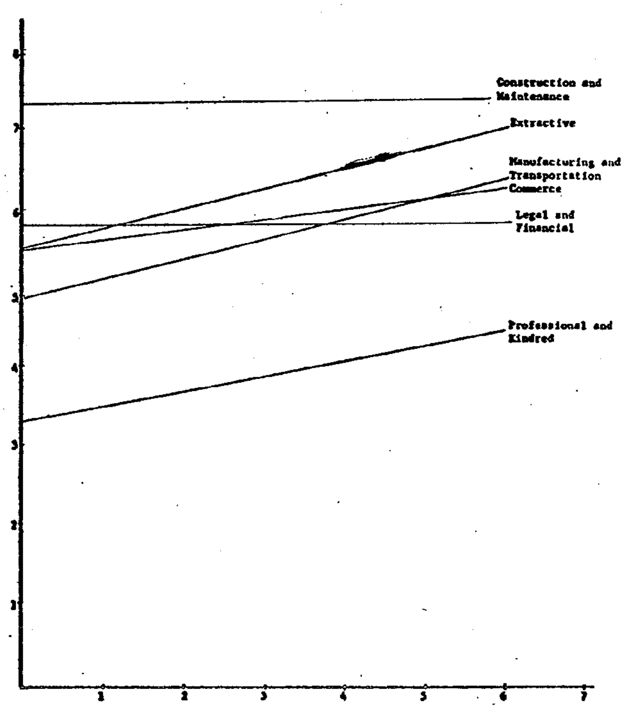

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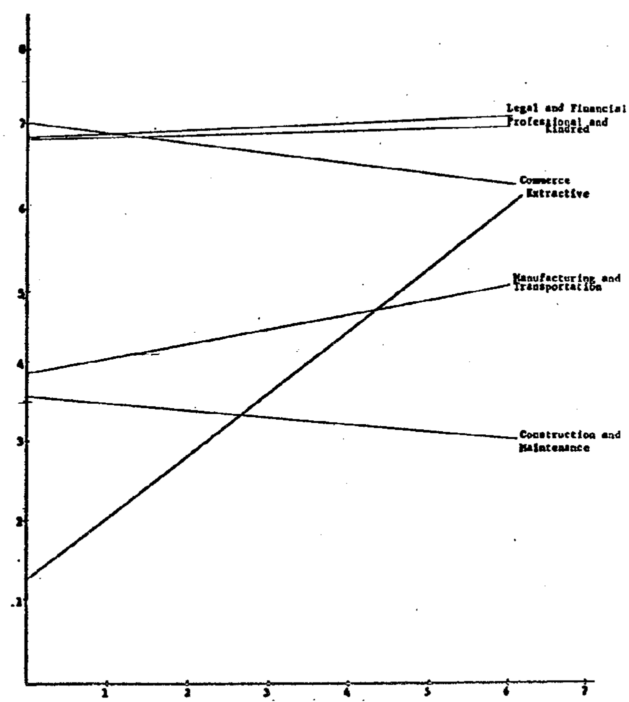


Object and Tool Complexity

Fig. 4A--Continued: ELEC74

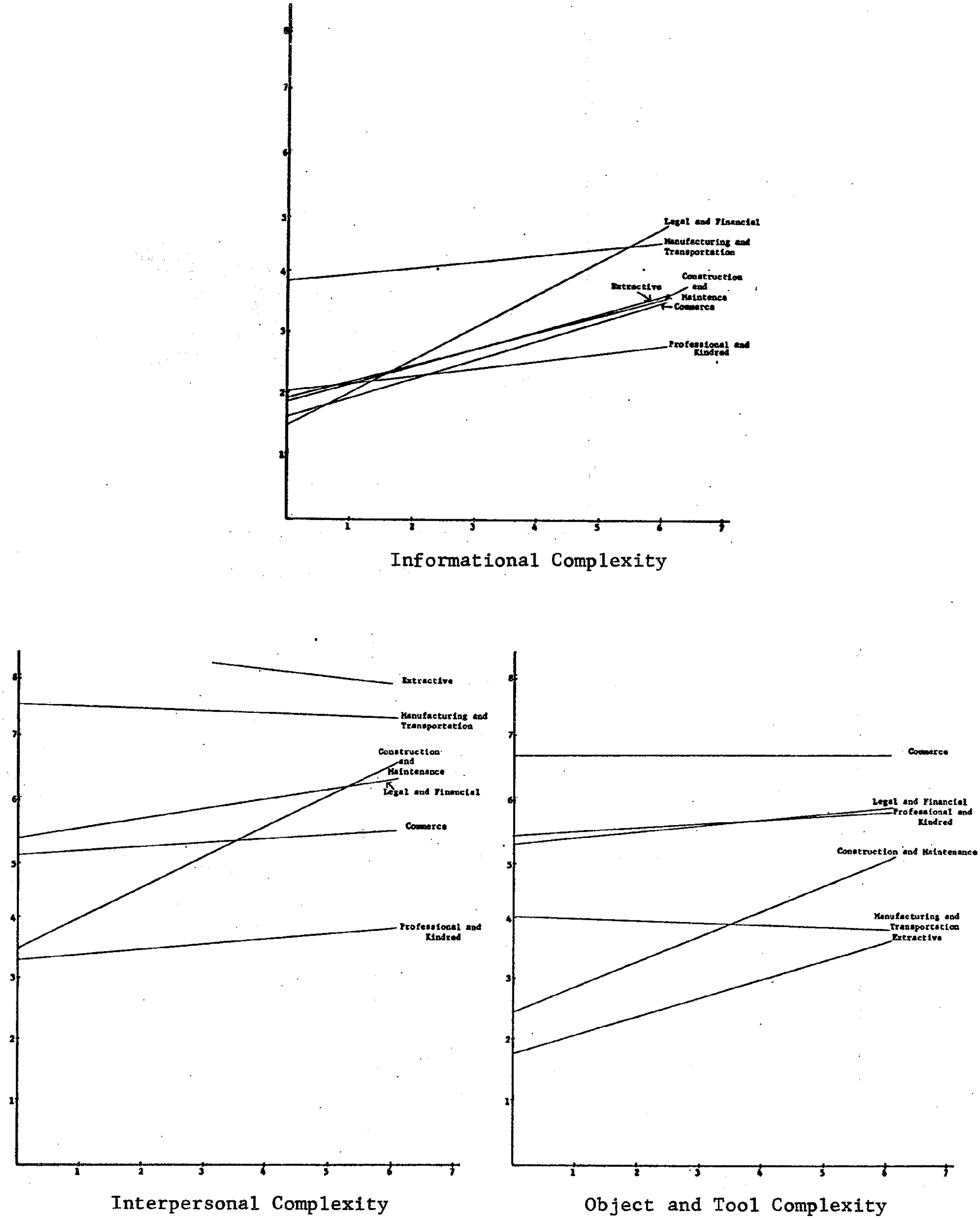
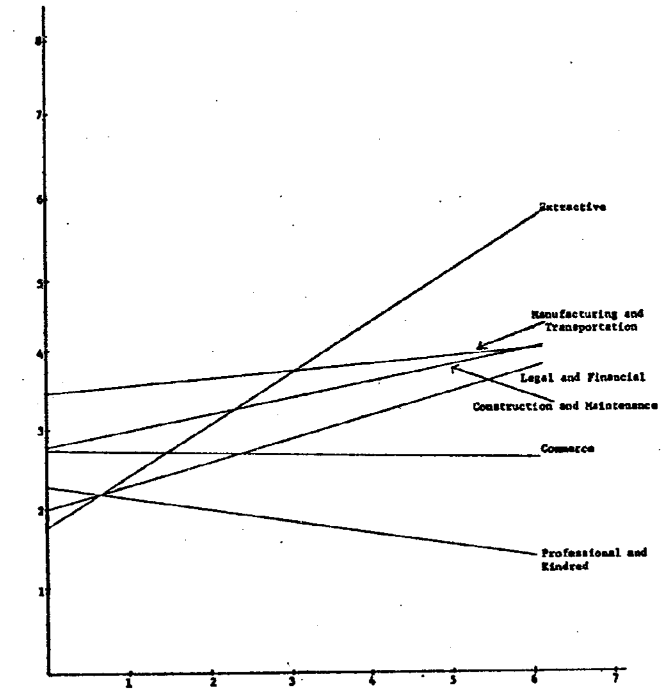


Fig. 4B--Respondent's Worker Trait Score Regressed on Father's Score for Each Year for Each Situs: Males Only. ELEC66.



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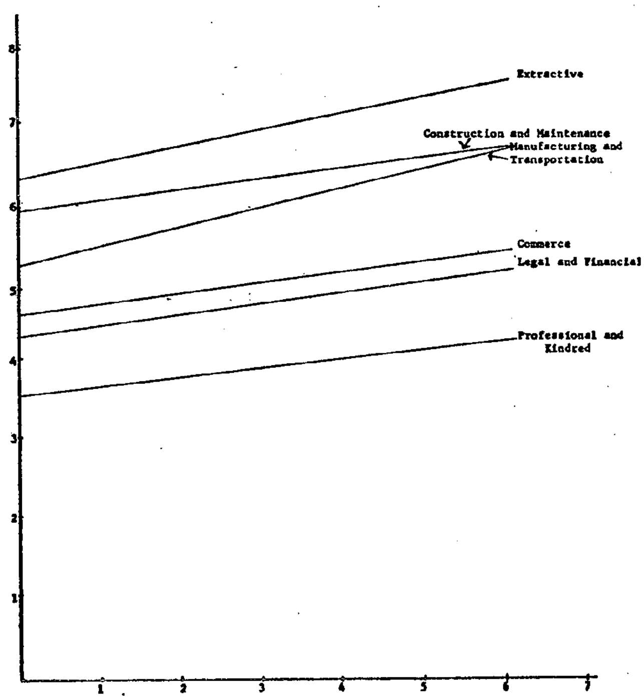

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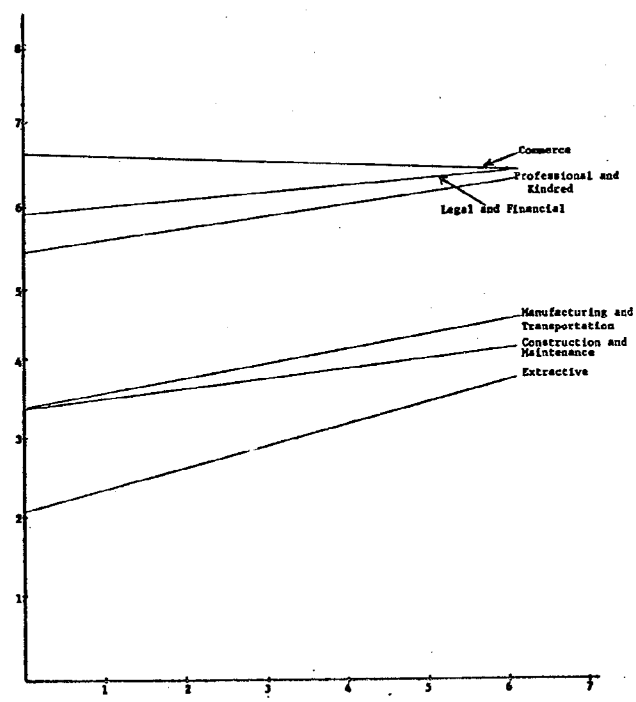


Object and Tool Complexity

Fig. 4B--Continued: ELEC68

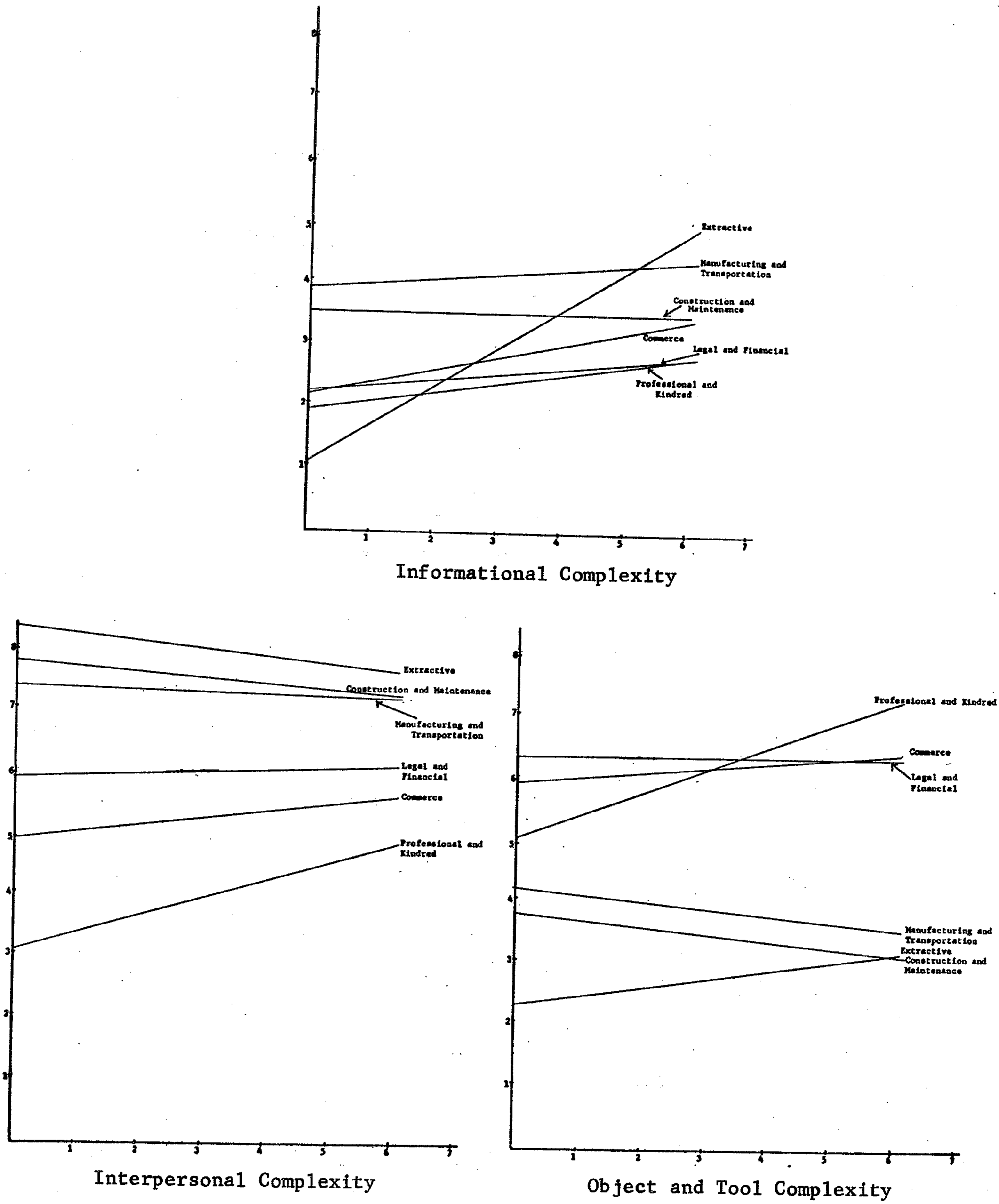


Fig. 4B--Continued: ELEC70

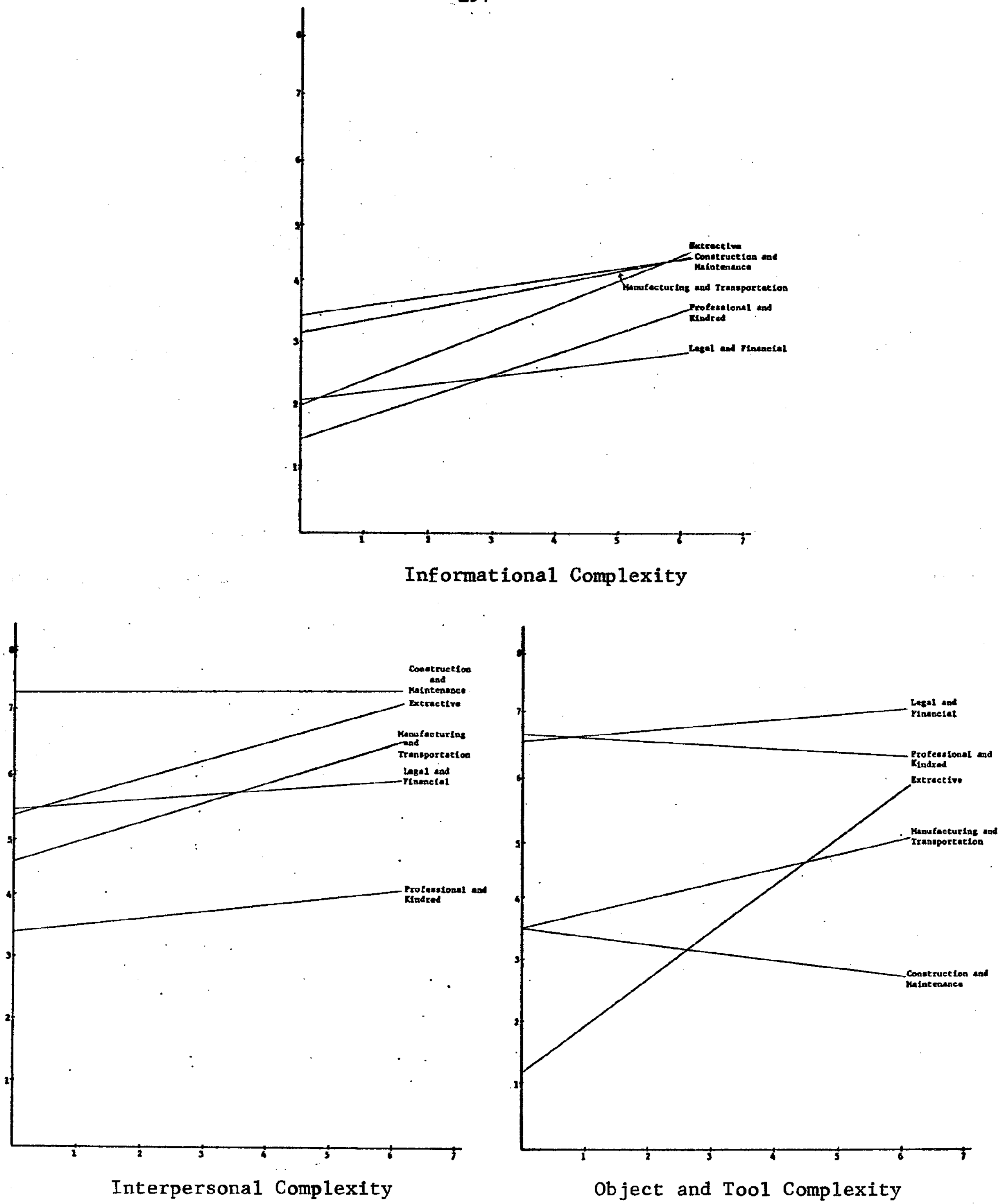
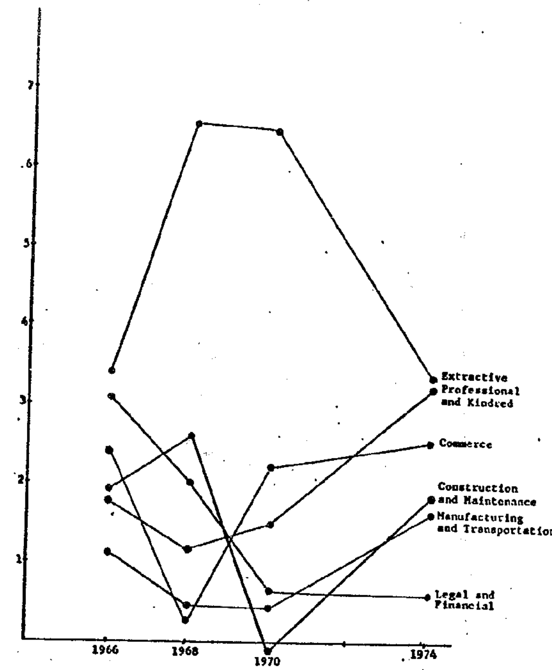


Fig. 4B--Coninued: ELEC74



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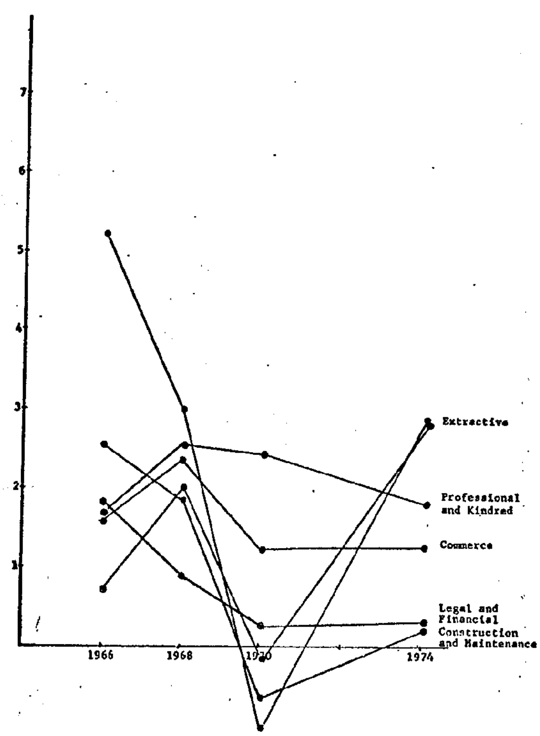
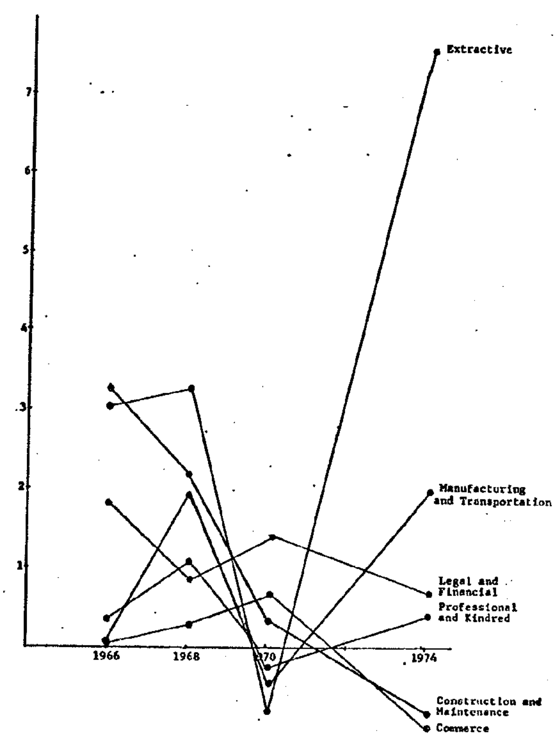
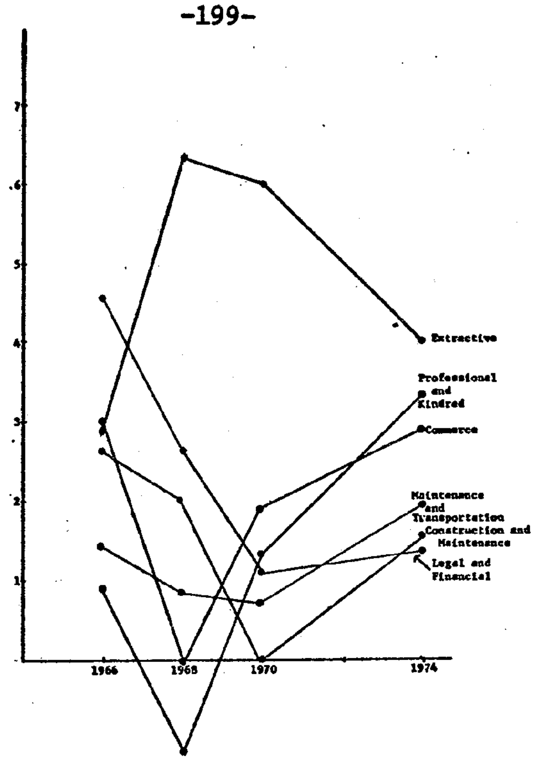


Interpersonal Complexity

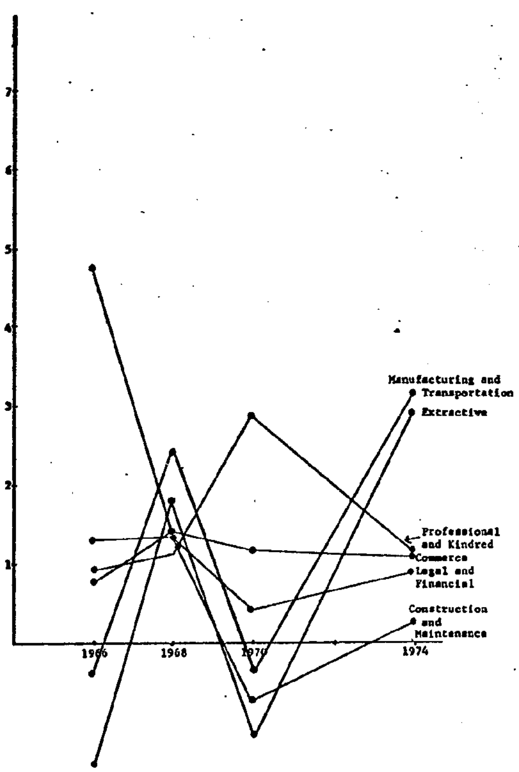


Object and Tool Complexity

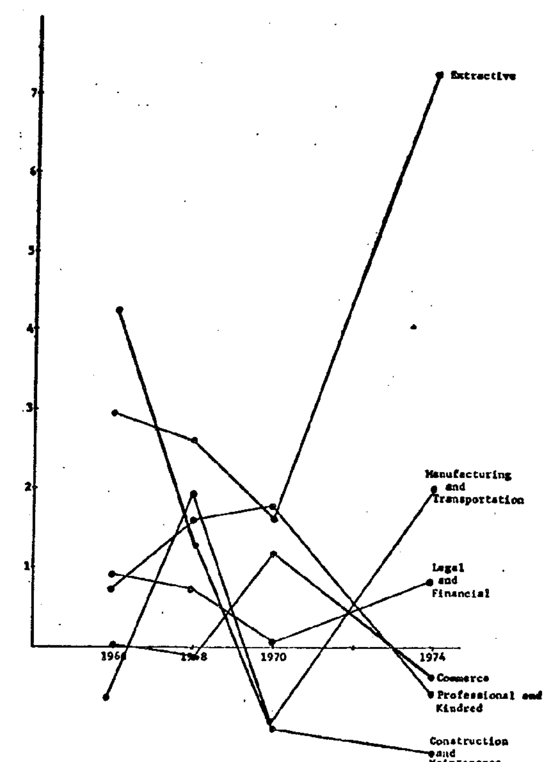
Fig. 5A--Regression Coefficients for Each Situs (Respondent's Score Regressed on Father's) Over Time: General Population



Informational Complexity



Interpersonal Complexity



Object and Tool Complexity

Fig. 5B--Regression Coefficients for Each Situs (Respondent's Score Regressed on Father's) Over Time: Males Only

TABLE 9

REGRESSIONS OF REGRESSION COEFFICIENTS (RESPONDENT'S ON FATHER'S TRAIT SCORES) ON MEAN WORKER TRAIT SCORES FOR RESPONDENTS, OVER ALL SITUSES

	ELEC66		ELEC68		ELEC70		GSS74	
	General Population	Males Only	General Population	Males Only	General Population	Males Only	General Population	Males Only
Informational Complexity								
(1) R^2 Saturated	.127	.192	.104	.131	.136	.156	.127	.142
(2) R^2 Additive	.121	.183	.082	.100	.114	.134	.120	.136
(3) F for interaction	1.033	.908	4.54	4.11	5.064	3.053	1.18	.79
Significance	>.1	>.1	<.005	<.005	<.001		>.1	<.05
(4) Regression coefficient slope on mean	-.091	-.042	-.097	.191	-.172	-.139	.008	-.036
(5) R^2 for slope on mean	.491	.067	.048	.208	.222	.207	.029	.046
(b =-.094; R^2 = .100 over all years for General Population) (b =-.007; R^2 = .001 over all years for Males Only)								
Interpersonal Complexity								
(1) R^2 Saturated	.295	.374	.285	.285	.228	.228	.292	.299
(2) R^2 Additive	.291	.361	.283	.284	.217	.216	.287	.292
(3) F for interaction	1.124	1.74	.638	.301	2.972	1.911	1.10	.92
Significance	>.1	>.1	>.1	>.1	<.025	<.05	>.1	>.1
(4) Regression coefficient slope on mean	-.068	-.017	.001	.025	-.138	-.152	.004	.027
(5) R^2 for slope on mean	.208	.011	.000	.404	.910	.949	.002	.085
(b =-.008; R^2 = .003 over all years for General Population) (b =-.018; R^2 = .019 over all years for Males Only)								
Object and Tool Complexity								
(1) R^2 Saturated	.331	.399	.301	.259	.328	.277	.329	.308
(2) R^2 Additive	.318	.376	.295	.254	.325	.265	.300	.274
(3) F for interaction	3.42	3.00	1.57	.801	.889	2.034	6.79	4.94
Significance	<.005	<.025	>.1	>.1	>.1	<.05	<.001	<.001
(4) Regression coefficient slope on mean	-.067	-.053	-.063	-.047	-.003	.020	-.083	-.080
(5) R^2 for slope on mean	.588	.294	.930	.627	.005	.066	.199	.178
(b =-.052; R^2 = .201 over all years for General Population) (b =-.039; R^2 = .107 over all years for Males Only)								

Two methodological notes might be made here. First, since we use the raw slope as opposed to a path coefficient here we must distinguish between the slope and the R^2 for our purposes. We will take the slope (for situs k, the quantity $b+d_k$) to be our best linear estimate of the increase in respondent's complexity level given a unit change in father's level and that the respondent occupies situs k. R^2, then, may be interpreted as a measure of the fit of the model. Second, in our analysis of covariance we will altogether too often find no significant interaction. Since the slopes cannot be presumed to differ, the question of whether the slopes in the various situses are ordered in the form specified by our hypothesis becomes moot; we cannot reject the null hypothesis that they do not differ at all. In so exploratory a work as this, however, we will continue to analyze the results with respect to our hypothesis. We proceed in this fashion for two reasons: first, the patterning of observed differences in the slopes may be of interest even though with these samples the differences do not attain significance; second, while the overall F-test might not allow us to reject the mull hypothesis, this doesn't imply that individual significant differences might not obtain. Thus, for future analysis, the knowledge that some cutoff point for our hypothesis exists might be useful indeed.

At the outset, we observe that, both relatively and absolutely, the coefficients are considerably more unstable than the means above were. Overall, the transmissibility of informational complexity shows very little trend-like change over the period, first declining and then increasing again. We note, however, that in all cases the introduction of the situs variable increases the fit of the model (in terms of overall variance explained) on the order of threefold. However, even with the introduction of the situs distinction, the fit of the linear advantage model remains poor (R^2=.127, .104,.136, and .127 over the period for the saturated model, including direct and interaction effects for situs). Further, Table 9 suggests that, by and large, this increase in fit is attributable to the direct rather than multiplicative effects of situs. In two of the four years covered the interaction effects fail to be significant (1966 and 1974). For the general population the variance explained by the interaction terms averages about 1.4 per cent. The extractive industries appear to provide the highest advantage of estimated complexity for the respondent, given high complexity for his father. We note also that it is in the extractive occupations that the best fit for a linear model is provided. The legal and financial and professional and kindred situses both reverse positions relatively; the former being a situs highly conducive (b=.311) to skill transmission in 1966 but declining to .066 in 1974 (a net decrease of .245), and professional and kindred occupations increasing (from .197 to .325 over the period, a net increase of .147). The other situses are either relatively consistent or snow no observable trend.

For the interpersonal complexity trait, in the aggregate, no discernible trend in transmissibility appears. The direct effect of situs is significant in all years, but in only one year can we reject the null hypothesis that the slopes are all equal (1970, $p<.025$). The R^2's for the saturated model average about .275, although the effect of the interaction terms is to explain an average .55 per cent of the variance in respondent's interpersonal complexity. Interpersonal complexity seems most transmissible in the extractive situs, although the behavior of the coefficients seems erratic (moving even to a negative .104 in 1970.) Professional and kindred occupations follow with more predictable variation in the slope coefficient. Commerce, legal and financial, and building and maintenance follow in a rough rank order.

For object and tool complexity, we find again mixed confirmation of our suspicions favoring differential transmissibility by situs. In two years, 1966 and 1974, we conclude that the slopes are not all equal. In all years, the average R^2 for the saturated model is an impressive .322, which represents a substantial average increase (.288) over the average R^2 for the model including only father's complexity level (.0345), but a less impressive increase over the full additive model (the average difference is only 1.3 per cent). The extractive situs again permits greatest transmission of advantage and disadvantage. Construction and maintenance declines sharply in transmissibility, both relatively and absolutely, in the period, until father's complexity becomes negatively correlated with respondent's (dropping from .328 in 1960 to -.082 in 1974). The behavior of the other coefficients is simply too erratic to be consistently ranked over the period.

Sex Differences in Intergenerational Transmission of Trait Complexity by Situs. While it might be expected that women would be less influenced by their father's skill level than men, the results seem to depend on which situs and what trait is under consideration. Figure 6 presents the comparison over time for each trait. The slope for males (along the abcissa) is plotted against the slope for the general population (along the ordinate) for each trait. Points above the diagonal representing the equation X=Y are characterized by greater parental influence on women than men; for points below that diagonal the reverse is true. The point next to the situs name is that for 1966; each point following represents a later time period . Lines moving toward the diagonal, of course, indicate a trend toward smaller differences in transmissibility by sex; points moving toward the (0,0) point indicate less transmissibility overall.

For data complexity, the situses of manufacturing and transportation and legal authority and finance are both more conducive to parental influence on complexity for men than for women. Since the lines are parallel to the diagonal over the period, no change in that difference seems to have occurred. Commerce, and to a lesser extent the extractive situs, show more transmissibility for women than men. But as both situses cross the diagonal in 1974, more influence of parental level for men is indicated. The professional and kindred occupations show a gradual movement toward equalization of parental influence between the sexes (the difference of slopes decreases in a regular fashion from .088 favoring women's "inheritance" to .013 favoring men's in 1974, a net change of .101). The construction and maintenance situs displays neither consistent difference nor clear trend.

With respect to interpersonal complexity, only manufacturing and transportation seem more conducive to parental influence for males than for the sample as a whole. By contrast, the commerce and professional and kindred situses seem to favor females in this respect, though the differences decrease over the period for commerce. Construction and maintenance seem

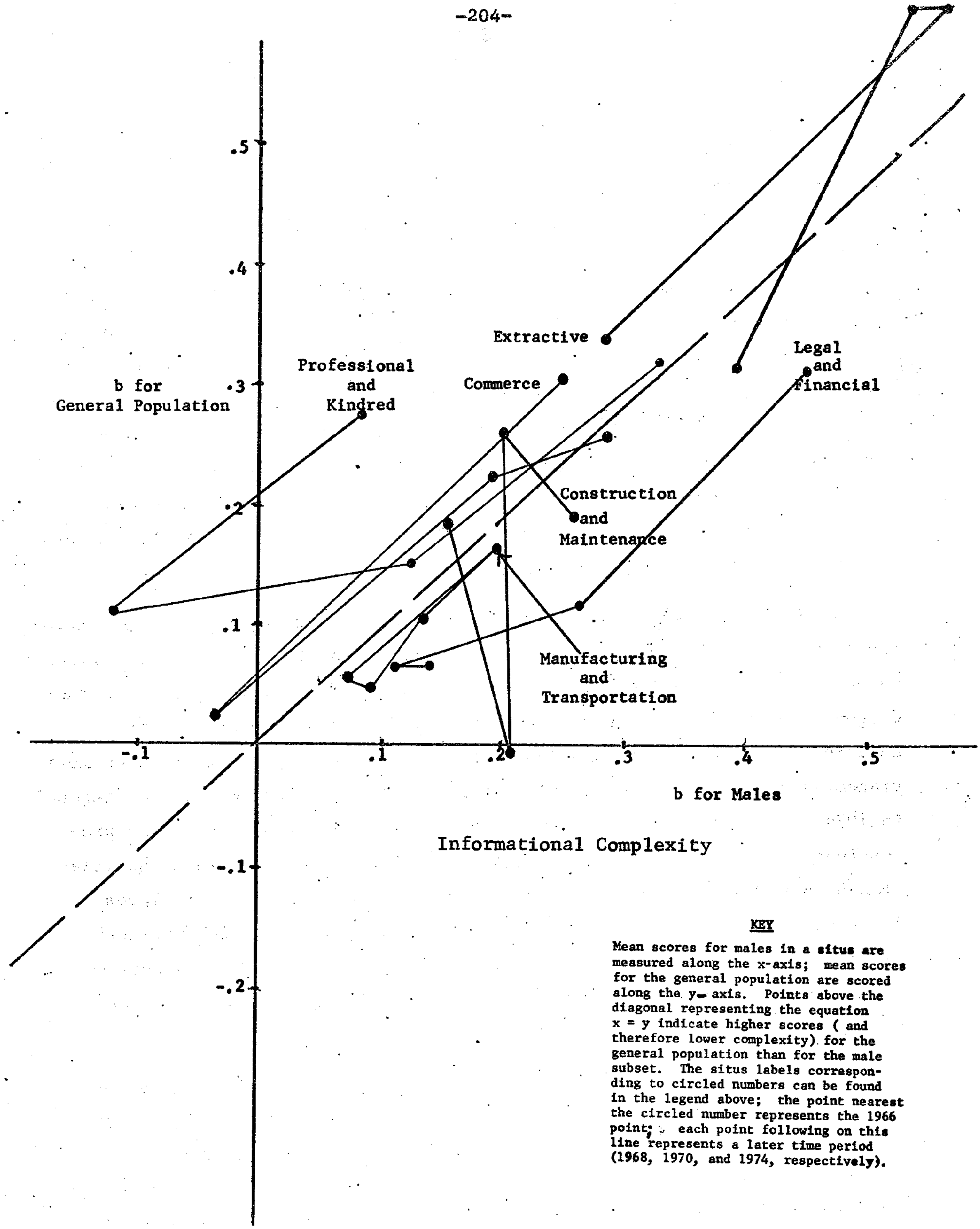


Fig. 6--Regression Coefficients (Males by General Population) for Each Situs Over Times

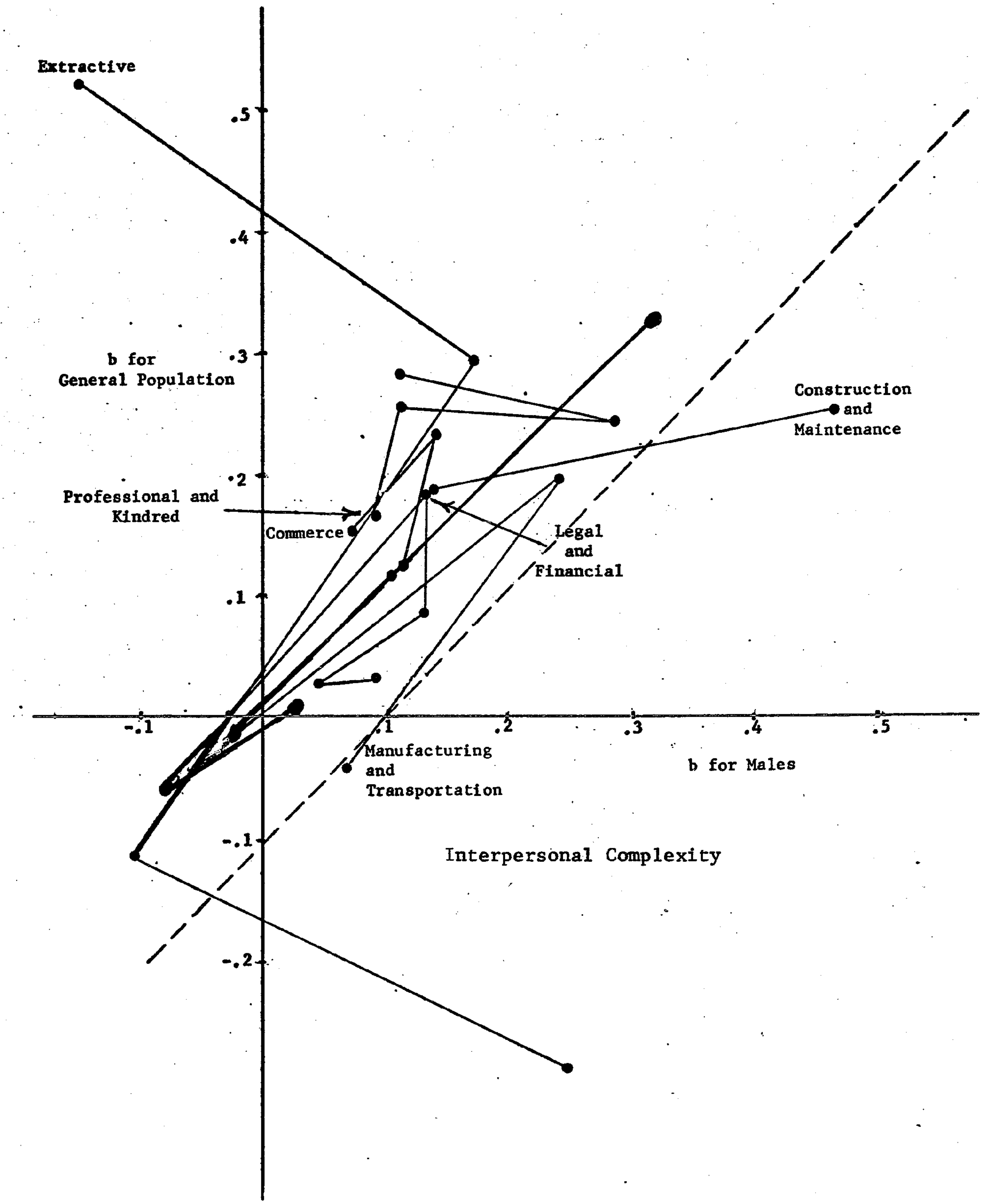


Fig. 6--(Continued)

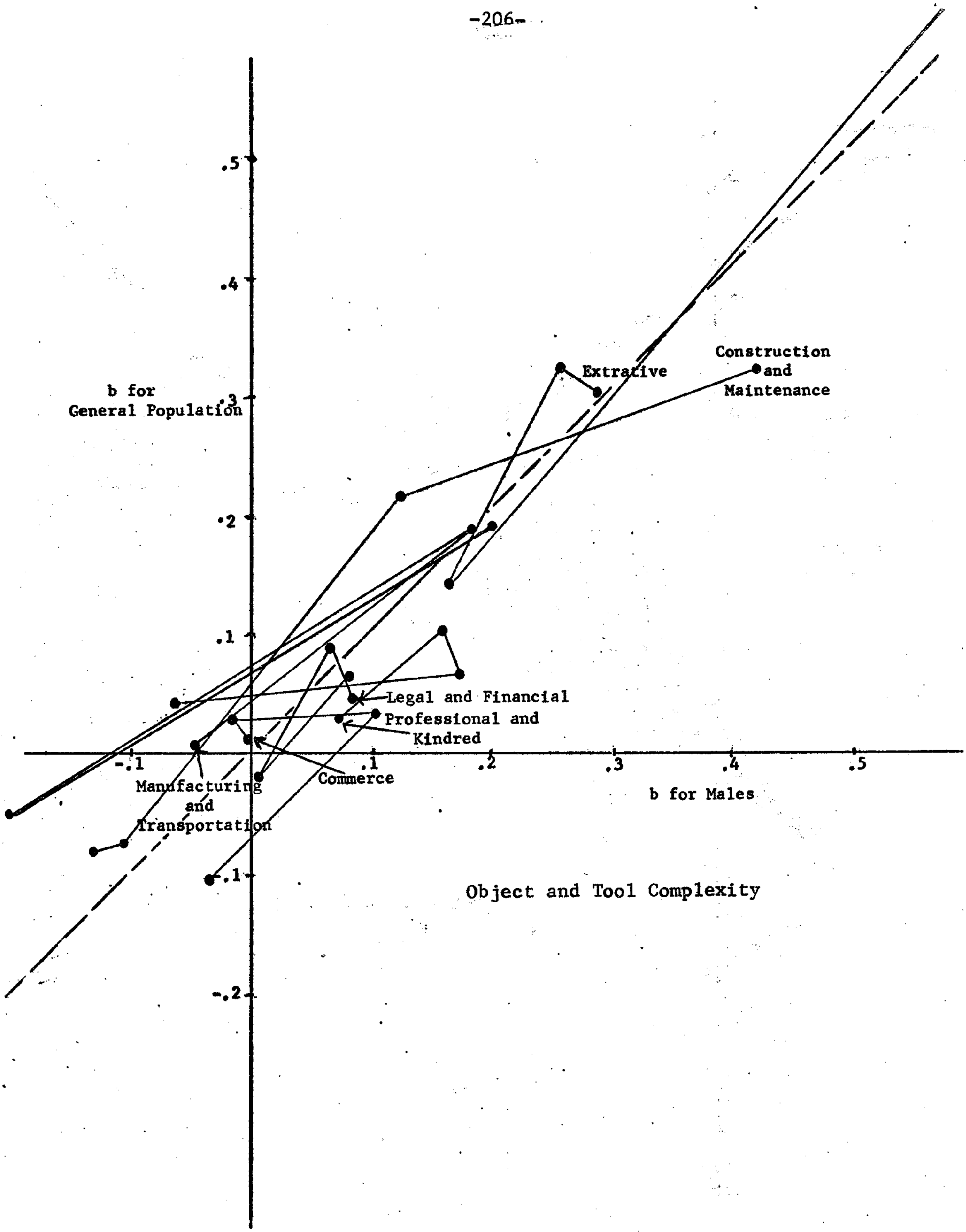


Fig. 6--(Continued)

to show more father's influence on complexity for males than females in 1966 (difference of slopes is .223), but the difference decreases sharply over the period (.007 in 1974, a decrease of .216 in difference). The behavior of the extractive situs is rather erratic.

Parental influence on object and tool complexity is probably least differentially distributed by sex. Most differences are small, and in all periods each situs favors males at one point and females at another. Move favorable to the disproportionate influence of fathers for males are the commerce and professional and kindred situses; construction and maintenance seems to favor influence on females.

Patterned Variability in Intergenerational Transmission of Trait Complexity by Situs

Our expectation was for the conduciveness of the situs to parental influence of respondents' trait complexity to be correlated with the mean trait complexity of the situs. This followed from the supposition that the highly developed complexities for a situs were likely to be focal to that situs, and that parental investments in and mastery of a particular trait would be most effective intergenerationally if the respondent occupied a situs in which that trait were focal. The last rows for each trait in Table 9 present the mixed confirmation of those expectations. Some of the information in Table 9 was presented earlier; we present it again for convenience.

Our hypothesis implies that the correlation between slope and mean will be negative (since the complexity scores are inverted, the greater the mean complexity, the greater the slope), and we find this to be the case in general. For informational complexity, we note that for the whole sample in 1974 the slope and mean are positively correlated (b=.008), and the R^2 is extremely small (.029). In the other years, all slopes are negative (-.091, -.097, -.172 for 1966, 1968, and 1970, respectively) and that for 1966 and 1970, we explain .491 and .222, respectively, of the variance in slope using the mean. Glancing back at Figure 4 , for 1966, the ordinal interaction pattern of 2b in Figure 1 appears rather clearly; nor should the coefficients relating the mean and the slope be considered small. In 1966, mean data complexity had a range across the situses of 1.682; with the coefficient of -.091, the range of expected slopes was from .287 to .134. The range of the actual slopes was from .341 to .115.

However, for males in 1968, the slope is correlated negatively with mean complexity, and the R^2 of .208 suggests that this negative coefficient should not be taken lightly. Looking again at Figure 4B, we observe a disordinal interaction, suggesting that for males in this year the influence of father's complexity is less as the mean complexity of the situs increases. Perhaps unfortunately, an explanation alternative to our hypothesis comes quickly to mind. Consider, for a moment, father's complexity as an ascriptive characteristic rather than an additional source of training and motivation. The incumbency of positions in situses characterized by high complexity, positions presumably highly sought after, should be less affected by ascriptively based advantages if one were to argue simply on the basis of achievement. Thus, we might expect by this argument that the effect of father's complexity would vary inversely with the complexity of that situs, resulting in the pattern observed in 1968 for males. That such a plausible alternative is not more generally supported by these data may be more surprising than the fact that our hypothesis not only is occasionally not confirmed, but contradicted.

Except for 1970, our data do not support the hypothesis that the effect of father's interpersonal complexity in a situs varies with the mean complexity of that situs. Only in 1970 do we find significant differences among the slopes, for the general population, and only in 1970 is the relation between slopes and means negative. However, looking back again to Figure 4A we note both in general and for males perfect ordinal interactions obtain. Also, for 1970 the fit of the model is extremely good (R^2=.911 for the general population and .949 for males). For males alone in 1968, however, complexity in the situs is negatively related to effect of father's interpersonal complexity (b=.025, R^2=.404). The situation evokes an explanation similar to the one adduced with respect to informational complexity above. Since this pattern occurs only in 1968 though (a positive slope with a substantial R^2), we are inclined to dismiss it as an eccentricity of that particular sample. However, as should be clear, the conditions under which the alternative meritocratic explanation might be plausible should be considered carefully in further analyses. For our present purposes, the remarkable but unfortunately uncorroborated support of our hypothesis in 1970 leads us to believe that our suspicions are at least partly justified.

Our hypothesis is confirmed best for the trait reflecting object and tool complexity. In three years, the model fits well for both sexes; although no relationship between parental impact and mean complexity level seems in evidence in 1970, a scan of the graphs in Figure 4A for 1966 and 1968 suggests the ordinal interaction pattern. In 1974 the pattern is less clear. The slopes are reasonably strongly negative in the years for which the R^2's are large: -.067 in 1966, -.063 in 1968, and -.083 in 1974. This is true for the male population as well, though to a lesser extent, in those years.

Summary, Discussion and Conclusions

Before suggesting any conclusions, it might be useful to review the argument. Both from theoretical and empirical bases, Benoit-Smullyan's distinction between social differentiation and social ranking of positions seems a sensible one, deserving of extensive testing on a cross-sectional basis. Consideration of Hatt's findings and arguments, as well as other more recent work (for example, Mortimer 1974, and Temme), suggest that the use of a single criterion variable representing a ranking of social valuation might obscure the patterns of mobility in the variables that form bases of social evaluation. Thus, worker traits reflecting complexity in three focal areas of occupational activity were employed as criterion variables to be examined within situs classes. Statistical effects of the situs classification in the three traits fall into three broad categories. First, the situs classification might directly affect the complexity level of the respondent. We found this to be true in every case: substantial and yet stable differences in the mean skill levels of the situses on each trait were observed. Further substantiating the use of situs analysis, these differences were not consistent across traits. Some situses (for example, legal and financial, or professional and kindred) were characterized by the highest informational complexity; others were characterized by the highest interpersonal complexity, but only modest informational complexity (e.g., commerce); still others by high object complexity, but low complexity on the other two traits (e.g., extractive and construction and maintenance). Second, aggregates of individuals might be differentially distributed in skill levels among the situses. This too was found to be the case. Women are characterized by lower complexity with respect to information and object and tool manipulation, yet over the period, were found to be in more interpersonally complex jobs. At least in 1974, these differences were largely a function of the differing distributions of respondents in situses by sex, although within situses, differences between male and female complexity levels still obtain. A third class of statistical effects of situs might be the differential association of characteristics among situses; that is, situs might interact on the correlation between variables. One set of variables that the literature suggested would be so affected were those relating parental to respondent characteristics. Here, too, our analysis uncovered evidence of such effects. Parental characteristics seem to be of differential effect depending on the eventual situs of the respondent. In particular, the hypothesis that effect would vary directly with the mean level of complexity in the situs received partial confirmation.

However, limitations to the present analysis suggest several directions for further research. First, it should be clear that the situs classification used in this analysis could be refined considerably. One particularly annoying aspect of the classification is the paucity of occupations in the extractive situs. We were able to classify only nine occupations therein, which left open the possibility that not skill transference but inheritance (in a rather strict sense) caused high correlations between father and respondent's skill traits. This raises the more general question of the confounding effect of real inheritance on the transfer of skills. The problem is particularly acute in situses in which parental prequisites are passed directly to the respondent, such as inheritable union membership or business ownership.

Second, as should be apparent, our classification of the statistical effects of situs presumed it to be first an antecedent, then a consequent, and finally an intervening variable. Nowhere in this report did we attempt to fit the situs classifciation into a larger system of variables (e.g., the Blau-Duncan path model for socio-economic achievement). Further, a more change-oriented analysis was blocked by three factors. First, the exposition of the model at a single point in time could not be curtailed since it was presumed that the reader would be unfamiliar with the uses here of the notions of situs and worker-trait complexity. Second, the time period covered was perhaps too brief to discern many changes over time. Finally, the instability of the results over time, especially at the more complex stages of the analysis, was so extreme that social change could not be easily separated from statistical noise.

The second point brings up a final puzzle mentioned in the analysis. Counterintuitively, for informational and object and tool complexity, father's occupations were characterized by substantially higher complexity than respondent's, even for male respondents. Decline in the latter form of complexity, the object and tool trait, is somewhat more understandable, because of the decline of the relatively autonomous craftsman. However, the differences in informational complexity occurred with the context of increasing complexity overall: to interpret the intergenerational differences at all as changes over time would require that at some time between the point that fathers began leaving the labor force and respondents began entering it in substantial numbers, a large decrease in informational complexity occurred. Yet, this supposition seems altogether unfounded. We suspect that this puzzle can be better apprehended in terms of cohort succession. If we treat, only for the moment and abstractly, the fathers and respondents as separate cohorts, we can interpret the relative increase in informational complexity for each as a social change effective for all cohorts. The advantage for fathers then might be a function of their more advanced stage in their occupational careers. (It will be recalled that the respondent reported his father's occupation for when he was 16; if we consider the modal age for bearing the first child to be 20, then the age of father at the time his occupation is reported will be most likely between 36 and 46 or so. This is to be constrasted with one much broader range and possibly younger average for the respondent. It is clear that any serious further analysis should consider the effects of cohort succession on differences between father and respondent.

Despite these limitations, this analysis has established the utility of horizontal divisions of the occupational structure for the understanding of skill levels in the work force, and the intergenerational transmission of these traits. Situses may be seen at least partly as contexts in which different skills and levels of skills are socialized and utilized, and partly as channels through which father's occupational characteristics may be seen to affect characteristics of the respondent's occupation.

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A STUDY OF TRENDS IN THE POLITICAL ROLE OF WOMEN, 1936-1974

Tom W. Smith

May 1975

At the heart of American Democracy lies a set of fundamental political axioms--"liberty and justice for all," "equal protection under the law," and the like. These axioms express the basic principles of the political system and form the central ideals of the national political ideology.[1] In practice, these axioms have often been violated by such qualifications as "except for blacks," "excluding sexual and political deviants," and "not in cases of national security." Yet, while the exceptions have often been the rule, they have never become the ideal. As Robert A. Dahl remarked, there has been a "common tendency ...to qualify universals in application while leaving them intact in rhetoric."[2] The disparity between the ideal of equal political rights and the actual political role of women serves as a prime example of this phenomenon. From the birth of the republic until 1890 laws and constitutions denied women a political role. Between 1890, when Wyoming granted women the right to vote, and the passage of the twentieth amendment in 1920, most legal barriers to political participation were removed. Since then, however, the barriers of public attitudes and behavior have perpetuated the disparity. In fact, in the half century since the political emancipation of women, these non-institutional obstacles have proven to be as formidable as the legal ones had been before.

To gauge trends in the political status of women during the period 1936 to 1974, this analysis will focus on (1) changes in the public attitude toward the political role of women; and (2) changes in the sexual differentials in elective office holding. Data on public opinion comes mainly from a series of questions asking people whether they would vote for a qualified woman for President. This question was asked in

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1. See Boorstin (1953: 8-35), and Hartz (1955).

2. Dahl (1961: Ch. 28). Also, on the disparity between principles and practices, see Prothro and Grigg (1960), and McClasky (1964).

six different versions a total of 12 times between 1936 and 1974 (for exact uses, see the Appendix to this paper). Marginals are available for all data points and more extensive analysis is possible for studies starting in 1949. Data on office holding come from records of the sexual composition of the United States Congress and the state legislatures from 1921 to 1974 (see notes to Tables 8 and 9). Together, the public opinion series on a woman president and the legislative office holding data provide information on both attitudes and behavior.

Turning to the marginal trend first, Figure 1 graphs the per cent "no," the per cent unwilling to vote for a woman. The upper line shows the change with the undecided or "don't knows" retained as a category; the bottom line excludes the "don't knows" from the analysis (see Tables 1-A, 1-B). The graph shows that although the direction of change has been consistent, the rate of change has varied considerably. There is a "staircase" effect, with relatively level stretches from 1936 to 1945 and from 1949 to 1969, and steep inclines between 1945 and 1949 and from 1969 through 1974. Regression analysis indicates that there were linear rates of decline for each of these four periods as follows: from 1936 to 1945, -.0060 a year; from 1945 to 1949, -.0337; from 1949 to 1969, -.0037; and from 1969 through 1974, -.0434 (see Table 1-C). Over the whole period, the rate was not strictly linear (since it contains the step pattern), but did contain a large linear component, with a rate of decrease of .0109 a year.

In order to explore what accounts for both the alternating periods of slow and rapid change and the overall trend toward less opposition to a woman president, the relationship between sex, cohort, and education, and voting for a woman president, were examined,

The sex difference (Figure 2) breaks down into three distinct periods for the time under study: a period of greater approval by women until 1955; a change in 1958 to a period of greater male approval through 1969; and a disappearance of all sexual differences after 1969. The overall trend has been non-linear, although there has been a statistically significant degree of convergence at an annual rate of +.003 per cent (Table 2).

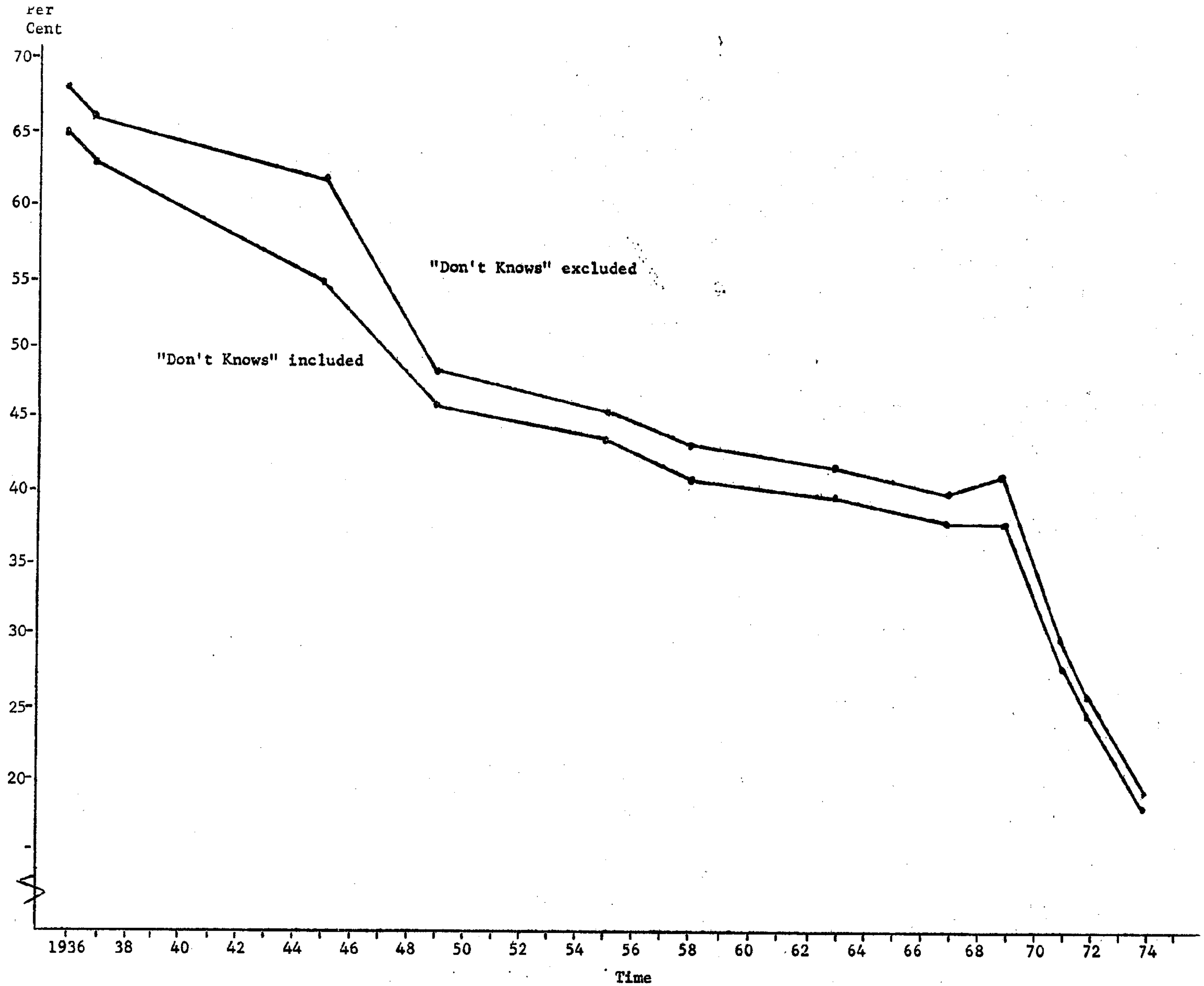

Fig. 1.--Proportion Unwilling to Vote for a Woman for President

TABLE 1-A

MARGINALS, "DON'T KNOWS" INCLUDED[a]

Data

Survey[b]	AIPO[c]	AIPO66[c]	AIPO360K[c]	AIPO448	AIPO543	AIPO604	AIPO676	AIPO744	AIPO776	AIPO834	GSS72	GSS74
Date	1936	8/37	12/45	9/49	2/55	9/58	7/63	4/67	3/69	7/71	3/72	3/74
Per Cent Yes	31.0	33.0	33.0	49.7	51.8	53.8	55.5	57.0	53.9	65.8	70.0	77.8
Per Cent No	65.0	63.0	55.0	46.8	44.2	41.3	40.4	38.9	38.8	28.7	25.1	19.1
Per Cent Don't Know	4.0 (n.d.)	4.4 (n.d.)	12.0 (n.d.)	3.5 (1440)	4.0 (1579)	4.9 (1506)	4.2 (1588)	4.1 (1505)	7.3 (1633)	5.2 (1531)	4.8 (1611)	3.1 (1479)

Statistical Analysis

Hypotheses	Model	x^2	df	p	Decision
For "NO"					
a) No change	p = pooled	1573.6	11	<.05	Reject
b) Linear change	p = a + bx	135.7	10	<.05	Reject
Reduction from linear term		1438.1	1	<.05	Significant
For "YES"					
a) No change	p = pooled	1701.0	11	<.05	Reject
b) Linear change	p = a + bx	210.7	10	<.05	Reject
Reduction from linear term		1490.3	1	<.05	Significant
For "DON'T KNOWS"					
a) No change	p = pooled	113.5	11	<.05	Reject
b) Linear change	p = a + bx	126.2	10	<.05	Reject

Final Model

Marginal proportion "YES": P = 1.06 - .0106 (YEAR - 1900)
Marginal proportion "NO" : p = -0.08 + .0104 (YEAR - 1900)
Marginal proportion "DON'T KNOW" = NON-LINEAR CHANGE

[a]No answers and missing values were excluded from the following studies, AIPO448 (5), AIPO543 (6), AIPO604 (8), AIPO776 (1), AIPO834 (31), GSS72 (2), and GSS73 (5).

[b]AIPO = American Institute of Public Opinion (Gallup)
GSS = General Social Survey, Conducted by National Opinion Research Center, funded by The National Science Foundation

[c]Data from Hazel Erskine, "The Polls: Women's Role," Public Opinion Quarterly, XXXV (Summer, 1971), 275-278. No data (n.d.) was available on number of cases. N = 1400 was used in calculations.

TABLE 1-B
MARGINALS, "DON'T KNOWS" EXCLUDED

Data

Survey[a]	AIPO[b]	AIPO66[b]	AIPO360K[b]	AIPO448	AIPO543	AIPO604	AIPO676	AIPO744	AIPO776	AIPO834	GSS72	GSS74
Date	1936	8/37	12/45	9/49	2/55	9/58	7/63	4/67	3/69	7/71	3/72	3/74
Per Cent No	68.0 (n.d.)	66.0 (n.d.)	62.0 (n.d.)	48.5 (1401)	46.0 (1516)	43.4 (1432)	42.1 (1522)	40.6 (1444)	41.9 (1514)	30.3 (1447)	26.4 (1533)	19.7 (1433)

Statistical Analysis

Hypothesis	Model	x^2	df	p	Decision
a) No change	p = pooled	896.7	11	< .05	Reject
b) Linear change	p = a + bx	83.4	10	< .05	Reject
Reduction from linear term		813.3	1	< .05	Significant

Final Model

Marginal proportion "No" = 1.08 - .0109 (year - 1900)

[a]AIPO = American Institute of Public Opinion (Gallup).

GSS = General Social Survey, conducted by the National Opinion Research Center, funded by the National Science Foundation.

[b]Data from Hazel Erskine, "The Polls: Women's Role," Public Opinion Quarterly XXXV (Summer, 1971), 275-278.

n.d. = No data on number of cases; N = 1400 used in calculations.

TABLE 1-C

CHANGE IN PROPORTION. "NO," "DON'T KNOWS" EXCLUDED

Period	Hypotheses	Model	x^2	df	p	Decision
1936-1945	a) No change	p = pooled	11.4	2	*	
	b) Linear change	p = a + bx	.6	1	>.05	Accept
	Reduction from linear term		10.8	1	<.05	Significant
1945-1949	a) No change	p = pooled	52.6	2	<.05	Reject
	b) Linear change	p = a + bx	0.0	1	>.05	Accept
1949-1969	a) No change	p = pooled	25.6	4	<.05	Reject
	b) Linear change	p = a + bx	2.8	3	>.05	Accept
1969-1974	a) No change	p = pooled	187.5	3	<.05	Reject
	b) Linear change	p = a + bx	4.4	2	>.05	Accept

Final Model

1936-1945 Marginal proportion "NO": p = .89 - .0060 (Year - 1900)

1945-1949 Marginal proportion "NO": p = 2.14 - .0337 (Year - 1900)

1949-1969 Marginal proportion "NO": p = .66 - .0037 (Year - 1900)

1969-1974 Marginal proportion "NO": p = 3.40 - .0434 (Year - 1900)

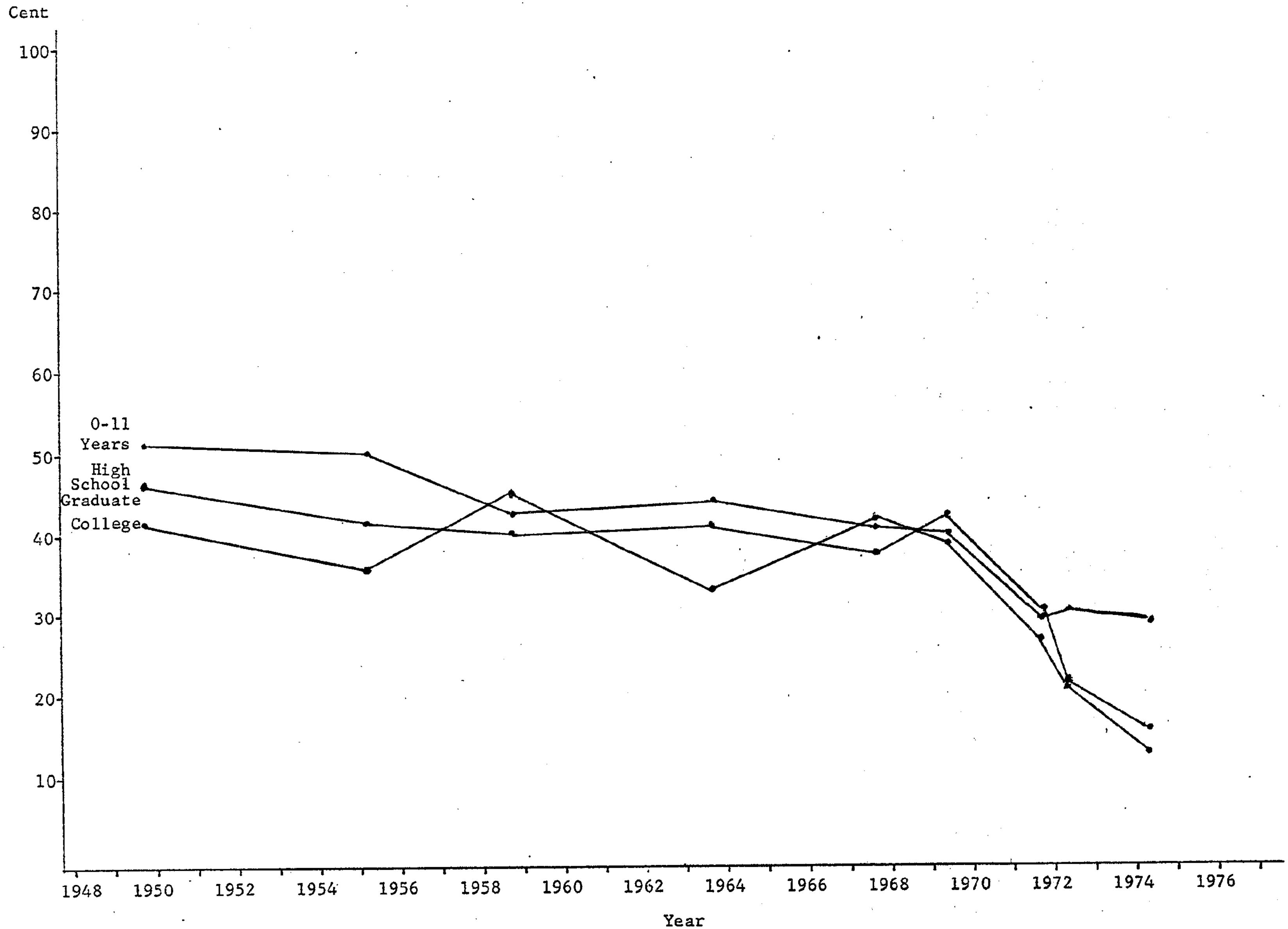

Fig.2.--Proportion Unwilling to Vote for a Woman for President by Education

TABLE 2

SEX DIFFERENCES

Data

Survey	AIPO448	AIPO543	AIPO604	AIPO676	AIPO744	AIPO776	AIPO834	GSS72	GSS74
Date	9/49	2/55	9/58	7/63	4/67	3/69	7/71	3/72	3/74
Per Cent No:									
Male	51.1 (669)	50.6 (753)	42.5 (689)	39.1 (742)	36.1 (710)	38.0 (756)	30.7 (713)	26.4 (762)	19.5 (671)
Female	46.0 (721)	41.7 (760)	44.3 (743)	45.0 (780)	45.0 (734)	45.8 (758)	30.0 (734)	26.3 (771)	19.9 (762)

Statistical Analysis

Category Difference (Base=Male)	Hypothesis	Model	x^2	df	p	Decision
Female	a) No difference	d = 0	43.3	9	< .05	Reject
	b) Constant difference	d = dp	41.5	8	< .05	Reject
	c) Linear change in difference	d = a + bx	33.0	7	< .05	Reject
	Reduction from linear term		8.5	1	< .05	Significant

Final Model

Female: Non-linear trend with significant linear component.

Linear Component: -.18 + .003 (Year - 1900)

Turning to the graph of educational differences (Figure 3), a great deal of variation over time is again apparent. Differences among the three education groups are both best-ordered and largest at the initial two and final two data points. The statistical analysis shows that, on the average, the high school graduates were less opposed to a woman for President than those without a high school diploma (d = -.048). The difference between the college-educated and the less-than-high-school-educated has been so erratic that no single estimate can apply reasonably well over all times. What can be said is that the college-educated are generally the least opposed to a woman president and that, on the average, the difference in proportions between them and the less-than-high-school-educated has been -.077 (see Table 3).

As with the educational differences, the cohort differences are notable at the beginning and end of the time series (see Figure 4). In these periods, the youngest cohorts are the most willing to vote for a woman for President, and the middle and old cohorts are less approving. The statistical analysis (see Table 4) shows that the difference in proportions between the new and middle cohorts has been widening at 2.7 per cent a year, that the difference between the middle and young cohorts has been non-linear and averages -.043, and that no notable difference exists between the middle and old cohorts.

Based on these relationships a time-cohort-education-woman president model was selected to explain the changes. Sex was not included because no marginal shifts occur over time and no consistent relationship exists over time between sex and voting for a woman president. It is therefore unlikely that sex would explain the continuing decline in opposition. The statistical analysis in Table 5-A shows that, pooled over all data points, being in the young and new cohorts and having a college education were all related with attitudes toward a woman President. Net of time and education, the new cohort differed from the middle cohort at a rate of -.0285 between 1963 and 1974, and the difference between the young and middle cohorts averaged -.036. Net of time and cohort, high school graduates, did not differ significantly from the less-than-high-school-educated, whereas the college-educated differed by -.057.

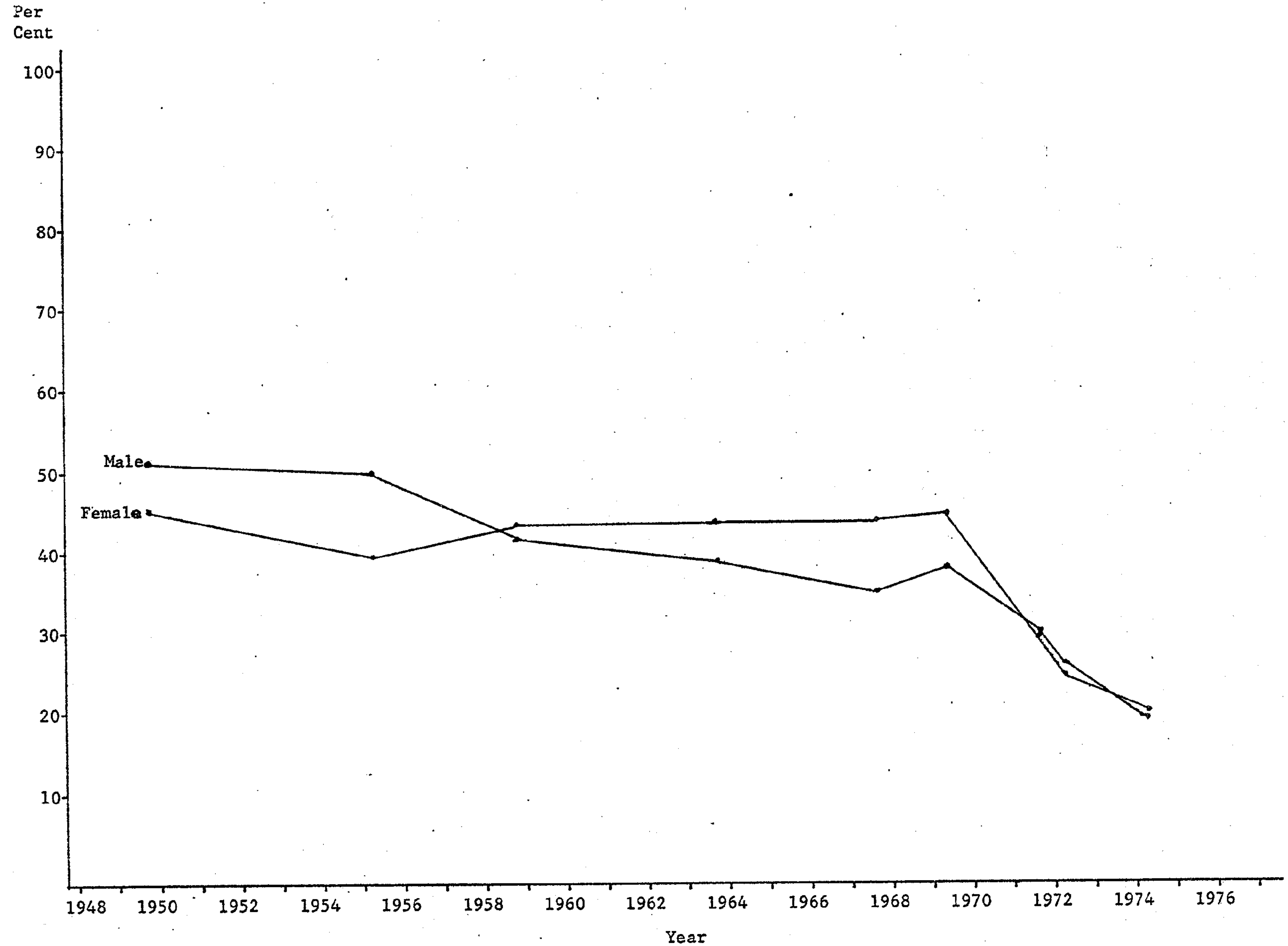

Fig. 3.--Proportion Unwilling to Vote for a Woman for President by Sex

TABLE 3

EDUCATION DIFFERENCES

Data

Survey	AIPO448	AIPO543	AIPO604	AIPO676	AIPO744	AIPO776	AIPO834	GSS72	GSS74
Date	9/49	2/55	9/58	7/63	4/67	3/69	7/71	3/72	3/74
Per Cent No:									
0-11 Years . . .	51.7 (686)	50.4 (823)	44.1 (753)	45.4 (727)	42.1 (610)	41.5 (579)	30.2 (556)	31.9 (605)	29.3 (491)
High School Graduate . . .	47.3 (389)	42.7 (429)	41.2 (452)	42.0 (512)	38.0 (513)	43.7 (574)	31.7 (526)	22.5 (458)	16.0 (474)
College	42.5 (315)	37.9 (253)	45.5 (224)	33.9 (283)	42.0 (319)	39.5 (357)	27.9 (355)	22.3 (435)	13.1 (465)

Statistical Analysis

Category Difference (Base=0-11)	Hypothesis	Model	x^2	df	p	Decision
High School Graduate	a) No difference	d = 0	51.4	9	$<.05$	Reject
	b) Constant difference	d = dp	25.8	8	*	
	c) Linear change in difference	d = a + bx	25.4	7	*	
	Reduction from linear term		0.4	1	$>.05$	Not significant
College	a) No difference	d = 0	84.3	9	$<.05$	Reject
	b) Constant difference	d = dp	31.5	8	$<.05$	Reject
	c) Linear change in difference	d = a + bx	31.6	7	$<.05$	Reject
	Reduction from linear term		- 0.1	1		Not significant

Final Model

High School Graduate	d = -0.048	σ = 0.010
College	Non-linear trend	

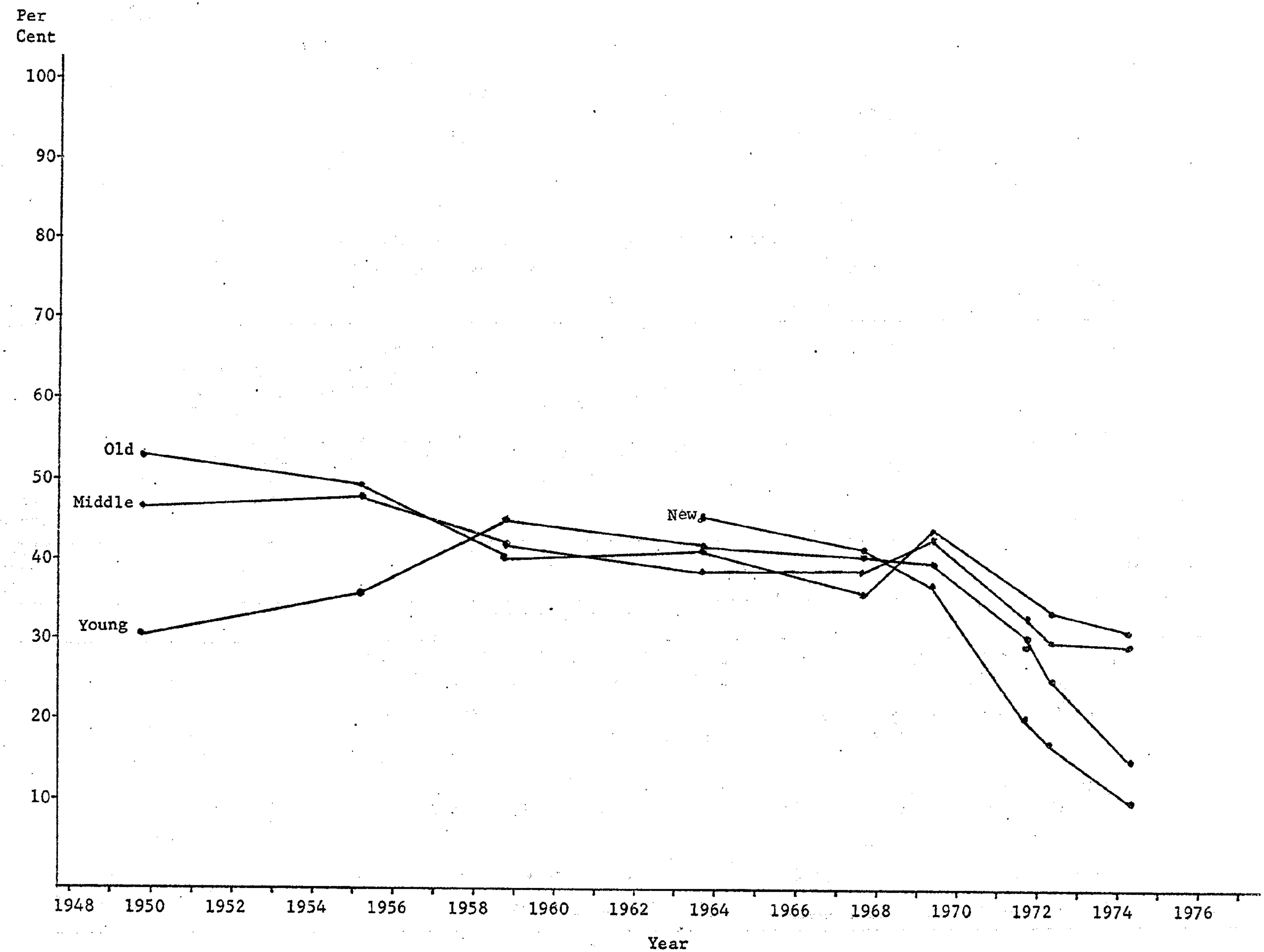

Fig. 4--Proportion Unwilling to Vote for a Woman for President by Cohort

TABLE 4

COHORT DIFFERENCES

Data

Survey	AIPO448	AIPO543	AIPO604	AIPO676	AIPO744	AIPO776	AIPO834	GSS72	GSS74
Date	9/49	2/55	9/58	7/63	4/67	3/69	7/71	3/72	3/74
Per Cent No:									
New	--	--	--	46.2 (78)	43.1 (187)	38.2 (283)	21.2 (448)	18.5 (481)	10.4 (511)
Young	31.6 (133)	37.0 (343)	45.7 (381)	43.6 (482)	42.7 (509)	40.4 (500)	31.2 (349)	25.7 (409)	15.9 (384)
Middle	47.5 (581)	48.0 (646)	43.5 (565)	39.1 (511)	39.6 (457)	43.3 (416)	34.0 (388)	31.6 (433)	30.4 (352)
Old	52.9 (658)	49.8 (504)	41.1 (474)	43.1 (432)	37.5 (327)	44.8 (297)	30.8 (249)	34.5 (206)	32.8 (180)

Statistical Model

Category Difference (Base=Middle)	Hypothesis	Model	x^2	df	p	Decision
New	a) No difference	d = 0	93.5	6	< .05	Reject
	b) Constant difference	d = dp	33.3	5	< .05	Reject
	c) Linear change in difference	d = a + bx	1.6	4	> .05	Accept
Young	a) No difference	d = 0	54.2	9	< .05	Reject
	b) Constant difference	d = dp	39.1	8	< .05	Reject
	c) Linear change in difference	d = a + bx	39.2	7	< .05	Reject
	Reduction in linear term		- 0.1	1	> .05	Not significant
Old	a) No difference	d = 0	9.5	9	> .05	Accept

Final Model

New	d = 1.85 - .0276 (year - 1900)
Young	d = Non-linear trend
Old	d = 0

TABLE 5

EDUCATION BY COHORT DIFFERENCES

Survey Date	AIP0448 9/49			AIP0543 2/55			AIP0604 9/58			AIP0676 7/63			AIP0744 4/67		
Per Cent No:	0-11 Years	High School Graduate	College	0-11 Years	High School Graduate	College	0-11 Years	High School Graduate	College	0-11 Years	High School Graduate	College	0-11 Years	High School Graduate	College
New	--	--	--	--	--	--	--	--	--	37.0 (27)	57.1 (28)	43.5 (23)	45.0 (20)	45.9 (37)	53.8 (26)
Young	25.6 (43)	34.7 (49)	34.2 (38)	45.8 (131)	31.2 (141)	31.4 (70)	46.7 (137)	42.1 (164)	51.3 (80)	45.2 (157)	44.9 (198)	39.4 (127)	41.1 (129)	41.6 (202)	49.1 (110)
Middle	52.3 (235)	43.1 (181)	45.1 (164)	50.4 (335)	49.0 (206)	38.2 (102)	43.3 (284)	43.6 (204)	(77)	42.8 (250)	40.2 (189)	23.6 (72)	45.6 (204)	37.2 (191)	32.0 (103)
Old	54.3 (398)	57.5 (146)	40.7 (108)	52.2 (347)	47.4 (76)	41.0 (78)	43.7 (327)	32.1 (81)	39.4 (66)	48.1 (283)	34.4 (90)	32.2 (59)	39.4 (249)	28.0 (75)	41.7 (72)

Data — Education

Survey Date	AIP0776 3/69			AIP0834 7/71			GSS72 3/72			GSS74 3/74		
Per Cent No:	0-11 Years	High School Graduate	College	0-11 Years	High School Graduate	College	0-11 Years	High School Graduate	College	0-11 Years	High School Graduate	College
New	32.7 (55)	39.8 (123)	39.0 (105)	17.7 (96)	22.9 (188)	21.3 (164)	22.4 (98)	15.8 (190)	19.2 (193)	17.0 (94)	8.3 (206)	9.5 (211)
Young	36.4 (151)	42.8 (222)	40.9 (127)	25.0 (120)	36.5 (148)	30.8 (78)	24.8 (149)	26.8 (149)	25.2 (111)	24.6 (114)	14.9 (148)	9.1 (121)
Middle	45.1 (173)	45.2 (157)	34.9 (83)	30.3 (188)	39.7 (126)	32.4 (71)	36.5 (211)	28.5 (123)	23.7 (97)	33.3 (159)	31.4 (102)	23.3 (90)
Old	42.8 (194)	50.0 (64)	47.4 (38)	42.3 (149)	31.0 (58)	42.1 (38)	39.0 (156)	20.0 (25)	24.2 (33)	36.9 (122)	29.4 (17)	20.0 (40)

TABLE 5-A

Statistical Analysis

Differences on Woman President	Hypothesis	Model	x^2	df	p	Decision
Time:						
1974 vs. 1949	a) No difference	d = 0	75.3	12	<.05	Reject
	b) Constant difference	d = C	8.6	11	>.05	Accept
Cohort:						
New vs. Middle	a) No difference	d = 0	87.4	18	<.05	Reject
	b) Constant difference	d = C	45.4	17	*	
	c) Linear change in difference over time	d = a+bx				
Young vs. Middle	a) No difference	d = 0	75.5	27	*	
	b) Constant difference	d = C	64.9	26	*	
	Reduction from constant term		10.6	1	<.05	Significant
Old vs. Middle	a) No difference	d = 0	32.5	27	>.05	Accept
Education:						
High School Graduate vs. Less Than High School	a) No difference	d = 0	62.2	33	*	
	b) Constant difference	d = C	54.6	32	*	
	Reduction from constant term		7.6	1	*	
College vs. Less Than High School	a) No difference	d = 0	82.6	33	*	
	b) Constant difference	d = C	55.0	32	*	
	Reduction from constant term		27.6	1	<.05	Significant

Final Model

1974 vs 1949	d = -.177	σ = .022
New vs Middle	d = 1.93-.0285 (Year-1900)	
Young vs Middle	d = -.036	σ = .011
Old vs Middle	d = 0	
High School Graduate vs Less than High School	d = 0	
College vs Less than High School	d = -.057	σ = .010

TABLE 5-B

Differences on Woman President	Hypothesis	Model	x^2	df	p	Decision
	Statistical Analysis					
Time:						
1955 vs. 1949	a) No difference	d = 0	12.0	9	>.05	Accept
Cohort:						
Young vs. Middle	a) No difference	d = 0	29.1	6	<.05	Reject
	b) Constant difference	d = C	8.0	5	>.05	Accept
Old vs. Middle	a) No difference	d = 0	8.0	6	>.05	Accept
Education:						
High School vs. Less Than High School	a) No difference	d = 0	11.8	6	>.05	Accept
College vs. Less Than High School	a) No difference	d = 0	21.4	6	*	
	b) Constant difference	d = C	4.7	5	>.05	Accept
	Reduction from constant term		16.7	1	<.05	Significant

Final Model

1955:	d = 0	
Young:	d = -.122	σ = .027
Old:	d = 0	
High School:	d = 0	
College:	d = -.102	σ = .025

TABLE 5-C

Statistical Analysis

Differences on Woman President	Hypothesis	Model	x^2	df	p	Decision
Time:						
1969 vs. 1958	a) No difference	d = 0	12.7	12	>.05	Accept
Cohort:						
New vs. Middle	a) No difference	d = 0	15.3	9	>.05	Accept
Young vs. Middle	a) No difference	d = 0	19.7	12	>.05	Accept
Old vs. Middle	a) No difference	d = 0	15.2	12	>.05	Accept
Education:						
High School vs. Less Than High School	a) No difference	d = 0	22.5	15	>.05	Accept
College vs. Less Than High School	a) No difference	d = 0	29.6	15	*	
	b) Constant difference	d = C	25.9	14	*	
	Reduction from constant term		3.7	1	>.05	Not significant

Final Model

All differences are zero.

TABLE 5-D

Statistical Analysis

Differences on Woman President	Hypothesis	Model	x^2	df	p	Decision
Time:						
1974 vs. 1971	a) No difference	d = 0	68.5	12	<.05	Reject
	b) Constant difference	d = C	26.4	11	*	
Cohort:						
New vs. Middle	a) No difference	d = 0	72.2	9	<.05	Reject
	b) Constant difference	d = C	75.0	8	>.05	Accept
Young vs. Middle	a) No difference	d = 0	26.7	9	*	
	b) Constant difference	d = C	10.0	8	>.05	Accept
	Reduction from constant difference		16.7	1	<.05	Significant
Old vs. Middle	a) No difference	d = 0	9.2	9	>.05	Accept
Education:						
High School Graduate vs. Less Than High School	a) No difference	d = 0	27.8	12	*	
	b) Constant difference	d = C	25.1	11	*	
College vs. Less Than High School	a) No difference	d = 0	31.5	12	*	
	b) Constant difference	d = C	19.6	11	>.05	Accept
	Reduction from constant term		11.9	1	<.05	Significant

Final Model

1974:	d = -.101	σ = .016
New:	d = -.140	σ = .017
Young:	d = -.076	σ = .019
Old:	d = 0	
High School Graduate	d = 0	
College:	d = -.057	σ = .017

In Figure 5.A, the effect of these relationships on the over-time change is graphed. Moving from left to right, the diagram translates as follows. Associated with each of the cohorts are their changing marginal proportions from 1949 to 1974. The new cohort's proportion increased by .357, the young cohort rose by .174, and the old cohort decreased by -.352. Flowing out of the cohorts to the educational categories are their proportion differences in education. The old cohort, for example, had -.046 fewer members with college education than the middle cohort had. The long arrows from the new and young cohorts to opposition are the differences in proportion between these cohorts and the middle cohort net of education. The double arrow from the new cohort indicates that the relationship was linear over time and the absence of an arrow from the old cohort to opposition indicates no relationship exists between these categories. Going on to the education categories, there is an exogenous arrow into the high school category indicating that some of the decline in the high school graduates' proportion cannot be accounted for by cohort change. From college to opposition, there is a significant difference in proportions net of time and cohort, but no difference between the high school graduates and the less-than-high-school-educated. Last of all, there is an exogenous arrow flowing into opposition that represents the change in opposition that is unaccounted for by either cohort or education.

In Table 6, the transmittances along the paths in Figure 5.A are calculated and the change in opposition is decomposed into its causally distinct components. Cohort turnover accounts for a change of -.038, and an additional -.0048 is accounted for by the effect of cohort turnover on the educational composition of the population. Most of the change (-.171), however, is caused by time effects, net of cohort and education. In brief, while part of the change results from the direct and indirect effects of cohort turnover, the largest component has been an across-the-board shift by the population as a whole.

One feature of the change that is not apparent from the statistical analysis pooled over time is the repetition of the variation in effects at different periods of time. In 1949 to 1955 and 1971 to 1974, the causal effects followed approximately the same pattern (see Table 5-B

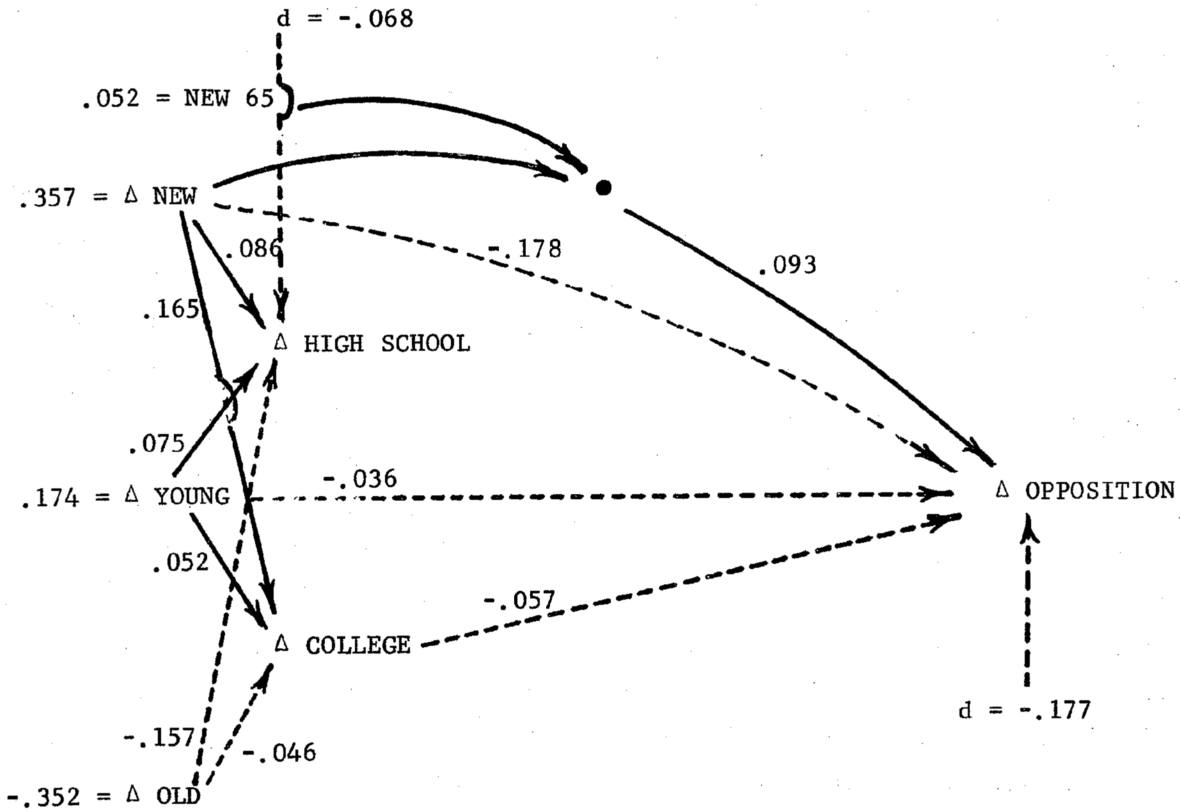

Fig. 5.A--Flow Graph Model of Change in Cohort, Education, and Woman President, 1949-1974

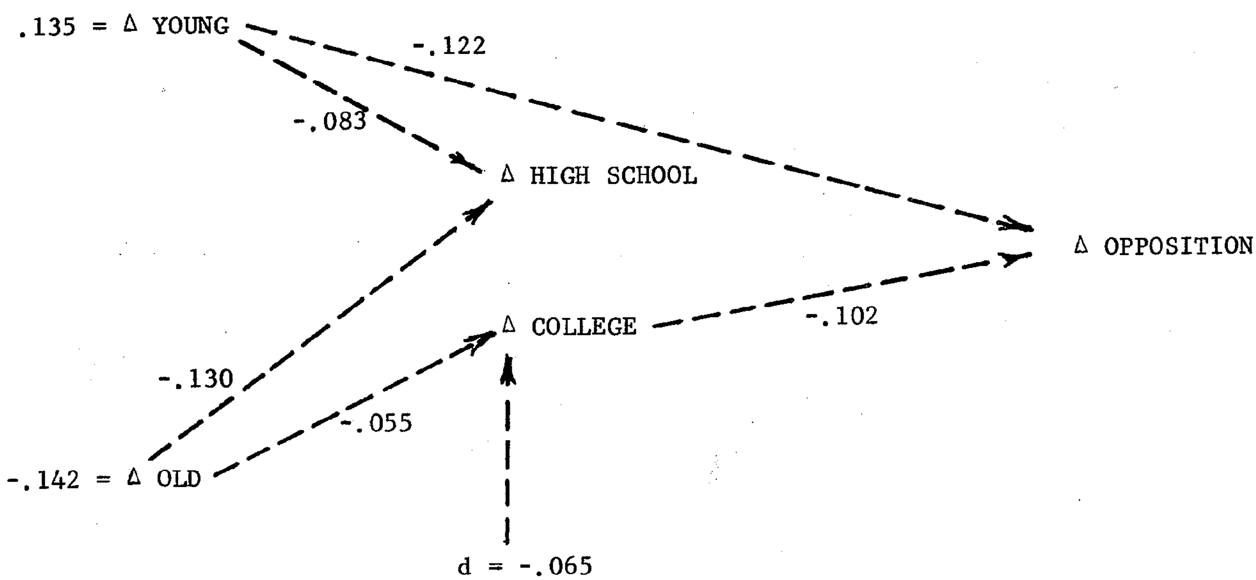

Fig. 5.B--Flow Graph Model of Change in Cohort, Education, and Woman President, 1949-1955

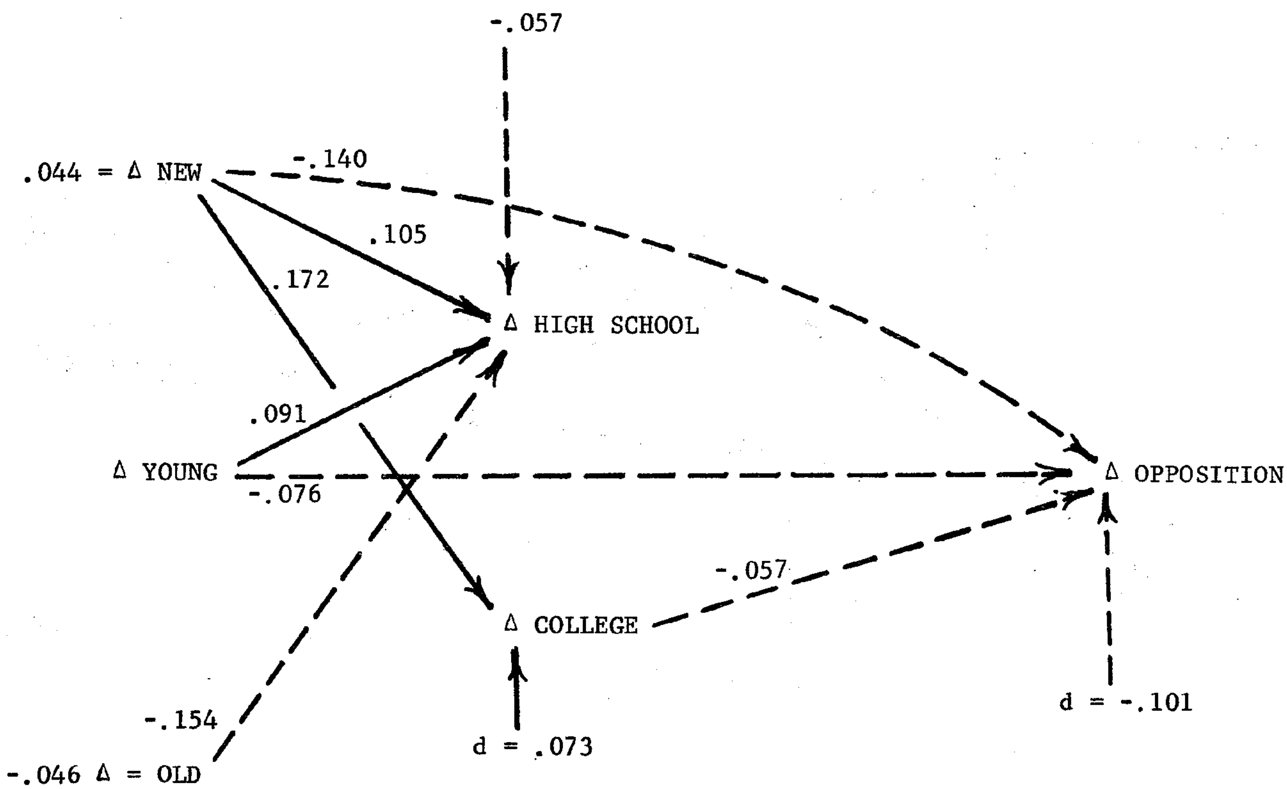

Fig. 5.C--Flow Graph Model of Change in Cohort, Education, and Woman President, 1971-1974

TABLE 6

DECOMPOSITION OF CHANGE IN WOMAN PRESIDENT
FROM FIGURE 5.1

Source		Change
Direct from Cohort:		
New - Opposition	.357 * (-.178 + .093) .052 * .093	-.0255
Young - Opposition	.174 * -.036	-.0063
Cohort via Education:		
New - College - Opposition	.357 * .165 * -.057	-.0034
Young - College - Opposition	.174 * .052 * -.057	-.0005
Old - College - Opposition	-.352 * -.046 * - .057	-.0009
Time net of Cohort and Education:		
1949 - 1974		-.1770
	Total Modeled Change	-.2136
	(Raw data	-.294)

and 5-D and Figures 5.B and 5.C). At both periods, paths flow from the younger cohort and the college-educated into opposition. In the 1958 to 1969 period, however, there is not a single significant path from any of the categories of cohort or education to opposition to a woman President (see Table 5-C). Since these three periods correspond approximately to the distinct periods of marginal change analyzed above, the following explanation for the alternating effects is possible. At certain times during the post-Depression era events have occurred that have tended to redefine the status of women in general, and attitudes toward a woman President in particular. These events have had a strong impact on all social groups, but have had the greatest effect on such change-prone groups as the young and the college-educated. When there has been no special impetus for change, the cohort and education differences have disappeared. In brief, on this issue, change is associated with differentiation and stability with homogenization.

Having hypothesied that the differing periods of marginal change and association are related to particular historical events, the next order of business is to describe the actions and forces involved. The 1930's can be seen as a period in which the traditional role of woman as mother and wife was still firmly rooted and attitudes on the political role of women reflected this perspective. This situation was fundamentally and permanently altered by the advent of World War II. One of the most dramatic changes (but by no means the only) was the influx of women into the labor market. In 1940, 25.4 per cent of all women of working age were in the labor force; by 1945, the participation rate had swelled to 35.7 per cent.[3] This entry of women into the labor force, as well as into the armed forces, community activities, and other non-traditional roles, altered both male and female attitudes on the place and abilities of women. In the political realm it lead to the growing acceptance of the notion that even the role of President could

[3] These and all subsequent figures on labor force participation are from Women's Bureau, Employment Standards Administration, Department of Labor (1973: 91).

be filled by a woman. The war, in brief, served as a catalyst for redefining the social, economic, and political roles of women (Chafe 1972: 175, 246-47).

By the end of the forties, however, the momentum triggered by the war had largely been dissipated. Sex roles had been modified and attitudes had changed, but there was little to sustain the role modification so forcefully effected by the war. One force that probably worked in that direction, though, was the continuing entry of women into the labor force. After the war, many women returned to domesticity, but the rate of participation in 1950 (33.9 per cent) was still well above the pre-war figure, and it continued to increase to 35.7 per cent in 1955 and 37.8 per cent in 1960. Countering this continued expansion of women's role was a movement towards the "revitalization of family." (Chafe 1972: 202-10; and O'Neil 1969: 338). The quality of family life became a topic of concern, and the traditional preoccupation of women with children was reinforced as the fertility rate soared from 85.9 per cent in 1945 to a high of 122.9 per cent in 1957.[4] The effect of this phenomenon was to freeze the political status of women. As Marjorie Lansing has noted:

> The 1950s were a disastrous decade for women.....The implication of the population boom produced adverse effects on the status of women in general. These years were accompanied by declines in the proportion of women seeking careers and graduate study, and unquestionably retarded the politicalization of women.[5]

In the sixties, the tide began slowly to reverse. Labor force participation rose more rapidly from 37.8 per cent in 1960 to 39.3 per cent in 1965 and to 43.4 per cent in 1970. At the same time, the fertility rate declined steadily from its peak in 1957 to 112.2 in 1962, 87.6 in 1967, and about 73.4 in 1972. A growing concern about the status of women was shown by the establishment in 1961 of the Presidential

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[4]These and all other figures on the fertility rate are from Executive Office of the President, Office of Management and Budget (1973: 252).

[5]Quoted in Costello (1973: 120-21).

Commission on the Status of Women and the popularity of Betty Friedan's critique of traditional sex roles, The Feminine Mystique (1963). Evidence of the political impact of these and related events can be seen in the sex differential in presidential voting. From the 1948 through the 1960 election, the differences between men and women in turnout rates averaged around 11 per cent. In the 1964 election, however, the male turnout rate exceeded that of women by only 3 percentage points. In subsequent elections, this lower rate has been maintained (see Table 7). Although these signs all seem to contribute to an expanding political role for women, the rate of decline of opposition to a woman President continued at its leisurely 1949 to 1958 pace. Apparently, to change this rate another catalyst was needed.

Between 1969 and 1971 the needed impetus appeared in the form of the women's liberation movement. Although this new feminist movement had been growing since the early sixties and had gained national standing with the formation of the National Organization of Women in 1966, the period from early 1969 to 1971 marked its emergence as a national force. Displaying a keen understanding of the importance of publicity and an ability to win the desired news coverage, the fledgling movement succeeded in broadcasting its message of equal rights into virtually every home in the country. The following count of magazine articles dealing with feminist issues clearly indicates both the timing and the magnitude of the shift in exposure: from March 1965 through February 1966, 14 articles; 1966-1967, 6; 1967-1968, 12; 1968-1969, 36; 1969-1970, 18; 1970-1971, 115; 1971-1972, 94; 1972-1973, 97; and 1973-1974, 57. Clearly, the 1970-1971 period marked the turning point in the women's liberation movement as coverage reached a record high. Since then, its coverage has diminished as its novelty has declined.[6]

The impact of this movement is apparent from the sudden drop in opposition to a woman President. When brought face to face with the contradictions between the ideal of political equality and long-accepted

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[6] The figures on magazine articles were obtained from a count of titles under feminist subject headings (e.g., "Woman-Equal Rights," "Women in Politics," and "Women's Liberation Movement") in the Readers Guide to Periodical Literature. Also, on the publicizing and growth of the women's movement during 1969-1970, see Carden (1974: 64-65), Freeman (1973: 37), Altbach (1974: 157), and Chafe (1972: 238).

TABLE 7

SEX DIFFERENCE IN VOTER TURNOUT IN PRESIDENTIAL ELECTIONS[a]

Year	Sex		Difference (M - W)
	Men	Women	
1920	65	35	30
1936	84	77	7
1940	68	49	19
1944	75	61	14
1948-A	69	56	13
1948-B	57	45	12
1952-A	72	62	10
1952-B	73	55	18
1956	80	69	11
1960	80	69	11
1964	73	70	3
1968-A	76	73	3
1968-B	69.8	66.0	3.8
1972-A	76	70	6
1972-B	64.1	62.0	2.1

[a]Figures for 1920 and 1944 from Robert E. Lane, Political Life (Glencoe, Ill.: The Free Press, 1959), pp. 21, 210. Figures for 1936 from American Institute of Public Opinion Poll for March, 1937 from Research in Progress by Lani Silver, University of Chicago. Figures for 1940, 1948-B, and 1952-B from Roper Surveys, cited in Helen B. Shaffer, "Women in Politics," Editorial Research Reports, I (1956), pp. 120-121. Figures for 1948-A, 1952-A, 1956, 1960, 1964, 1968-A, and 1972-A from Survey Research Center Surveys cited in Marjorie Lansing, "The American Woman: Voter and Activist," in Women in Politics, edited by Jane S. Jaquette (New York: John Wiley, 1974), p. 8. Figures for 1968-B and 1972-B are from the Current Population Surveys of the Bureau of the Census.

practice of sexual discrimination, the American public rallied to its principles and began to change its attitudes.

Yet before congratulating the American public for finally living up to its ideals, it is necessary to inquire about whether public behavior has kept up with attitudes. If holding political office was truly independent of sex, approximately one-half of all elective offices would be held by women. This is hardly the case. Office holding has been and remains heavily male dominated. In executive office holding (i.e., President, Vice President, and state governors) there has been only the most minute change. Four women have served as governor of a state: Nellie Taylor Ross, widow of the previous governor, was elected in Wyoming in 1925; "Ma" Ferguson, wife of the impeached governor "Pa" Ferguson, was elected in Texas in 1924 , and again in 1932; and Lurleen Wallace, wife of Governor George Wallace, who could not succeed himself in office, was elected in Alabama in 1966; but the one sign of change was the 1974 election in Connecticut of the fourth, the first politically self-made woman governor, Ella Grasso.[7]

In the legislative branch the situation is somewhat different. As Table 8 shows, there was a small but steady rise in the number of women in Congress from 1921 to 1961, a slump from 1961 to 1969, and then a rise from 1969 through 1975. Even at its "peak" women have never constituted more than 4 per cent of the Congress, and since 1951 their representation has varied within the narrow range of from 11 to 19 seats. Turning to the figures on state legislatures (see Table 9), the trend appears to be about the same as to the time periods: a steady rise to about 1963, an apparent decline until 1969, and a rise through 1975. The magnitudes, however, differ. The proportion of women in state legislatures has been higher than the proportion in Congress. Also, the increase in the number of female legislators has risen sharply since 1970, and by 1975 nearly 8 per cent of all legislators were women.

Despite the changes in recent years it is still safe to observe that political office holding is a male domain and that the rate of

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[7]On women in politics, see Jaquette (1974), Gruberg (1968), and Lamson (1968).

TABLE 8

WOMEN IN THE UNITED STATES CONGRESS, 1921-1975[a]

Year	Number of Women	Year	Number of Women
1921	4	1949	10
1923	1	1951	11
1925	3	1953	15
1927	5	1955	18
1929	9	1957	16
1931	8	1959	17
1933	8	1961	19
1935	8	1963	13
1937	9	1965	12
1939	9	1967	12
1941	10	1969	11
1943	9	1971	13
1945	11	1973	14
1947	8	1975	18

[a]Figures for 1921-1963 in Werner, "Women in the State Legislatures," p. 42. Figures for 1965-1969 in Helen B. Shaffer, "Status of Women," Editorial Research Report (August 5, 1970), p. 57. Figures for 1971-1975 from National Women's Political Caucus.

TABLE 9

WOMEN IN STATE LEGISLATURES, 1921-1975[a]

Year Taking Office	Number of Women[b]	Year Taking Office	Number of Women
1921	31	1952	235
1923	95	1953	296
1925	146	1955	308
1927	135	1957	321
1929	153	1959	349
1931	154	1960	315
1933	136	1961	328
1935	138	1962	234
1937	141	1963-64	351
1939	154	1969	305
1941	144	1970	306
1943	188	1971	315
1945	228	1972	344
1947	221	1973	441
1949	218	1974	465
1951	249	1975	593

[a]Figures from 1921 to 1951, from 1953 to 1959, and for 1963/64 are from Emmy E. Werner, "Women in the State Legislatures," Western Political Quarterly, XXI (March, 1968), p. 42. Figures for 1952 from Martin Gruberg, Women in American Politics: An Assessment and Sourcebook (Oshkosh, Wis.: Academia Press, 1968), p. 201. Figures for 1961 from The Book of the States, 1964-65 (Chicago: The Council of State Governments, 1964), p. 436. Figures for 1962 from American Women: The Report of the President's Commission on the Status of Women and Other Publications of the Commission (New York: Charles Scribner's Sons, 1965), p.   Figures for 1969, 1974, 1975 from Business and Professional Women's Foundation. Figures for 1971 from Mary Costello, "Women Voters," Editorial Research Reports (Oct. 11, 1972), p. 1. Figures for 1960, 1972 and 1973 from Nancy Gager, ed., Women's Rights Almanac, 1974 (Bethesda, Md.: Elizabeth Cady Stanton, n.d.).

[b]Figures on the number of legislators vary according to whether they are pre- or post-election figures and due to interelection vacancies and appointments. Two sources not infrequently report different numbers for the same year. When such minor discrepancies occurred, the number from the more authorative source was selected.

change in this has been well behind the rate of change in attitudes toward women in politics or toward a woman President. Figure 6 illustrates the situation. The top of the graph represents total intolerance; the bottom, total tolerance--the ideal of political equality regardless of sex. The trend in specific attitudes is represented by the change in the proportion unwilling to vote for a woman for President between the two end points. The corresponding aspect of actual behavior would be Presidential office holding by sex, which, of course, shows a constant level of perfect intolerance (represented by a level line at the top of the graph). A second, less direct measure of objective behavior is the trend in the sex composition of state legislatures (1.0 - (the proportion of female legislators * the proportion of females in the adult population)). Now, the trend in attitudes has been toward greater tolerance. The trend in objective behavior has also been in that direction although it has not reached to the Presidential level as yet. The difference is that, while the disparity between both attitudes and objective behavior and the ideal have been narrowing, the difference between the specific attitude and actual electoral behavior has been widening. Attitude, in brief, has changed faster than behavior.

The reasons for the low and lagging level of office holding can be classified as historical, social, and political. In the first place, historical events got things off to a bad start. The passage of the Twentieth amendment in 1920 was the last great reform of the Progressive era. Once women had gained the vote, the "return to normalcy" of Harding, Coolidge, and Hoover had set in. Retrenchment, not reform, became the rule of the day. In this climate, the innovation of female candidates sparked little enthusiasm. (Chafe 1972: 29; and O'Neil 1969: 262-64). Also, to a large extent, the feminist leaders of the suffrage campaign did not push for female office holders; instead, they declined to work within the established parties and followed a non-partisan approach to politics (Lawson 1968: 19-20; Chafe 1972: 26; O'Neil 1969). Along with these historical reasons, several entrenched social processes retarded the political involvement of women. Subtle differences in

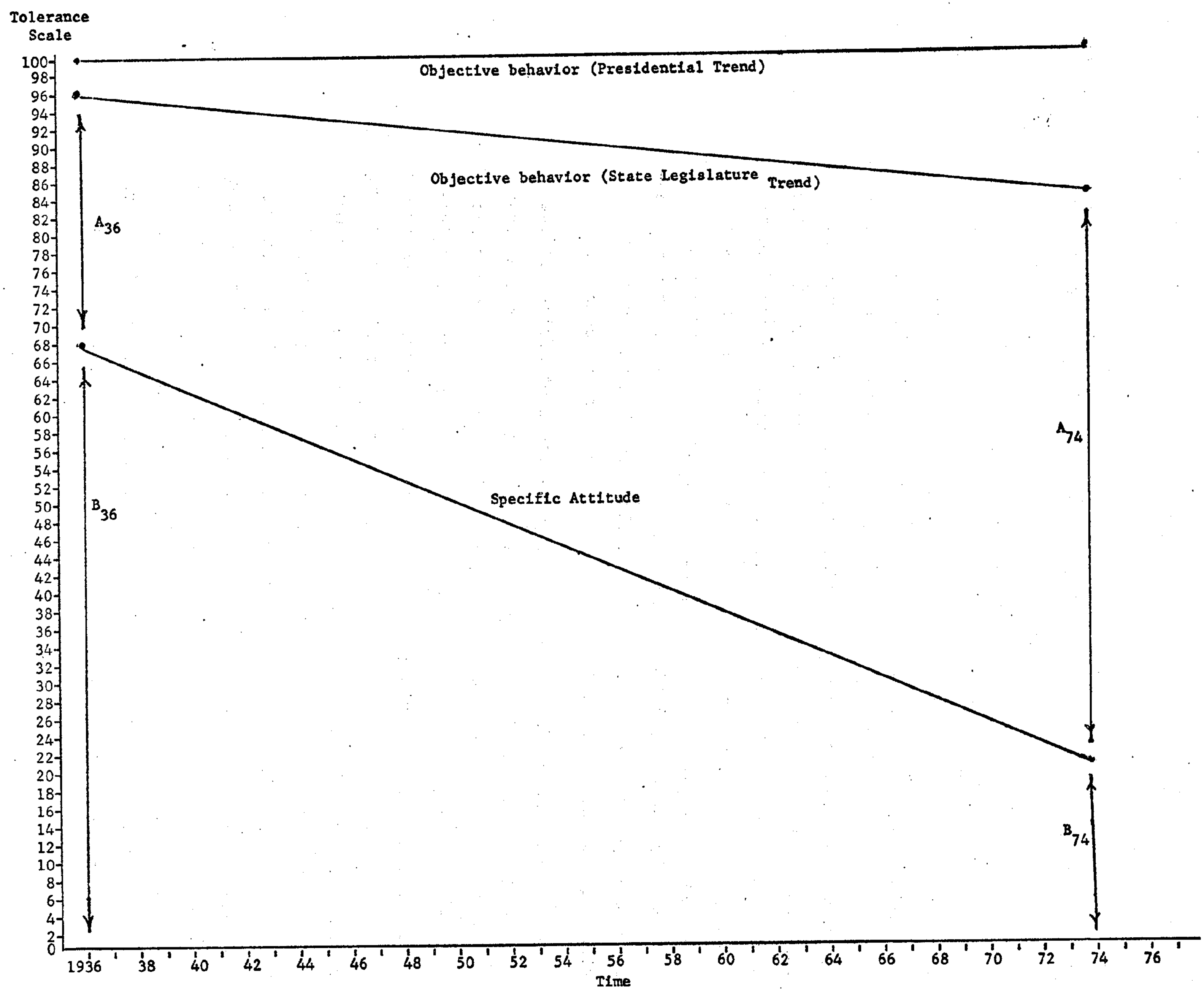

Fig. 6.--Comparison of the Change in Tolerance of Women in Politics: Ideal, Specific Attitude, and Objective Behavior, 1936-1974

childhood socialization have made women less likely to consider a political career as either desirable or appropriate. As Fred I. Greenstein explained in his seminal article, "Sex Related Political Differences in Childhood":

> Children's political sex differences do not flow from a rationalistic developmental sequence in which the girl learns "politics is not for girls," hence "I am not interested in politics." Rather there is a much more subtle and complex process in which, through differential opportunities, rewards and punishments which vary by sex, and through mechanisms such as identification with one or the other parent, a sex identity is acquired. Among other things this learning process associates girls with the immediate environment and boys with the wider environment. Political responses, developing as they do relatively late in childhood, fall into the framework of already present non-political orientations. (Greenstein 1961: 369).

With this process reinforced by the overt prejudice of males and denigration by women themselves, the result has been that few women have seriously contemplated a political career.[8]

For those few hearty souls who have sought a career in public office, political obstacles have arisen. The first has been the party regulars. Dedicated to the goal of maximizing party power, they have considered women candidates poor electoral risks. As the Democratic wheelhorse John Bailey remarked, "The only time to run a woman is when things look so bad that your only chance is to do something dramatic."[9] Adding to this pragmatic reason has been a large reserve of male prejudice, which is typlified by Dr. Edgar Berman's "raging hormone theory" on why a woman should not be President. The final obstacle has been the electorate itself. Although never conclusively shown, it is frequently argued that a qualified woman candidate for any office will lose more votes than she gains because of her sex. (Of course, under the

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[8] See Lamson (1968: 25-26), Grubert (1968: 26), Werner (1968: 40-41), and Amundsen (1971: 85).

[9] Quoted in Lamson (1968: 23).

ideal of political equality, she should not gain or lose any votes because of her sex.)[10] In sum, while it is hard to apply ideals universally and difficult to translate favorable attitudes into political offices, in the case of the political role of women, it appears that the first step has been accomplished and the second is now underway.

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[10]There is evidence of an anti-woman vote from the surveys cited in this paper, and there is evidence of a lack of a "women's" vote (i.e., block voting). There is, however, little information on the question of a pro-woman vote.

APPENDIX

Study	Question Wording
AIPO(1936) AIPO66	Would you vote for a woman for president if she was qualified in every other respect?
AIPO360K AIPO543	If the party whose candidate you most often support nominated a woman for President of the United States, would you vote for her if she seemed best qualified for the job?
AIPO448	If the party whose candidate you most often support nominated a woman for President of the United States, would you vote for her if she seemed qualified for the job?
AIPO604	If your party nominated a woman for President, would you vote for her if she seemed qualified for the job?
AIPO676, AIPO776, AIPO834	If your party nominated a woman for President, would you vote for her if she qualified for the job?
AIPO744, GSS72, GSS74	If your party nominated a woman for President, would you vote for her if she were qualified for the job?

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A TREND ANALYSIS OF ATTITUDES TOWARD CAPITAL PUNISHMENT, 1936-1974

Tom W. Smith

May 1975

In the ongoing debate over capital punishment, opponents and proponents each claim that both God and public opinion are on their side.[1] As evidence of God's favor, abolitionists have the Fifth Commandment, "Thou shalt not kill," and arguments in favor of the sancity of human life, the virtue of mercy, and the goal of redemption. Supporters, however, might quote Leviticus 24:7, "He who kills a man shall be put to death," and argue for the preservation of justice. As proof of public opposition, abolitionists point to such things as the century-long trend to reduce the number of capital crimes, the steady decline in the number of executions since the 1930s, and the present rarity of death sentences. They conclude with Justice Thurgood Marshall that capital punishment "is morally unacceptable to the people of the United States as this time in their history."[2] In rebuttal, supporters note that numerous attempts to repeal the death penalty by referendum and legislative action have failed, that both the federal government and a large majority of the states authorize the death penalty, and that juries continue to hand down death sentences. They are well represented by Justice Lewis F. Powell's assessment that "the weight of the evidence indicates that the public generally has not accepted either the morality or the social merit of the views so passionately advocated by the articulate spokesmen for abolition."[3] In sum, looking to the same

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[1]Examples of the pro and con positions can be found in Bedeau, 1964; McCafferty, 1972; and Sellin, 1967.

[2]Furman v. Georgia, 92 S. Ct., 2726ff, 33 L. Ed., 2nd, 418. It was in this case that the Supreme Court ruled by a five to four vote that existing laws and procedures for capital punishment were cruel and unusual and thereby unconstitutional.

[3]*Ibid.*, p. 487.

sources for evidence, opponents and proponents come to diametrically opposite conclusions on the acceptability of the death penalty.

While hard evidence of God's opinion is unavailable, the American public has had its opinion probed in at least 26 national surveys since 1936 (see Appendix 1: Uses and Question Wordings). When unavailable studies and variant question wordings are pruned from this list, there remain 14 studies for which marginals are available (AIPO studies 1936, 59, 105, 522, 625, 704, 729, 746, 774, 839 and 846 and three General Social Surveys, GSS72, GSS73, and GSS74) and 10 studies for which data files are available (AIPO studies 522, 625, 704, 746, 774, 839, 846 and GSS72, GSS73, and GSS74). The marginal time series covers the full time span of 38 years; the data file series spans 21 years from 1953 to 1974. In either case, a long and rich vein of data exists to examine trends in public opinion on capital punishment.

To carry out the trend analysis, categorical linear flow graph analysis has been employed. Linear flow graph analysis translates linear equations into diagrams. There are three simple conventions for transforming equations into graphs: (1) variables become points; (2) coefficients are connected to arrows that join points; and (3) constants are attached to the origin of unlabeled arrows merging with a variable. While linear flow graphs are simply visual expressions of equations and add no unique mathematical properties, they assist causal inferences, help to solve relationships, and facilitate mathematical calculations. Categorical linear flow graph analysis extends graph theory to contingency table data. In this system, the variable values are categorical proportions, the coefficients are differences in proportions, and constants are proportions in a non-base category on a dependent variable among those in the base category on a prior variable. (A base category is the arbitrarily selected category of each variable from which the differences in proportions are calculated.) The disadvantages of categorical linear flow graph analysis are the necessity of arbitrarily selecting base categories and the method's strong appetite for N, which restricts the number of variables that can be used. Its advantages are that it permits the application of linear flow graph analysis to categorical data without level-of-measurement assumptions, that it handles interactions in a straightforward manner, that relationships are expressed in terms of readily understandable differences in proportions, and that the system is especially congenial to over-time analysis.[4]

Equipped with the statistical tool, we can now consider the trend analysis of public opinion. The marginal porportion opposing the death penalty is graphed in Figure 1. The bottom line retains "don't knows" as a category (see Table 1-A); the upper line is figured after the "don't knows" have been excluded (see Table 1-B). Examination of the graph shows that opposition to capital punishment has gone over a series of peaks and valleys since 1936. In the late thirties a bit over one-third of the population opposed the death penalty; in 1953 this fell to 28 per cent. This drop may, however, be somewhat misleading. Two events in 1953 probably decreased opposition temporarily. The first was the execution on June 19th, about five and a half months before the survery, of the "atomic spies" Ethel and Julius Rosenberg. The second was the kidnap-murder of six-year old Bobby Greenlease by Carl Hall and Bonnie Heady on October 7th. It is quite likely that strong public approval of capital punishment in these particular cases depressed the level of opposition registered in the survey.[5] After 1953, opposition apparently gained ground until, in 1966, a majority opposed capital punishment. Since 1966, the trend in opposition to capital punishment has been downward, and it has fallen sharply since 1971. Overall, the marginals on capital punishment from 1936 to 1974 indicate non-linear change (see Statistical Analysis in Tables 1-A and 1-B).

To get at the nature of this non-linear trend, the time under study was broken into periods of rising opposition (1936-1966) and

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[4]For a concise and clear introduction to linear flow graphs see Stinchcombe, 1968. On categorical linear flow graphs, see Davis, forthcoming. On special techniques for handling over-time changes, see Davis, in press, and Taylor, 1975.

[5]One indication of the impact of the Greenlease and Rosenberg cases can be seen in that in 1937 only 58 per cent of those who supported capital punishment favored its application to women, while in 1953, 96 per cent did (see Erskine, 1971: 298). This dramatic rise probably results from the fact that two of the four defendants in the Greenlease and Rosenberg cases were women.

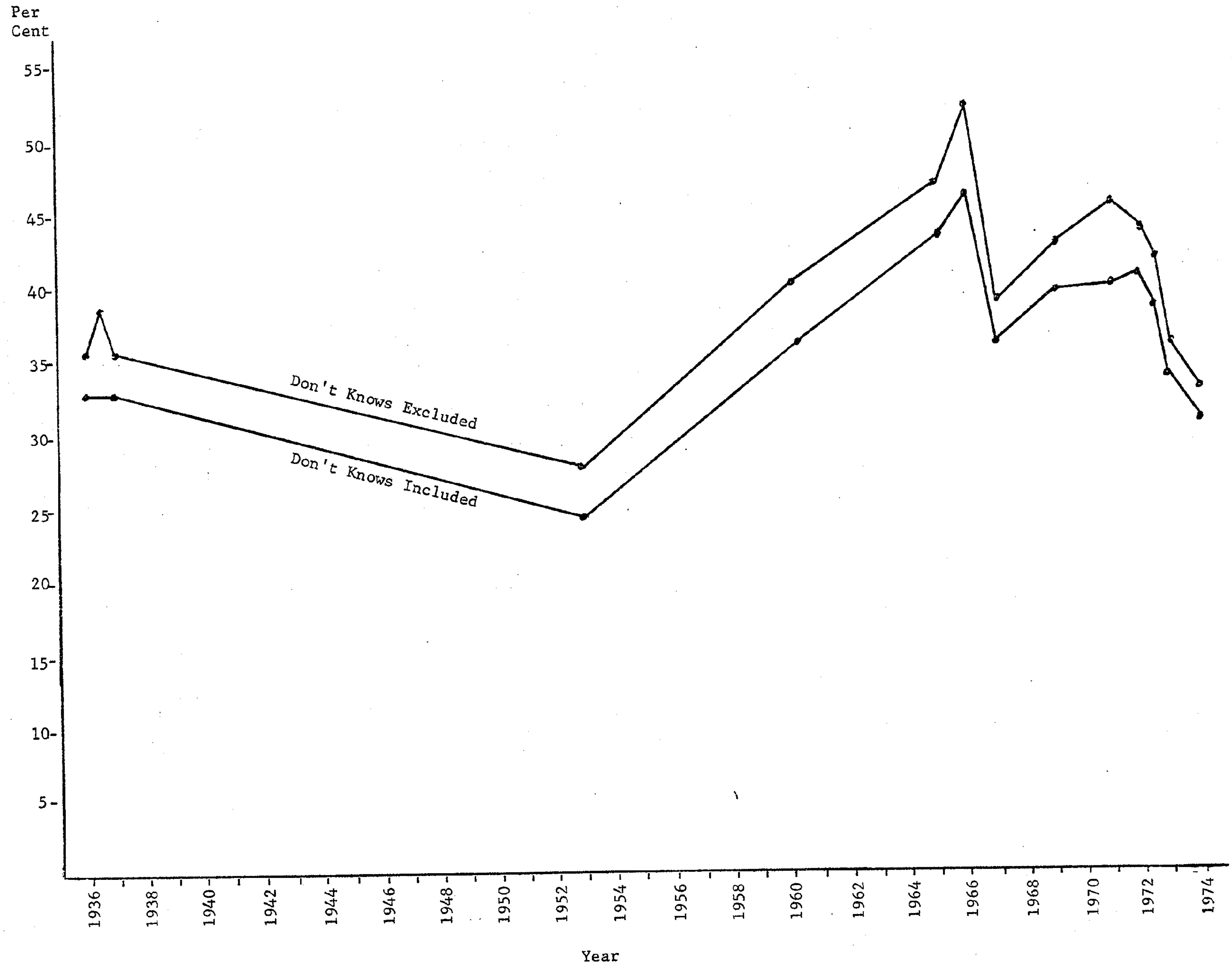

Fig. 1--Marginals for Per Cent Opposing Death Penalty

TABLE 1-A

MARGINALS, "DON'T KNOWS" INCLUDED[a]

Data							
Survey	AIPO[b]	AIPO59[b]	AIPO105[b]	AIPO522[c]	AIPO625	AIPO704	AIPO729[b]
Date	4/36	11/36	11/37	11/53	3/60	2/65	7/66
Per Cent:							
Yes	62.0	61.0	60.0	63.8	52.7	45.4	42.0
No	33.0	39.0	33.0	25.0	36.2	44.0	47.0
Don't Know .	5.0	*[d]	7.0	11.2	11.2	10.6	11.0
N	n.d.	n.d.	n.d.	(1496)	(2973)	(1689)	n.d.
Survey	AIPO746	AIPO774	AIPO839	AIPO846	GSS72	GSS73	GSS74
Date	6/67	1/69	10/71	2/72	3/72	3/73	3/74
Per Cent:							
Yes	55.7	51.3	48.2	50.9	53.0	60.2	63.0
No	36.7	40.1	40.5	41.5	39.3	34.8	31.8
Don't Know .	7.5	8.6	10.3	7.6	7.8	5.0	5.1
N	(1518)	(1503)	(1558)	(1509)	(1609)	(1492)	(1480)

[a]Missing cases and no answers were excluded from the following studies: AIPO522 (2), AIPO625 (12), AIPO846 (4), GSS72 (4), GSS73 (12), and GSS74 (4).

[b]Data from Hazel Erskine, "The Polls: Capital Punishment," Public Opinion Quarterly, XXXIV (Summer, 1970), 290-307. There was no data (n.d.) on the number of cases; for statistical analysis, 1,400 was used as the number of cases.

[c]The categories "qualified yes" and "qualified no" were grouped with the "don't knows."

[d]Figures probably exclude "don't knows."

TABLE 1-A--Continued

Statistical Analysis

	Hypothesis	Model	x^2	df	p	Decision
For per cent:						
Yes	1) No change	p = pooled	388.5	13	<.05	Reject
	2) Linear change	p = a + bx	317.1	12	<.05	Reject
	Reduction from linear term		81.4	1	<.05	Significant
No	1) No change	p = pooled	279.9	13	<.05	Reject
	2) Linear change	p = a + bx	246.8	12	<.05	Reject
	Reduction from linear term		33.1	1	<.05	Significant
Don't know	1) No change	p = pooled	163.8	12	<.05	Reject
	2) Linear change	p = a = bx	167.9	11	<.05	Reject
	Reduction from linear term		-4.1	1	>.05	Not significant

Final Model

Marginal proportion "Yes":	Non-linear change with significant linear component
Marginal proportion "No":	Non-linear change with significant linear component
Marginal proportion "Don't Know":	Non-linear change

TABLE 1-B

MARGINALS, "DON'T KNOW" EXCLUDED[a]

Data

Survey	AIPO[b]	AIPO59[b]	AIPO105[b]	AIPO522[c]	AIPO625	AIPO704	AIPO729[b]
Date	4/36	11/36	11/37	11/53	3/60	2/65	7/66
Per Cent							
Yes	64.0	61.0	64.0	71.9	59.3	52.5	47.0
No	36.0	39.0	36.0	28.1	40.7	47.5	53.0
N	n.d.	n.d.	n.d.	(1329)	(2641)	(1460)	n.d.

Survey	AIPO746	AIPO774	AIPO839	AIPO846	GSS72	GSS73	GSS74
Date	6/67	1/69	10/71	2/72	3/72	3/73	3/74
Per Cent							
Yes	60.3	56.2	53.9	55.1	57.7	63.4	66.5
No	39.7	43.8	46.1	44.9	42.6	36.6	33.5
N	(1403)	(1373)	(1394)	(1394)	(1484)	(1417)	(1404)

Statistical Analysis

Hypothesis	Model	x^2	df	p	Decision
For per cent No:					
1) No change	p = pooled	317.0	13	<.05	Reject
2) Linear change	p = a + bx	273.0	12	<.05	Reject
Reducation from linear term		44.0	1	<.05	Significant

Final Model

Marginal Proportion "No": Non-linear change with significant linear component

[a]Missing cases and no answers were e cluded from the following studies, AIPO522 (2), AIPO625 (12), AIPO846 (4), GSS72 (4), GSS73 (12), and GSS74 (4).

[b]Data from Erskine, "Capital Punishment." No data (n.d.) available on number of cases. For statistical analysis 1350 was used as the number of cases.

TABLE 1-C

CHANGE IN PROPORTION "NO", "DON'T KNOWS" EXCLUDED

Statistical Analysis

Period	Hypothesis	Model	x^2	df	p	Decision
1936-1966	1) No change	p = pooled	237.4	9	<.05	Reject
	2) Linear change	p = a + bx	172.3	8	<.05	Reject
	Reduction from linear term		65.1	1	<.05	Significant
1966-1974	1) No change	p = pooled	147.9	7	<.05	Reject
	2) Linear change	p = a + bx	85.0	6	<.05	Reject
	Reduction from linear term		62.9	1	<.05	Significant
1971-1974	1) No change	p = pooled	71.3	4	<.05	Reject
	2) Linear change	p = a + bx	6.5	3	>.05	Accept

Final Model

Marginal proportion "No" (1936-66): Non-linear change with significant linear component

Marginal proportion "No" (1966-74): Non-linear change with significant linear component

Marginal proportion "No" (1971-74): 3.79 - .0467 (Year - 1900) falling opposition (1966-1974). For both of these periods the trends were still found to be non-linear (see Table 1-C). Only for the years 1971-1974 was a definite linear trend evident (see Table 1-C). In both periods, however, the degree of linearity was much higher than it had been for the entire period (1936-1974). In brief, the trend in opposition since 1936 cannot be simply defined as an inverted-V with its apex in 1966, but these periods of rising and falling opposition are a major feature of the 38 years of change.

One last notable feature from the marginals is the relatively high level of "don't know" responses. Over time, they average .079 of all responses (missing cases excluded). This level is above that found on other general opinion questions, and indicates that people find this a difficult question to take sides on.[6] This difficulty probably stems from the gravity of the decision involved. The relatively high level of "don't knows" may also help to account for some of the fluctuations in the marginals, since the same forces that create a large number of undecided people may produce a low level of certitude among those who take sides. In other words, the opinion of many people may be tentative and fluid rather than absolute and fixed.

This notion of a loosely anchored swing group receives support from several questions that have explored the intensity of feelings on capital punishment (see Appendix 2: Questions Relating to the Reasons and Conditions for Supporting or Opposing Capital Punishment). About a fifth of the population in 1968 and 1973 absolutely opposed the death penalty: 18 per cent would never vote for the death penalty, 16 per cent would never apply it to first degree murders, and 16 per cent would never convict a person who would automatically receive the death penalty (see questions A, F, and G). Around 30 per cent strongly favored its use with 28 per cent who would use it for all first degree murders and 39

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[6]The proportion of "don't know" responses on capital punishment for the three General Social Surveys (1972, 1973, 1974) averaged .060. The proportion of "don't knows" on 13 other questions that asked yes/no responses on concrete domestic policies (including items on gun registration, the legalization of marijuana, wiretapping, school busing, divorce laws, sex education, birth control information, and abortions) was .036. A similar difference appears to exist on Gallup surveys.

per cent who could always vote for conviction in cases carrying an automatic death penalty (see questions F and G). The remaining 50 per cent believe in the conditional or selective use of the death penalty. A 1973 Harris survey offers further illustration: 59 per cent supported the death penalty, 10 per cent were undecided, and 31 per cent opposed the penalty. Here, 28 per cent would always use the death penalty for first degree murder, 56 per cent would use it selectively (including the "don't knows"), and 16 per cent would never use it. Assuming that all of the "never-use-it" group were opponents and that all of the "always-use-it" group were proponents, then of the 59 per cent who favored capital punishment, 28 per cent were universalists and 31 per cent were conditionalists (the 10 per cent undecided were all conditionalists), and of the 31 per cent opposed to the death penalty, 15 per cent were conditionalists and 16 per cent were total abolitionists. This indicates that a large proportion of both proponents and opponents are neither totally in favor of nor totally opposed to the death penalty.

Having examined the change in the marginals on capital punishment, the next step is to analyze the relationship of independent variables to capital punishment during the years from 1953 to 1974 for which data files are available. Inspection of the data files revealed that over-time analysis of the relationship between the following demographic variables and capital punishment was possible: sex, race, religion, cohort, income, education, and political party affiliation.

Turning to basics first, Figure 2 graphs the sex differential on capital punishment. The graph indicates that women are consistently more opposed to the death penalty than are men. This difference is constant over time and the difference in proportions averages .115 (i.e., pooled over all surveys, the proportion of women expressing opposition to capital punishment minus the proportion of men registering opposition equals .115; see Table 2). Both the direction of this difference and its consistency can be explained by differences in the socialization processes of girls and boys (Watson, 1965: 433-36; and Phelps and Austin, 1975; this difference also manifests itself on war issues, see Mueller, 1973: 146-47). Racial differences between whites and blacks are shown in

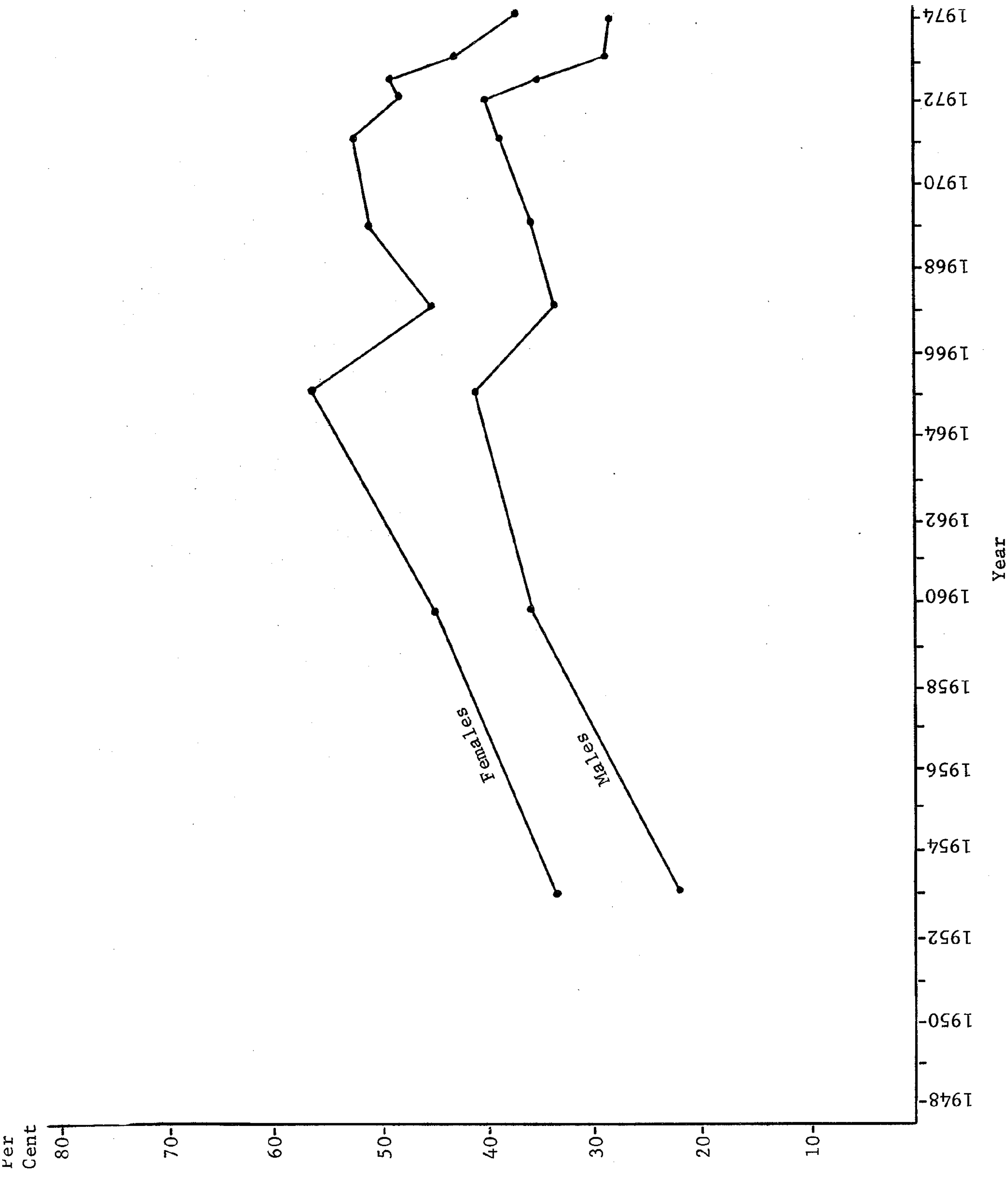

Fig. 2--Per Cent Opposing Death Penalty by Sex

TABLE 2

SEX DIFFERENCES

Data

Survey	AIPO522	AIPO625	AIPO704	AIPO746	AIPO774
Date	11/53	3/60	2/65	6/67	1/69
Per Cent No:					
Male	22.6 (656)	36.3 (1289)	41.6 (754)	34.1 (710)	36.2 (698)
Female	33.6 (670)	45.0 (1350)	56.9 (756)	45.5 (693)	51.7 (675)

Survey	AIPO830	AIPO846	GSS72	GSS73	GSS74
Date	10/71	2/72	3/72	3/73	3/74
Per Cent No:					
Male	39.3 (707)	40.9 (700)	34.9 (765)	29.7 (669)	29.6 (668)
Female	53.1 (687)	49.0 (694)	49.7 (719)	42.8 (748)	37.1 (736)

Statistical Analysis

Category Differences (Base = Male)	Hypothesis	Model	x^2	df	p	Decision
Female	1) No difference	d = 0	231.0	10	<.05	Reject
	2) Constant difference	d = C	12.7	9	>.05	Accept

Final Model

Female: d = .115 σ = .008

Figure 3. At all time points, blacks have been more opposed to the death penalty than whites. Each group has generally followed the national trends, but the differential has not been constant: since 1953 the gap has been widening at an average of about 1 per cent a year (see Table 3). The direction of this difference is easily understood in light of the disproportionate application of the death penalty to blacks (Wolfgang and Riedel, 1973). The widening of the gap might well be a result of the civil rights movement, which increased black sensitivity to such inequalities.

Figure 4 shows the difference between Protestants and Catholics on capital punishment. Catholics have fairly consistently registered less support for the abolition of capital punishment than Protestants, although the percentage difference has never exceeded -8, and has averaged only -.042 (see Table 4). The reason for this difference is obscure, but it is worth noting that many Protestant demoninations have taken official positions agains the death penalty (Sellin, 1967: 121-22).

Figure 5 shows cohort differences on capital punishment. There has never been a significant difference between the middle cohort and either the young or old cohorts. The new cohort, however, has consistently been more opposed to capital punishment than any of the older cohorts. Since the emergence of the new cohort in the 1965 survey, the new and middle cohorts have differed by an average of .106 (see Table 6). This difference seems to be a true cohort effect (rather than an age difference) since the young cohort in 1953 and 1960 did not show a similar difference, and because the difference has not changed as the new cohort has aged.

Figure 6 shows the income differential on capital punishment. For the abbreviated time period for which data is available (1965-1974), there has been a constant relationship between low income and opposition to the death penalty. The differences in proportions between the middle and wealthy groups and the less well off have been .066 and .100 respectively. This difference most probably reflects a greater interest in order by the economically secure groups, as well as a belief among the

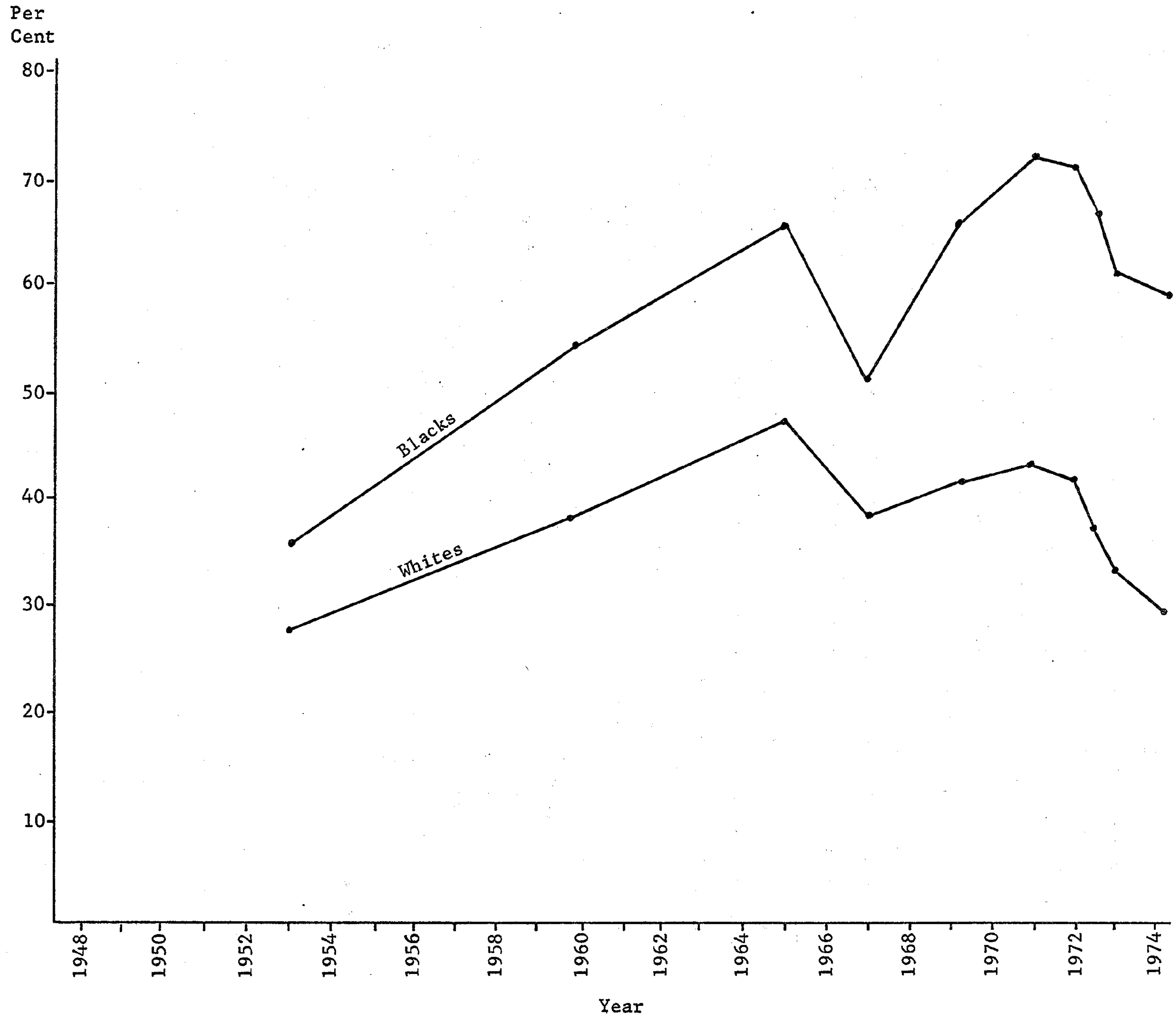

Fig. 3--Per Cent Opposing Death Penalty by Race

TABLE 3

RACE DIFFERENCES[a]

Data

Survey	AIPO522	AIPO625	AIPO704	AIPO746	AIPO774
Date	11/53	3/60	2/65	6/67	1/69
Per Cent No:					
Whites	27.6 (1226)	38.8 (2324)	47.6 (1314)	38.8 (1269)	41.8 (1262)
Blacks	36.0 (89)	54.2 (308)	66.7 (135)	51.8 (83)	66.7 (96)

Survey	AIPO839	AIPO846	GSS72	GSS73	GSS74
Date	10/71	2/72	3/72	3/73	3/74
Per Cent No:					
Whites	43.6 (1262)	42.1 (1263)	37.6 (1245)	33.0 (1238)	30.2 (1240)
Blacks	72.5 (120)	71.8 (131)	68.1 (235)	61.7 (167)	60.1 (158)

Statistical Analysis

Category Difference (Base = Whites)	Hypothesis	Model	x^2	df	p	Decision
Blacks	1) No difference	d = 0	361.6	10	<.05	Reject
	2) Constant difference	d = c	32.2	9	*	
	3) Linear change in difference	d = a + bx	3.9	8	>.05	Accept
	Reduction from linear change		28.3	1	<.05	Significant

Final Model

Blacks: -.53 + .0112 (Year - 1900)

[a]Those who were neither whites nor blacks were excluded.

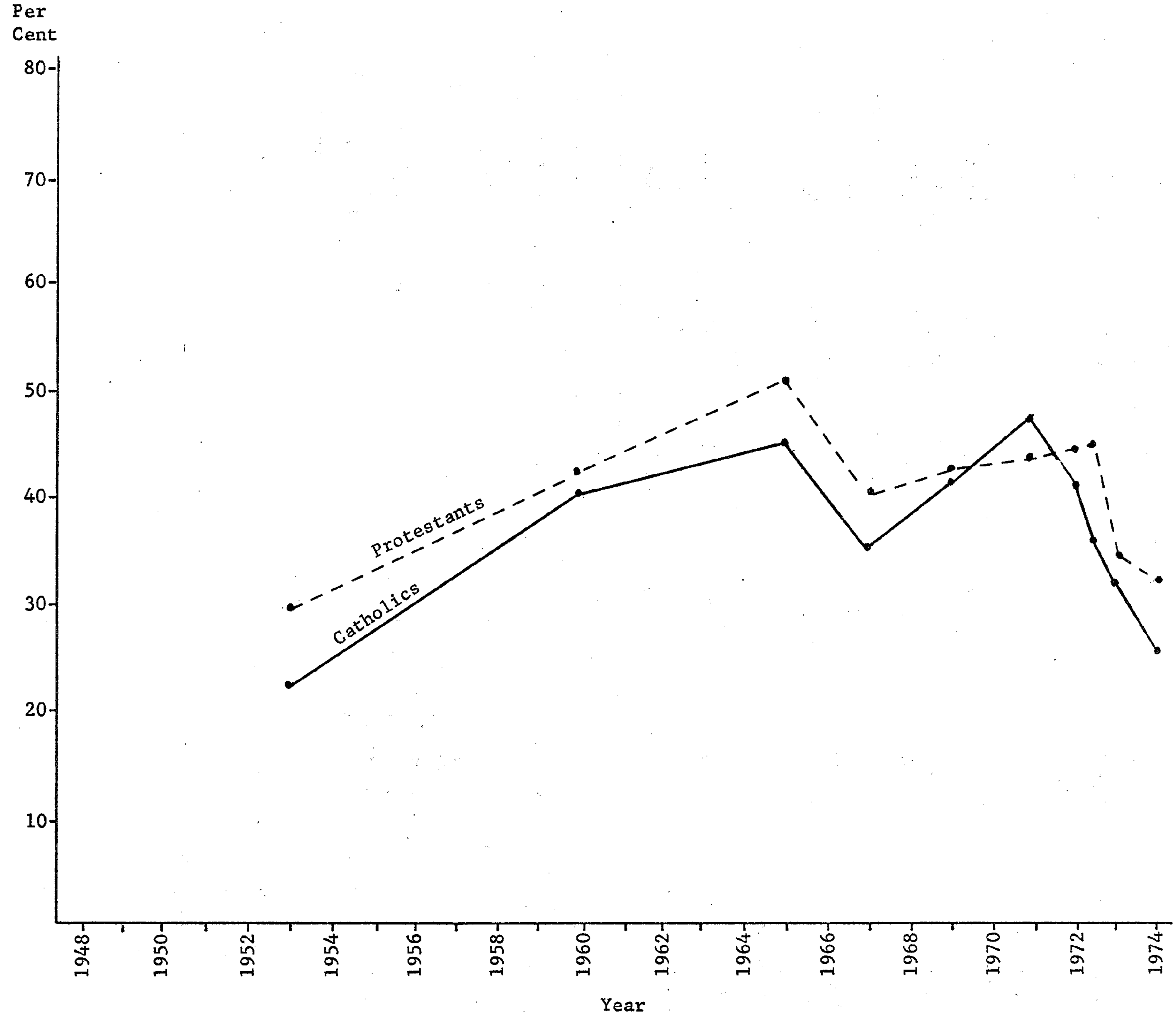

Fig. 4--Per Cent Opposing Death Penalty by Religion

TABLE 4

RELIGIOUS DIFFERENCES[a]

Data

Survey	AIPO522	AIPO625	AIPO704	AIPO746	AIPO774
Date	11/53	3/60	2/65	6/67	1/69
Per Cent No:					
Protestants . .	29.7 (930)	42.3 (1607)	51.0 (1059)	41.2 (934)	43.9 (897)
Catholics . . .	22.1 (307)	40.1 (755)	45.2 (343)	35.1 (342)	41.5 (335)

Survey	AIPO839	AIPO846	GSS72	GSS73	GSS74
Date	10/71	2/72	3/72	3/73	3/74
Per Cent No:					
Protestants . .	44.0 (897)	45.1 (854)	45.5 (939(	35.1 (883)	33.4 (905)
Catholics . . .	47.5 (356)	42.2 (377)	36.2 (387)	33.5 (370)	26.1 (357)

Statistical Analysis

Category Difference (Base = Protestants)	Hypothesis	Model	x^2	df	p	Decision
Catholics	1) No difference	d = 0	35.6	10	*	
	2) Constant difference	d = c	14.5	9	>.05	Accept
	Reduction from constant term		21.1	1	<.05	Significant

Final Model

Catholics: d = -.042 σ = .009

[a]Those who were neither Protestant nor Catholics were excluded.

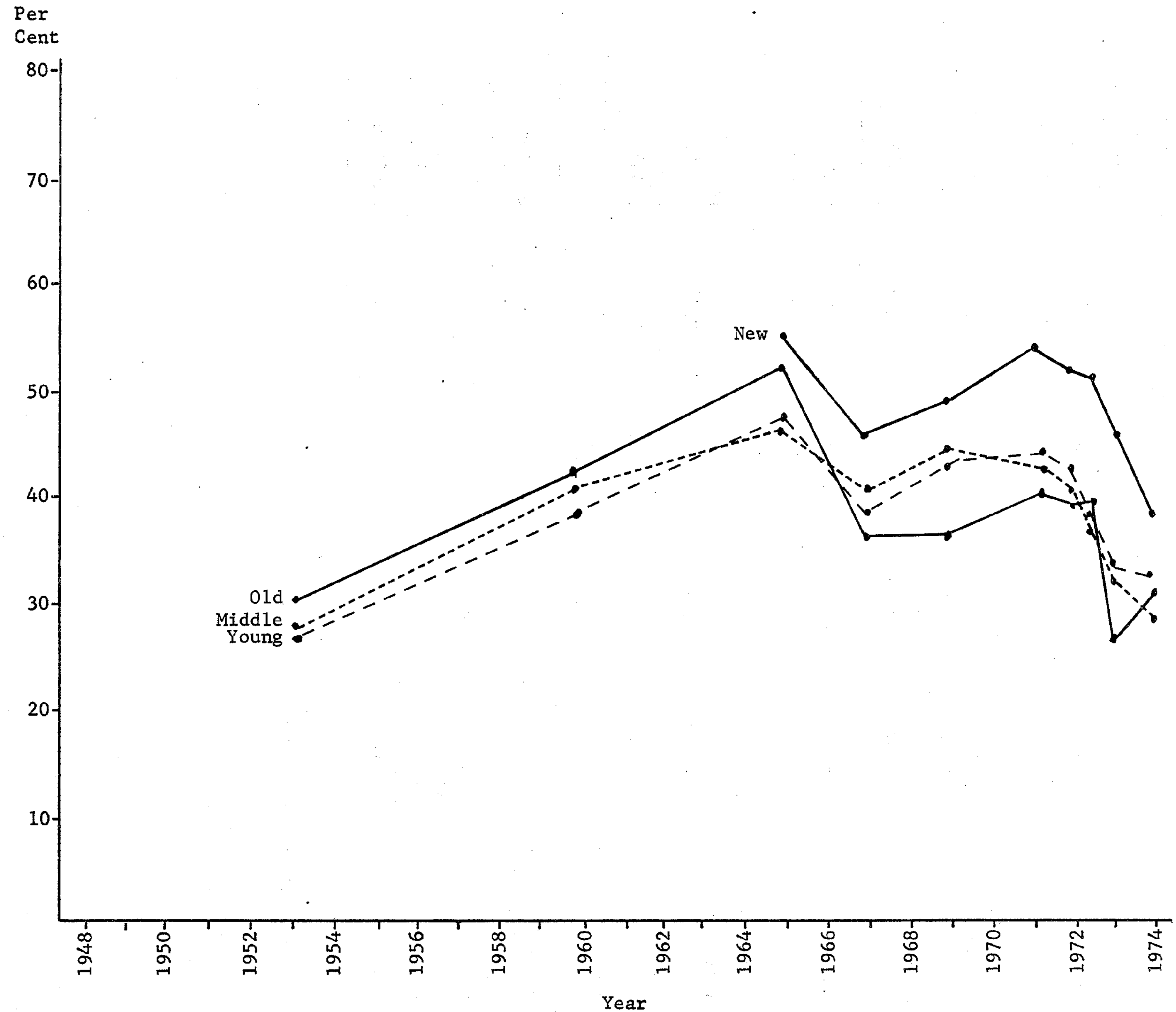

Fig. 5--Per Cent Opposing Death Penalty by Cohort

TABLE 5

COHORT DIFFERENCES[a]

Data

Survey	AIPO522	AIPO625	AIPO704	AIPO746	AIPO774
Date	11/53	3/60	2/65	6/67	1/69
Per Cent No:					
New	-	-	55.1 (156)	46.2 (199)	49.2 (242)
Young	26.5 (294)	38.7 (852)	47.6 (532)	38.7 (468)	43.6 (447)
Middle . . .	27.2 (526)	40.9 (925)	46.9 (450)	40.3 (424)	44.9 (421)
Old	30.0 (504)	42.7 (832)	52.6 (342)	36.6 (287)	36.4 (247)
Survey	AIPO839	AIPO846	GSS72	GSS73	GSS74
Date	10/71	2/72	3/72	3/73	3/74
Per Cent No:					
New	54.1 (414)	52.3 (463)	51.6 (473)	46.7 (467)	38.2 (505)
Young	44.3 (386)	42.5 (386)	38.3 (405)	33.3 (408)	32.8 (381)
Middle . . .	43.0 (335)	40.5 (338)	37.1 (404)	32.0 (375)	28.3 (336)
Old	40.3 (221)	39.0 (200)	39.6 (197)	26.4 (163)	31.3 (176)

Statistical Analysis

Category Difference (Base = Middle)	Hypothesis	Model	x^2	df	p	Decision
New	1) No difference	d = 0	74.0	8	<.05	Reject
	2) Constant difference	d = c	6.9	7	>.05	Accept
Young	1) No difference	d = 0	3.7	10	>.05	Accept
Old	1) No difference	d = 0	12.2	10	>.05	Accept

Final Model

New: d = .106 = .013
Young: d = 0
Old: d = 0

[a]The old cohort was born in 1906 or earlier, the middle cohort was born between 1907 and 1923, the young cohort was born from 1924 to 1939, and the new cohort was born from 1940 on.

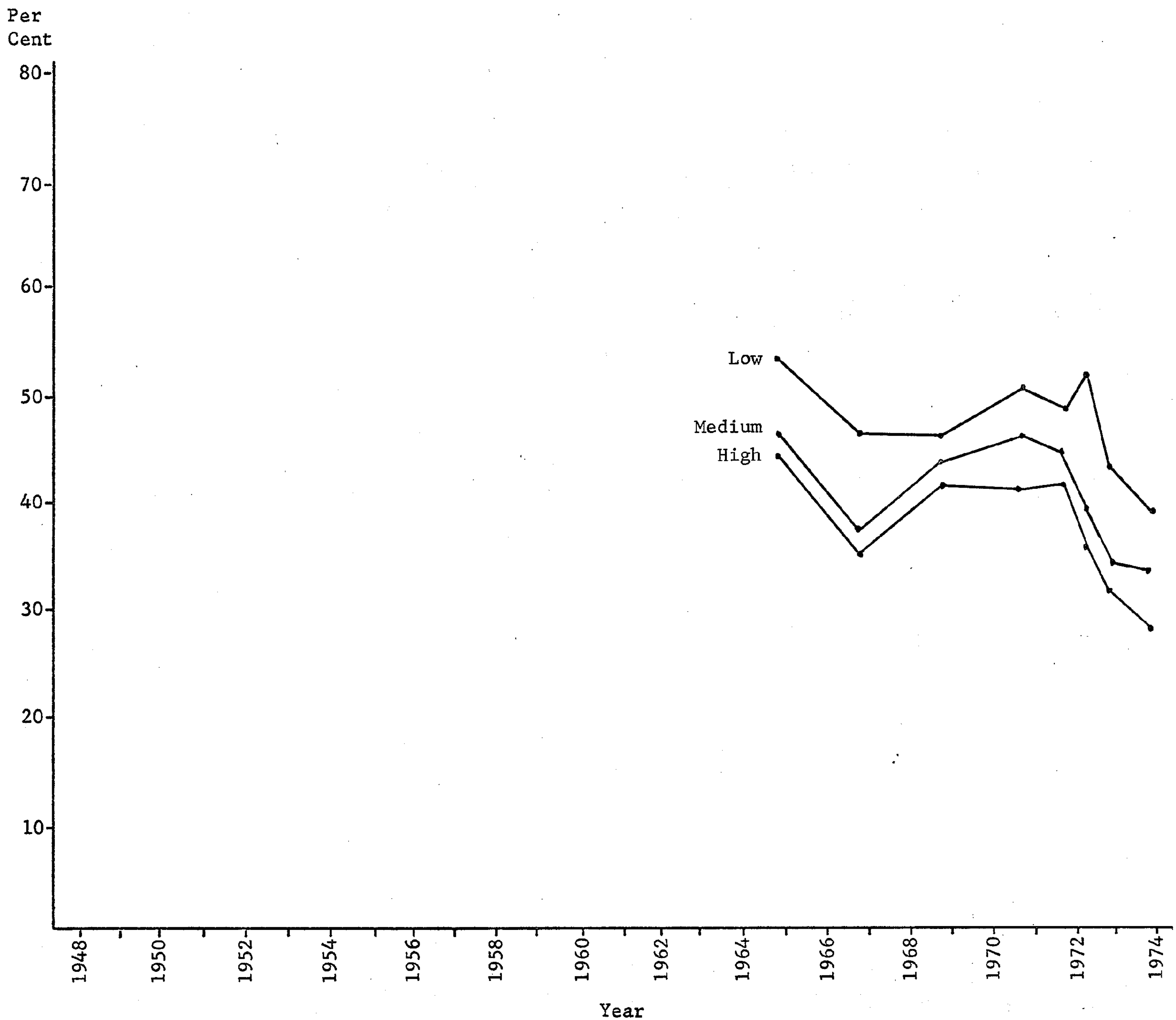

Fig. 6--Per Cent Opposing Death Penalty by Income

TABLE 6

INCOME DIFFERENCES[a]

Data

Survey	AIPO704	AIPO746	AIPO774	AIPO839	AIPO846	GSS72	GSS73	GSS74
Date	2/65	6/67	1/69	10/71	2/72	3/72	3/73	3/74
Per Cent:								
Low . . .	53.8 (403)	46.8 (417)	46.2 (403)	50.9 (381)	49.2 (386)	52.9 (399)	43.8 (402)	39.5 (387)
Medium .	47.2 (513)	37.2 (611)	44.1 (533)	46.2 (524)	44.8 (536)	39.4 (526)	34.4 (567)	32.9 (495)
High. . .	45.6 (544)	35.9 (359)	41.5 (422)	41.1 (453)	42.0 (443)	36.6 (435)	32.0 (353)	28.4 (412)

Statistical Analysis

Category Difference (Base = Low)	Hypothesis	Model	x^2	df	p	Decision
Medium	1) No difference	d = 0	43.5	8	>.05	Reject
	2) Constant difference	d = c	11.4	7	>.05	Accept
High	1) No difference	d = 0	75.7	8	<.05	Reject
	2) Constant difference	d = c	7.2	7	<.05	Accept

Final Model

Medium: -.066 = .012
High: -.100 = .012

[a]Income was collapsed into three categories of approximately equal size. To achieve this the following cuts were made:

Surveys	Categories: Low	Medium	High
AIPO704	to $3,999	$4,000-6,999	$7,000 +
AIPO746	to $4,999	$5,000-9,999	$10,000 +
AIPO774	to $4,999	$5,000-9,999	$10,000 +
AIPO839	to $5,999	$6,000-10,999	$11,000 +
AIPO846	to $5,999	$6,000-11,999	$11,000 +
GSS72	to $5,999	$6,000-12,499	$12,500 +
GSS73	to $6,999	$7,000-14,999	$15,000 +
GSS74	to $6,999	$7,000-14,999	$15,000 +

poorer group of class inequities in the judical system in general, and the punishment of capital crimes in particular (Wald, 1971; Overby, 1971).

Figure 7 presents the educational differences on capital punishment. The graph and data indicate that high school graduates register the least support for abolition, that the less-educated are more in favor of abolition (by an average of .038 over the high school graduates), and that the college-educated favor abolition the most (by an average of .061 over the high school graduates). Since this relationship seemed rather curious, the relationship was reexamined with income introduced as a control variable. On the eight studies where this was possible, the pooled zero-order difference between the less-educated and high school graduates was .040; between the college-educated and high school graduates it was .061; between the middle and poorer income group it was -.066; and between the wealthier and poorer income group it was -.100. With income introduced as an intervening variable, the difference between the less-educated and high school graduates disappeared and the difference between the college-educated and the high school graduates increased to .073. Net of education, the difference between the middle and poor income groups rose to -.076, and the wealthy to poor difference became -. 134 In brief, income was creating a spurious difference between the less-educated and high school graduates, while supressing the relationship between the college-educated and high school graduates, and between the middle and wealthy groups and the less well off.

In Figure 8, party differences on capital punishment are shown: Democrats show the greatest opposition to capital punishment; the Independents are less opposed; and the Republicans are the least opposed. The Republican-Democrat difference has not been constant, however, but has been widening at a rate of .049 a year (see Table 9). This party difference appears to reflect liberal-conservative ideological cleavage on this issue. In 1974 at least, the difference between conservatives and liberals was greater than that between Republicans and Democrats (see Table 10).[7]

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[7]Also on this point, see Zeisel, 1968: 19-24.

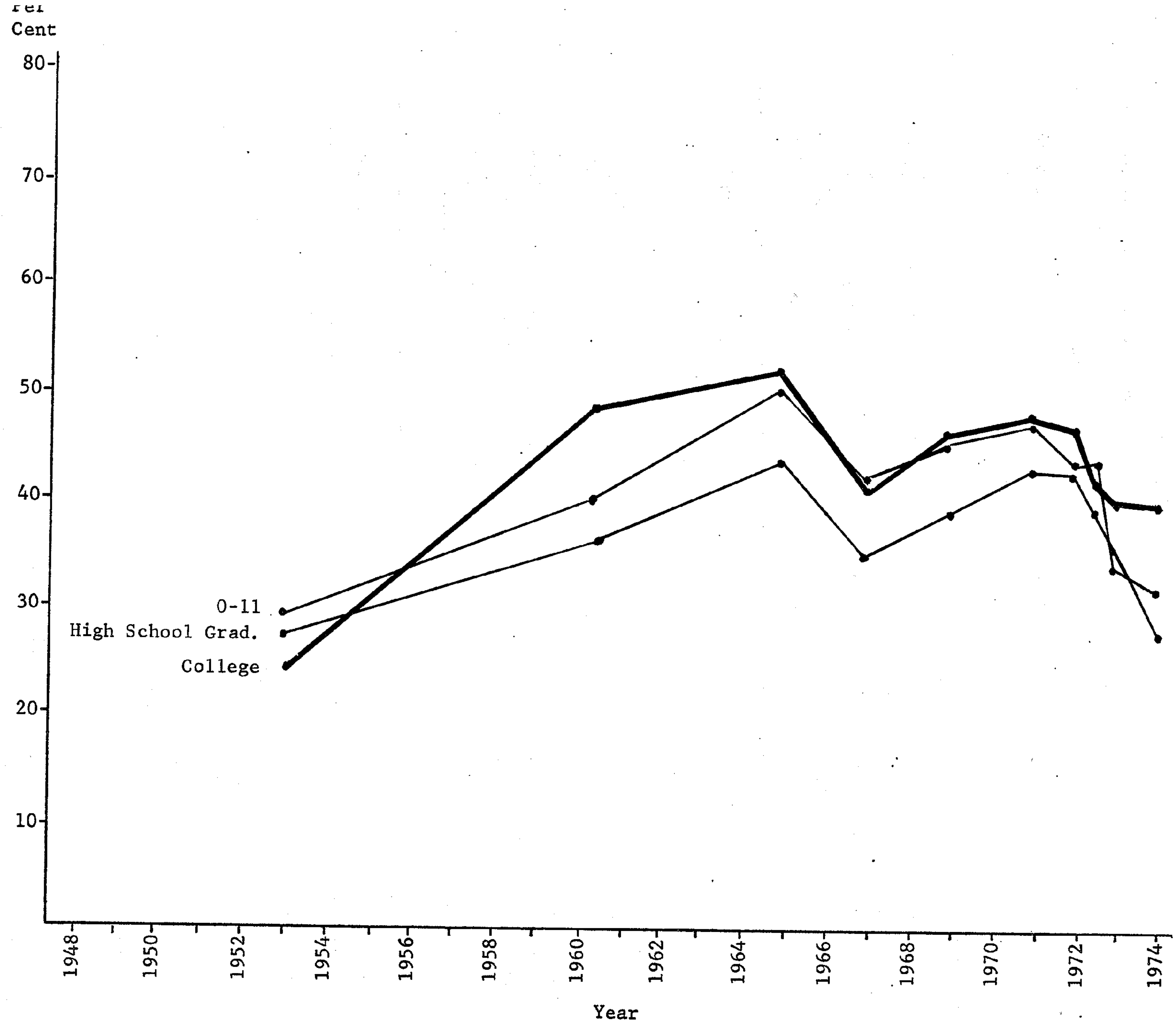

Fig. 7--Per Cent Opposing Death Penalty by Education

TABLE 7

EDUCATIONAL DIFFERENCES

Data

Survey	AIPO522	AIPO625	AIPO704	AIPO746	AIPO774
Date	11/53	3/60	2/65	6/67	1/69
Per Cent:					
Less than High School	29.4 (680)	40.7 (1412)	51.1 (655)	42.6 (531)	46.0 (500)
High School Graduate	27.7 (404)	36.5 (816)	44.7 (524)	35.5 (512)	39.8 (490
College	24.2 (236)	49.6 (407)	52.8 (326)	41.5 (354)	46.4 (375)

Survey	AIPO839	AIPO846	GSS72	GSS73	GSS74
Date	10/71	2/72	3/72	3/73	3/74
Per Cent:					
Less than High School	47.8 (471)	43.9 (506)	44.5 (580)	34.2 (511)	32.2 (475)
High School Graduate	43.2 (530)	43.6 (491)	39.9 (467)	35.7 (460)	28.6 (469)
College	47.9 (386)	47.5 (394)	43.0 (433)	40.3 (442)	40.0 (457)

Statistical Analysis

Category Difference (Base = High School)	Hypothesis	Model	x^2	df	p	Decision
Less than High School	1) No Difference	d = 0	24.5	10	*	
	2) Constant difference	d = c	7.4	9	>.05	Accept
	Reduction from constant term		17.1	1	<.05	Significant
College	1) No difference	d = 0	52.4	10	<.05	Reject
	2) Constant difference	d = c	17.8	9	*	

Final Model

Less than High School: d=.038 σ= .009
College: d=.061 σ= .010

TABLE 8

EDUCATION BY INCOME DIFFERENCES

	Data											
Survey	AIPO704			AIPO746			AIPO774			AIPO839		
Date	2/65			6/67			1/69			10/71		
	Low	Med.	High	Low	Med.	High	Low	Med.	High	Low	Med.	High
Per Cent No:												
Less than High School	53.8 (290)	50.9 (220)	39.3 (122)	49.3 (274)	36.8 (201)	29.4 (51)	46.8 (252)	50.8 (191)	24.5 (53)	50.8 (236)	50.0 (168)	27.8 (54)
High School Graduate	54.9 (91)	37.9 (206)	46.3 (214)	40.8 (98)	33.3 (273)	36.5 (137)	42.3 (104)	38.2 (220)	40.1 (162)	52.7 (91)	41.5 (248)	40.0 (180)
College	50.0 (20)	60.0 (85)	48.6 (208)	47.6 (42)	45.2 (135)	37.1 (170)	53.5 (43)	44.5 (119)	46.9 (207)	47.1 (51)	51.9 (106)	45.2 (219)
Survey	AIPO846			GSS72			GSS73			SS74		
Date	2/72			3/72			3/73			3/74		
	Low	Med.	High	Low	Med.	High	Low	Med.	High	Low	Med.	High
Per Cent No:												
Less than High School	48.3 (238)	42.2 (187)	36.1 (72)	51.4 (251)	38.2 (191)	37.0 (92)	38.4 (237)	29.4 (177)	26.9 (52)	34.2 (222)	28.0 (150)	25.4 (59)
High School Graduate	48.9 (92)	45.0 (220)	39.3 (168)	52.2 (92)	37.5 (200)	34.3 (137)	53.3 (92)	33.9 (227)	26.5 (117)	34.5 (87)	32.5 (200)	20.7 (145)
College	50.9 (53)	48.1 (129)	46.3 (203)	60.7 (56)	43.9 (132)	37.9 (206)	50.0 (72)	40.0 (160)	37.0 (184)	60.3 (78)	38.9 (144)	34.6 (208)

TABLE 8--Continued

Statistical Analysis						
Category Difference (Base = High School and Low)	Hypothesis	Model	x^2	df	p	Decision
Less than High School	1) No difference	d = 0	39.8	24	*	
	2) Constant difference	d = c	39.7	23	*	
	Reduction from constant term		.1	1	>.05	Not Significant
College	1) No difference	d = 0	60.3	24	*	
	2) Constant difference	d = c	24.5	23	>.05	Accept
	Reduction from constant term		35.8	1	<.05	Significant
Medium	1) No difference	d = 0	71.2	24	*	
	2) Constant difference	d = c	31.1	23	>.05	Accept
	Reduction from constant term		30.1	1	<.05	Significant
High	1) No difference	d = 0	120.8	24	<.05	Reject
	2) Constant difference	d = c	26.6	23	>.05	Accept

Final Model

Less than High School:	d = 0	
College:	d = .073	σ = .012
Medium:	d = -.076	σ = .012
High:	d = -.134	σ = .014

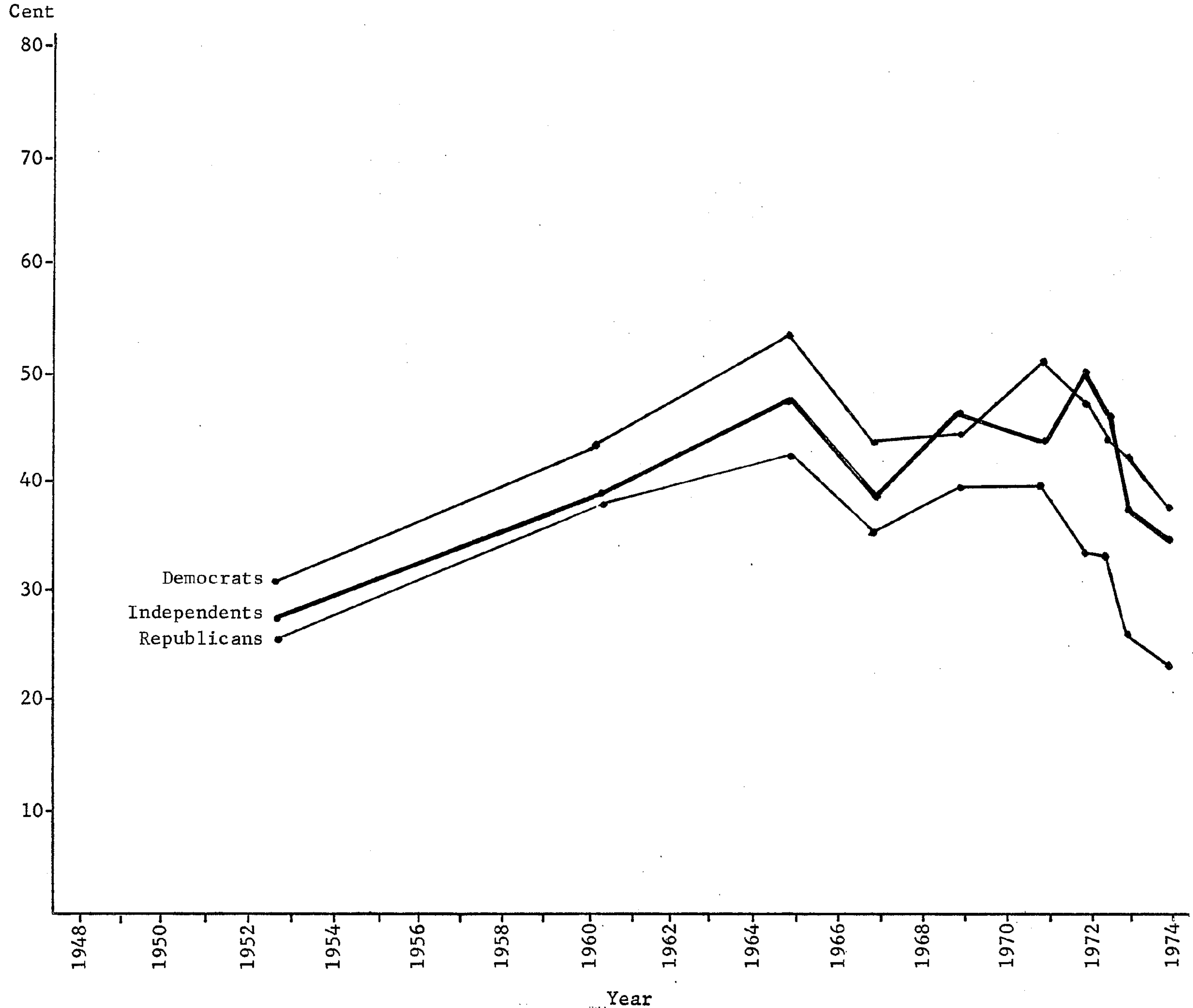

Fig. 8--Per Cent Opposing Death Penalty by Party

TABLE 9

PARTY DIFFERENCES[a]

Data

Survey	AIPO522	AIPO625	AIPO704	AIPO746	AIPO774
Date	11/53	3/60	2/65	6/67	1/69
Per Cent No:					
Republican	25.1 (410)	38.0 (729)	42.8 (402)	35.6 (410)	39.7 (388)
Independent	27.1 (291)	38.5 (620)	47.9 (338)	38.5 (351)	46.6 (397)
Democrat	30.4 (605)	43.2 (1218)	53.7 (751)	43.5 (609)	44.6 (547)

Survey	AIPO839	AIPO846	GSS72	GSS73	GSS74
Date	10/71	2/72	3/72	3/73	3/74
Per Cent No:					
Republican	39.9 (363)	33.7 (338)	33.2 (337)	25.8 (325)	23.2 (311)
Independent	43.8 (361)	50.6 (439)	46.3 (393)	37.7 (488)	34.9 (433)
Democrat	51.0 (649)	47.3 (573)	44.8 (688)	42.1 (580)	37.6 (585)

Statistical Analysis

Category Difference (Base = Democrat)	Hypothesis	Model	x^2	df	p	Decision
Republican	1) No difference	d = 0	119.0	10	<.05	Reject
	2) Constant difference	d = c	17.3	9	*	
	3) Linear change in difference	d = a + bx	6.6	8	>.05	Accept
	Reduction from linear term		10.7	1	<.05	Significant
Independent	1) No difference	d = 0	19.7	10	*	
	2) Constant difference	d = c	11.7	9	>.05	Accept
	Reduction from constant term		8.0	1	<.05	Significant

Final Model

Republican: d = 0.21 - .0047 (Year - 1900)

Independent: d = -.027 σ = .010

[a]Members of third parties are excluded.

TABLE 10

COMPARISON OF PARTY AND IDEOLOGY DIFFERENCES

Data

	Democrat	Independent	Republican	Liberal	Moderate	Conservative
Survey	GSS74					
Date	3/74					
Per Cent No:	37.6 (585)	34.9 (433)	23.2 (311)	46.3 (404)	29.6 (541)	25.1 (394)

Statistical Analysis

Category Difference (Base = Democrat, Liberal)	Hypothesis	Model	x^2	df	p	Decision
Independent	1) No difference	d = 0	.08	1	>.05	Accept
Republican	1) No difference	d = 0	21.5	1	<.05	Reject
Moderate	1) No difference	d = 0	27.5	1	<.05	Reject
Conservative	1) No difference	d = 0	41.0	1	<.05	Reject

Final Model

Party		Ideology		
Independents:	d = 0	Moderate:	d = -.167	σ = .032
Republican:	d = -.145	Conservative:	d = -.212	σ = .033

In the foregoing analysis, capital punishment was found to be associated with each of the independent demographic variables tested. Constant differences were found for categories of sex, religion, cohort, income, and education. Linear differences were discovered for categories of race and for the Republican-Democrat difference among political parties. With these over-time relationships established, it is now possible to consider the potential contribution of these independent variables to the marginal changes on capital punishment. Two factors must be considered: first, the differences in proportions on the dependent variable among the categories of the independent variables (which have already been inspected); and second, the marginal shifts over time in the proportion of cases in the categories of the independent variable. The relationship between these two factors is illustrated in Table 11-A. If there is no relationship between an independent and a dependent variable (i.e., if d = 0), then the independent variable will not contribute to or help explain any of the change in the dependent variable regardless of whether or not there are marginal shifts (see cells A and B, Table 11-A). Likewise, if there is a stable relationship between the independent and dependent variables (i.e., d = c) and no marginal shifts, there will be no effects of the independent variable on the change in the dependent variable (see cell C). However, if a constant relationship exists and there are marginal shifts, then the independent variable will help to explain the change in the dependent variable (see cell D). When there is linear change over time in the relationship between the independent and dependent variables, the independent contributes to the change in the dependent variable whether or not there are changes in the marginals of the independent variable (see cells E and F). In brief, by considering both the relationship between an independent and a dependent variable and the marginal changes of the independent variable, it is possible to test whether this variable has contributed to the marginal changes in the dependent variable (cases D, E, F) or has had no effect on the observed changes (cases A, B, C).

This scheme has been applied to the independent variables examined above. Table 11-B shows that sex, religion, and income have no effect on

TABLE 11-A

TYPOLOGY FOR TESTING CONTRIBUTION OF INDEPENDENT VARIABLE ON CHANGE IN DEPENDENT VARIABLE

Differences in Proportions:	Marginals of Independent Variable: 1) No change	Marginals of Independent Variable: 2) Change
1) No difference (d = 0)	A	B
2) Constant difference (d = c)	C	D
3) Linear change in difference (d = a + bx)	E	F

TABLE 11-B

TESTING THE CONTRIBUTION OF SELECTED DEMOGRAPHIC VARIABLES TO CHANGE ON CAPITAL PUNSIHMENT

Variable	Over Time Difference in Proportions	Marginal Shifts Over Time	Case
Sex:			
Female vs. Male	d = .115	*	C
Race:[a]			
Black vs. White	d = -.53 + .0122 (Year - 1900)	.045	F
Religion:			
Catholic vs. Protestant	d = -.042	*	C
Cohort:			
New vs. Middle	d = .106	+.358	D
Young vs. Middle	d = 0	+.048	B
Old vs. Middle	d = 0	-.255	B
Education:[b]			
0-11 vs. High School	d = .038	.147	D
College vs. High School	d = .061	-.176	D
Income:[c]			
Middle vs. Low	d = -.066	*	C
High vs. Low	d = -.100	*	C
Party:			
Republican vs. Democrat	d = 0.21 - .0047 (Year - 1900)	-.080	F
Independent vs. Democrat	d = -.027	.103	D

*Not significant at .05 level.

[a]The small gain in the proportion of blacks is an artifact of sampling variation. The censuses for 1950 and 1970 show less than a one percent gain for adult blacks.

[b]When income is controlled the 0=11 vs. High School difference becomes 0 and thus a type "B" case.

[c]By cutting income into equal thirds the possibility of marginal shifts was eliminated. If fixed dollar value had been used there would have been marginal shifts and income would be a type "D" case.

the changes in capital punishment, and that race, cohort, education, and party all play a role. With the identification of these change variables it is possible to construct a causal model to explain the observed change in the capital punishment marginals.[8]

For the sake of clarity two relatively uncomplicated four-variable models were tested. In the first model, the prior variable is time; the intervening variables are, first, cohort and, next, party preference; and the final dependent variable is capital punishment. This model is presented in a flow graph in Figure 9 and the accompanying statistical analysis is in Table 12-A. Starting at the left side, the graph translates as follows. The terms feeding into the cohort categories are their marginal changes from 1953 to 1974. Flowing out from the cohort categories to the party categories are the differences in proportions between cohorts on party preference. The dual arrows from the new cohort to Republican represent the fact that over time the new cohort has become increasingly less Republican (i.e., linear differentiation). The long arrow from the new cohort to opposition indicates that net of time and party , the new cohort is associated with opposition to capital punishment (or, more precisely, controlling for time and party, the new cohort gives .103 more opposition responses than the middle cohort does). The absence of arrows from the young and old cohorts shows that there are no independent effects from these categories. Moving on to the party variable, there are no exogenous arrows entering the system, since there is no effect between time and party net of cohort (i.e., the marginal changes in parties over time are explained by cohort). From the party categories to capital punishment are two broken arrows (dashed lines signify negative differences in proportions) indicating that, net of time and cohort, there is a direct effect between party and capital punishment. The negative signs signify that being either a Republican or an Independent lead to less opposition to capital

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[8]Non-change variables can, of course, be put in a change model and would be especially appropriate if they explained or supressed change variables.

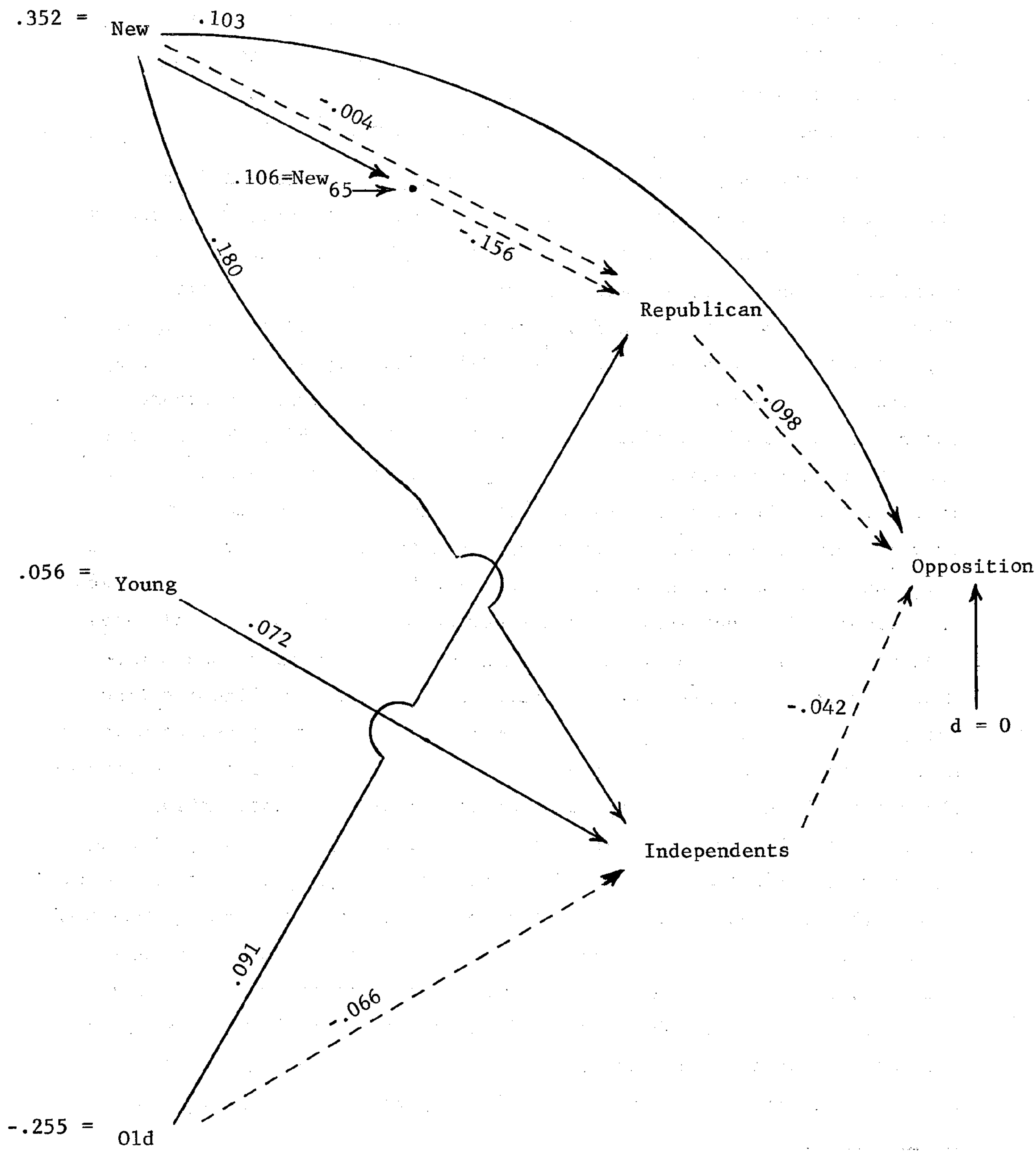

Fig. 9--Flow Graph Model of Change in Cohort, Party, and Capital Punishment, 1953-1974

TABLE 12

COHORT BY PARTY DIFFERENCES

Data

Survey	AIPO522			AIPO625			AIPO704		
Date	11/53			3/60			2/65		
	Dem.	Ind.	Rep.	Dem.	Ind.	Rep.	Dem.	Ind.	Rep.
Per Cent No:									
New	-	-	-	-	-	-	60.9 (64)	46.0 (50)	58.5 (41)
Young	32.1 (131)	17.7 (79)	26.7 (75)	35.7 (353)	38.9 (244)	42.7 (239)	52.8 (269)	45.9 (135)	38.0 (121)
Middle	28.8 (240)	28.4 (109)	23.5 (170)	48.8 (443)	37.2 (258)	27.2 (195)	51.3 (234)	46.2 (93)	39.2 (120)
Old	31.3 (233)	32.7 (101)	26.1 (165)	45.0 (407)	40.7 (118)	40.1 (282)	56.1 (173)	54.5 (55)	47.2 (108)

Survey	AIPO746			AIPO774			AIPO839			AIPO846		
Date	6/67			1/69			10/71			2/72		
	Dem.	Ind.	Rep.	Dem.	Ind.	Rep.	Dem.	Ind.	Rep.	Dem.	Ind.	Rep.
Per Cent No:												
New	50.0 (78)	45.6 (68)	40.0 (50)	53.9 (76)	53.6 (97)	34.9 (63)	55.6 (178)	58.7 (143)	42.9 (84)	57.3 (164)	56.8 (199)	30.8 (78)
Young	42.4 (198)	35.8 (137)	38.0 (121)	40.5 (173)	47.1 (155)	44.9 (107)	54.8 (166)	36.7 (109)	35.8 (106)	43.7 (151)	46.1 (128)	37.5 (96)
Middle	46.6 (204)	34.5 (94)	35.1 (113)	44.6 (193)	44.7 (103)	44.0 (109)	48.9 (184)	35.9 (64)	35.7 (84)	41.1 (175)	43.8 (73)	35.4 (82)
Old	36.1 (119)	40.0 (50)	34.2 (114)	44.6 (101)	31.6 (38)	32.0 (103)	44.3 (106)	16.7 (36)	46.1 (76)	47.0 (83)	41.7 (36)	29.1 (79)

Survey	GSS72			GSS73			GSS74		
Date	3/72			3/73			3/74		
	Dem.	Ind.	Rep.	Dem.	Ind.	Rep.	Dem.	Ind.	Rep.
Per Cent No:									
New	52.0 (175)	55.2 (183)	43.5 (85)	54.4 (169)	48.4 (182)	31.8 (88)	43.5 (186)	35.9 (209)	29.7 (74)
Young	41.5 (195)	41.6 (113)	27.2 (81)	33.9 (171)	33.8 (139)	31.2 (77)	36.8 (171)	35.3 (116)	22.4 (76)
Middle	43.5 (216)	32.4 (71)	27.6 (105)	40.8 (174)	26.7 (90)	22.8 (101)	30.3 (142)	32.9 (103)	19.4 (79)
Old	41.2 (102)	40.0 (25)	34.4 (64)	33.8 (65)	32.4 (37)	14.3 (56)	37.6 (85)	29.6 (27)	21.1 (57

TABLE 12-A--Continued

Statistical Analysis

Category Differences on Capital Punishment	Hypothesis	Model	x^2	df	p	Decision
Time:						
1974 vs. 1953	1) No difference	d = 0	12.5	12	>.05	Accept
Cohort:						
New vs. Middle	1) No difference	d = 0	88.3	24	<.05	Reject
	2) Constant difference	d = c	29.4	23	>.05	Accept
Young vs. Middle	1) No difference	d = 0	41.7	30	>.05	Accept
Old vs. Middle	1) No difference	d = 0	39.2	30	>.05	Accept
Party:						
Republican vs. Democrat	1) No difference	d = 0	175.7	38	<.05	Reject
	2) Constant difference	d = c	70.1	37	*	Accept
Independent vs. Democrat	1) No difference	d = 0	69.8		*	
	2) Constant difference	d = c	51.0		>.05	Accept
	Reduction from constant term		18.8		>.05	Significant

Final Model

New: d = .103 σ = .014
Young: d = 0
Old: d = 0

Republican: d = -.098 σ = .010
Independent: d = -.042 σ = .010

punishment than being a Democrat. The last, but perhaps most important, is the exogenous arrow that flows into capital punishment. It indicates that net of cohort and party there was no difference in opposition to capital punishment between 1953 and 1974.

When all the paths in Figure 9 are added up, the change in opposition to capital punishment from 1953 to 1974 can be decomposed into causally distinct components. As Table 13 shows, opposition to capital punishment increased by .0421 from 1953 to 1974.[9] Most of this change (.0363) is accounted for by the emergence of the pro-abolitionist new cohort. The remaining change (.0058) is accounted for by cohort effects on party preference. This effect works as follows: Cohort succession has increased the proportion of Independent and decreased the proportion of Republicans. The increase in Independents tends to decrease the level of opposition while the decrease of Republicans tends to increase opposition to capital punishment. The net effect is to increase opposition (i.e., the positive transmittances through Republican are greater than the negative transmittances through Independent). In sum, the entire increase in opposition to capital punishment can be explained as the result, direct or indirect, of cohort succession.

Returning to the analysis of marginal trends with which we began this investigation, we noted there that after 1966 opposition to capital punishment declined. In light of the fact that cohort succession explains an <u>increase</u> in opposition since 1953, it is of special interest to see what has caused the decrease since 1966. To examine this change, the eight data files available from 1965 to 1974 were examined (with the 1966 survey unavailable, the 1965 study becomes the pivotal point). Figure 10 presents the flow graph and Table 12-B the statistical analysis. Compared with Figure 9, most coefficients change only slightly and, except for the appearance of a path between young and Republican and an exogenous term into Independent, the causal relations remain similar. The one major difference is the appearance of a -.178 difference from time to capital punishment net of cohort and party. Turning to Table 14, the enormous impact of this new term becomes immediately apparent.

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[9]As Table 13 indicates, the observed change from the raw data was .053, but the model change totaled only .0421. This difference results primarily from the setting of non-significant paths to zero.

TABLE 13

DECOMPOSITION OF CHANGE IN CAPITAL PUNISHMENT
FROM FIGURE 9

Source		Change
Direct from Cohort:		
New - Opposition	.352 * .103	.0363
Cohort via Party:		
New - Republican - Opposition	.352 * [-.004 + (-.156) * -.098 .106 * -.156 * -.098	.0071
New - Independent - Opposition	.352 * .180 * -.042	-.0027
Young - Independent - Opposition	.056 * .072 * -.042	-.0002
Old - Republican - Opposition	-.255 * .091 * -.098	.0023
Old - Independent - Opposition	-.255 * -.066 * -.042	-.0007
	Total Modeled Change	.0421
	(Raw Data	.053)

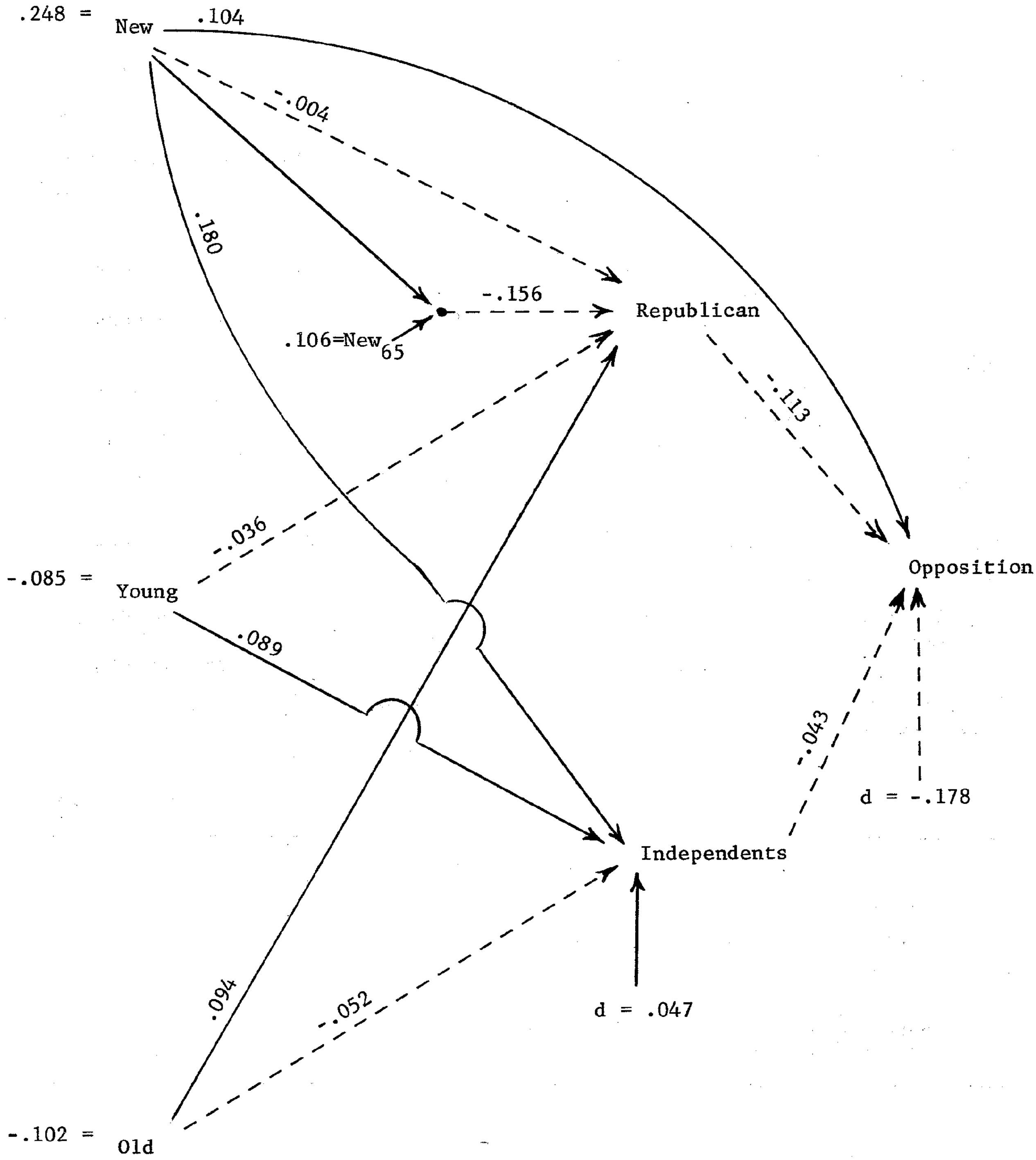

Fig. 10--Flow Graph Model of Change in Cohort, Party, and Capital Punishment, 1965-1974

TABLE 12-B

STATISTICAL ANALYSIS

Differences on Capital Punishment	Hypothesis	Model	x^2	df	p	Decision
Time:						
1974 vs. 1965	1) No difference	d = 0	95.0	12	<.05	Reject
	2) Constant difference	d = c	6.6	11	>.05	Accept
Cohort:						
New vs. Middle	1) No difference	d = 0	90.1	24	<.05	Reject
	2) Constant difference	d = c	29.4	23	>.05	Accept
Young vs. Middle Middle	1) No difference	d = 0	11.9	24	>.05	Accept
Old vs. Middle	1) No difference	d = c	27.6	24	>.05	Accept
Party:						
Republican vs. Democrat	1) No difference	d = 0	138.2	32	<.05	Reject
	2) Constant difference	d = c	38.6	31	>.05	Accept
Independent vs. Democrat	1) No difference	d = 0	53.4	32	*	
	2) Constant difference	d = c	39.4	31	*	
	Reduction from constant term		14.0	1	<.05	Significant

Final Model

Time:	d = -.178	σ =.019
New:	d = .104	σ = .013
Young:	d = 0	
Old:	d = 0	
Republican:	d = -.113	σ = .011
Independent:	d = -.043	σ = .011

TABLE 14

DECOMPOSITION OF CHANGE IN CAPITAL PUNISHMENT FROM FIGURE 10

Source		Change
Direct from Cohort:		
New - Opposition	.248 * .104	.0258
Cohort via Party:		
New - Republican - Opposition	.248 * -.160 * -.113	.0064
	.106 * -.156 * -.113	
New - Independent - Opposition	.248 * .180 * -.043	-.0019
Young - Republican - Opposition	-.085 * -.036 * -.113	-.0003
Young - Independent - Opposition	-.085 * -.089 * -.043	.0003
Old - Republican - Opposition	-.102 * .094 * -.113	.0011
Old - Independent - Opposition	-.102 * -.052 * .043	-.0002
Party Net of Cohort:		
Independent - Opposition	.047 * -.043	-.0020
Time Net of Cohort and Party:		
1965 - 1974 - Opposition		-.178
	Total Modeled Change	-.149
	(Raw Data	-.163)

From 1965 to 1974 the direct impact of the emergence of the new cohort was to increase opposition by .0258; the impact of cohort through party was .0054; and the result of the growth of the Independents net of cohort was -.0020. Together, these account for a net change of .0294. When this is combined with the unexplained time change of -.178, the total modeled change becomes -.149. This indicates that although cohort succession continues to increase opposition to the death penalty, there has been a large decrease in opposition across all categories of cohort and party. Thus, the cohort flow is being washed out by a counter current from time.

To examine change in capital punishment further, a second model was tested with time as the prior variable, cohort as the first intervening variable and education as the second, and capital punishment as the dependent variable. The 1953 to 1974 analysis showed much the same results as the party model did (see Figure 11 and Tables 15-A and 16). The emergence of the pro-abolitionist new cohort accounts for an increase in opposition of .0403. The sum effect of cohort on education is a virtually nil -.0024 (it would be positive if income was controlled for), and a growth in the college-educated unaccounted for by cohort accounts for a .0046 increase in opposition. When the 1965 to 1974 model was tested, the similarity of results was again apparent. The new cohort accounts for a .0288 increase; the impact of the new cohort via education was .0024; and the independent impact of the increase in the college group was .0038--for a net change of .0350. This gain in opposition was once again overwhelmed by a -.181 change from time net of cohort and education, giving a total modeled change of -.1460.

To review, the small increase in opposition from 1953 to 1974 can be well explained by either of the models, but neither model can account for the large inverted-V change that occurred between these end points. It is probable that by considering cohort, education, income, and party together as intervening variables the explained proportion would rise, but the net gain would probably be marginal. Instead of pursuing this course, we decided to examine the alternative model that capital punishment is related to concern about crime in general and

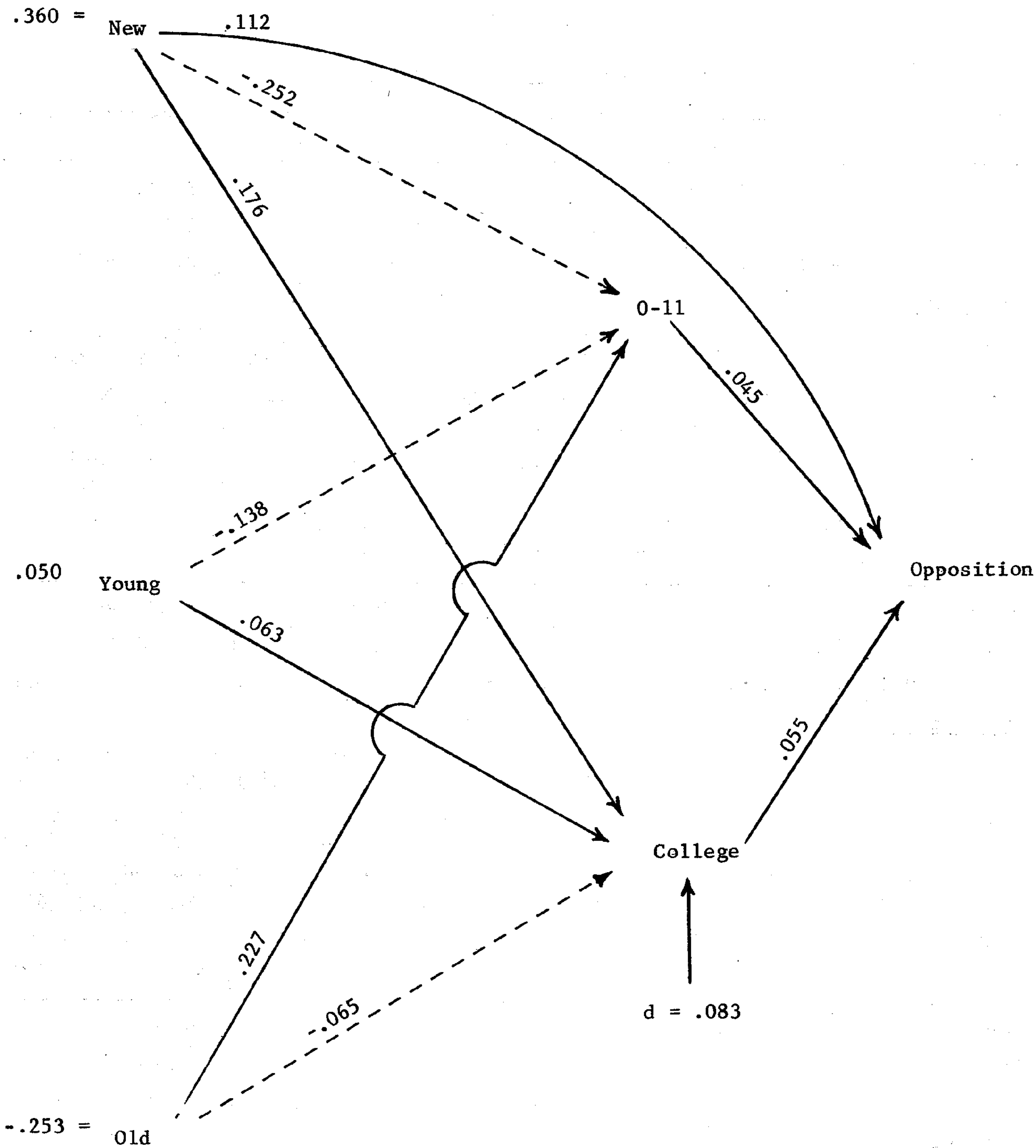

Fig. 11--Flow Graph Model for Change in Cohort, Education, and Capital Punishment, 1953-1974

TABLE 15-B

COHORT BY EDUCATION DIFFERENCES

Data

Survey	AIPO522			AIPO625			AIPO704		
Date	11/53			3/60			2/65		
	>H.S.	H.S.	H.S.+	>H.S.	H.S.	H.S.+	>H.S.	H.S.	H.S.+
Per Cent No:									
New	-	-	-	-	-	-	58.3 (36)	51.4 (70)	57.1 (49)
Young	32.0 (100)	23.9 (134)	23.3 (60)	42.0 (295)	26.5 (362)	56.4 (195)	48.4 (161)	42.7 (227)	54.5 (143)
Middle	27.5 (233)	28.4 (183)	23.4 (107)	38.6 (477)	43.3 (307)	43.6 (140)	46.9 (213)	46.6 (148)	46.0 (87)
Old	30.1 (346)	31.8 (85)	26.5 (68)	40.9 (631)	42.6 (130)	51.5 (68)	55.6 (232)	41.2 (68)	56.1 (41)

Survey	AIPO746			AIPO774			AIPO839			AIPO846		
Date	6/67			1/69			10/71			2/72		
	>H.S.	H.S.	H.S.+	>H.S.	H.S.	H.S.+	>H.S.	H.S.	H.S.+	>H.S.	H.S.	H.S.+
Per Cent No:												
New	44.8 (29)	39.2 (97)	56.2 (73)	61.5 (39)	41.9 (93)	50.9 (110)	58.4 (177)	49.7 (169)	55.5 (164)	51.7 (87)	51.7 (180)	52.6 (194)
Young	40.8 (130)	33.7 (196)	43.2 (139)	43.0 (135)	39.4 (188)	50.8 (124)	53.1 (113)	40.6 (175)	40.8 (98)	43.0 (135)	40.3 (149)	45.1 (102)
Middle	45.3 (192)	38.5 (143)	32.6 (89)	49.4 (168)	40.6 (155)	45.3 (95)	44.7 (132)	40.2 (122)	44.4 (81)	42.8 (145)	39.7 (126)	37.3 (67)
Old	40.4 (171)	31.8 (66)	31.2 (48)	41.0 (156)	32.0 (50)	23.7 (38)	41.4 (140)	38.8 (49)	40.0 (30)	41.0 (139)	27.3 (33)	42.9 (28)

Survey	GSS72			GSS73			GSS74		
Date	3/72			3/73			3/74		
	>H.S.	H.S.	H.S.+	>H.S.	H.S.	H.S.+	>H.S.	H.S.	H.S.+
Per Cent No:									
New	52.0 (100)	45.9 (181)	56.8 (192)	40.8 (103)	41.1 (175)	54.5 (187)	35.9 (92)	32.9 (207)	44.7 (206)
Young	42.7 (143)	36.3 (146)	35.3 (116)	33.1 (130)	38.1 (139)	28.8 (139)	34.8 (112)	24.7 (146)	41.0 (122
Middle	43.9 (196)	33.9 (115)	26.4 (91)	34.9 (172)	28.0 (118)	32.1 (84)	29.5 (149)	26.5 (98)	28.4 (88)
Old	41.0 (139)	41.7 (24)	33.3 (33)	27.2 (103)	22.2 (27)	28.1 (33)	30.0 (120)	23.5 (17)	36.8 (38)

TABLE 15-A --Continued

Statistical Analysis						
Differences on Capital Punishment	Hypothesis	Model	x^2	df	p	Decision
Time:						
1974 vs. 1953	1) No difference	d = 0	9.4	12	>.05	Accept
Cohort:						
New vs. Middle	1) No difference	d = 0	98.3	24	<.05	Reject
	2) Constant difference	d = c	28.5	23	>.05	Accept
Young vs. Middle	1) No difference	d = 0	50.5	30	*	
	2) Constant difference	d = c	50.3	29	*	
Old vs. Middle	1) No difference	d = 0	28.3	30	>.05	
Education:						
Less than High School	1) No difference	d = 0	67.9	38	*	
	2) Constant difference	d = c	45.7	37	>.05	Accept
	Reduction from constant term		22.2	1	>.05	Significant
College	1) No difference	d = 0	111.8	38	<.05	Reject
	2) Constant difference	d = c	84.4	37	*	

TABLE 16

DECOMPOSITION OF CHANGE IN CAPITAL PUNISHMENT
FROM FIGURE

Source		Change
Direct from Cohort:		
New - Opposition	.360 * .112	.0403
Cohort via Education:		
New - 0-11 - Opposition	.360 * -.252 * .045	-.0041
New - College - Opposition	.360 * .176 * .055	.0035
Young - 0-11 - Opposition	.050 * -.138 * .045	-.0003
Young - College - Opposition	.050 * .063 * .055	.0002
Old - 0-11 - Opposition	-.253 * .227 * .045	-.0026
Old - College - Opposition	-.253 * -.065 * .055	.0009
Education Net of Cohort:		
College - Opposition	.083 * .055	.0046
Time Net of Cohort and Education:		
1953 - 1974 - Opposition		
	Total Modeled Change	.0425
	(Raw Data	.056)

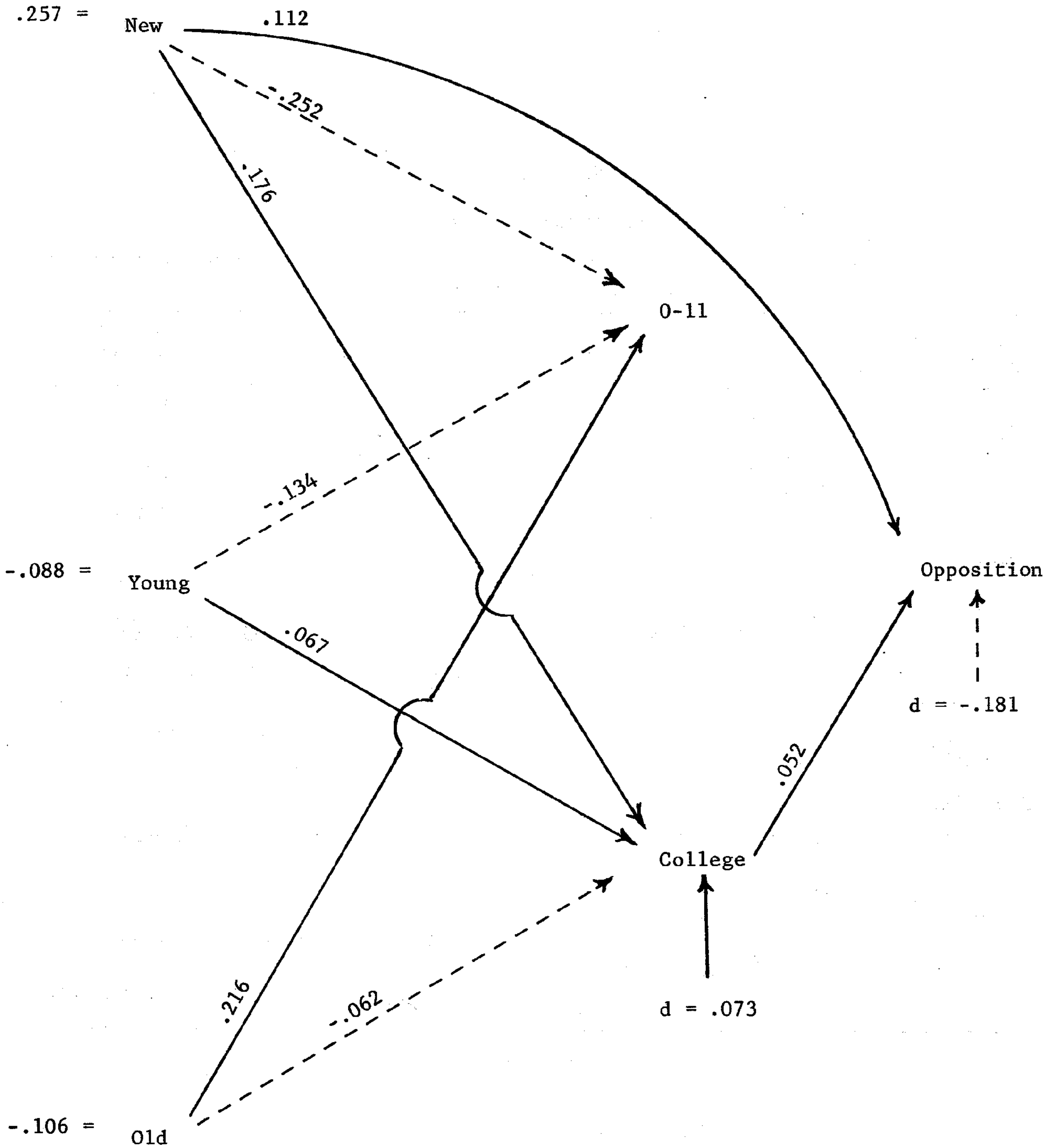

Fig. 12--Flow Graph Model for Change in Cohort, Education and Capital Punishment, 1965-1974

TABLE 15-B

STATISTICAL ANALYSIS

Differences on Capital Punishment	Hypothesis	Model	x^2	df	p	Decision
Time:						
1974 vs. 1965	1) No difference	d = 0	96.8	12	<.05	Reject
	2) Constant difference	d = c	4.0	11	>.05	Accept
Cohort:						
New vs. Middle	1) No difference	d = 0	98.3	24	<.05	Reject
	2) Constant difference	d = c	28.4	23	>.05	Accept
Young vs. Middle	1) No difference	d = 0	21.5	24	>.05	Accept
Old vs. Middle	1) No difference	d = c	24.3	23	>.05	Accept
Education:						
0-11 vs. High School	1) No difference	d = 0	41.6	32	>.05	Accept
College vs. High School	1) No difference	d = 0	59.2	32	*	
	2) Constant difference	d = c	39.4	31	>.05	Accept
	Reduction from constant term		19.8	1	<.05	Significant

Final Model

1974:	d = -.181	σ = .019
New:	d = +.112	σ = .013
Young:	d = 0	
Old:	d = 0	
0-11:	d = 0	
College:	d = .052	σ = .012

TABLE 17

DECOMPOSITION OF CHANGE IN CAPITAL PUNISHMENT
FROM FIGURE

Source		Change
Direct from Cohort:		
New - Opposition	.257 * .112	.0288
Cohort via Education:		
New - College	.257 * .176 * .052	.0024
Young - College	-.088 * .067 * .052	-.0003
Old - College	-.106 * -.062 * .052]	+.0003
Education Net of Cohort:		
College - Opposition	.073 * .052	.0038
Time Net of Cohort and Education:		
1965 - 1974 - Opposition		-.181
	Total Modeled Change	-.1460
	(Raw Data	-.154)

murder in particular, and that concern about crime is in turn related to the crime rate. Although the propositions seem eminently logical, there is unfortunately little direct evidence. Since this is the case, it was necessary to test the model by considering such indirect evidence as the relationship between criminal victimization and capital punishment and between methods of criminal control and capital punishment.

The first association explored was the relationship between criminal victimization and capital punishment. In the General Social Surveys for 1973 and 1974, three questions relating to criminal experiences were asked ("During the last year--that is, between March and now--did anyone break into or somehow illegally get into your apartment/home?", "During the last year, did anyone take something directly from you by using force--such as a stickup, mugging, or threat?", and "Have you ever been threatened with a gun or shot at?"--this last question asked in 1973 only), and a fourth question appeared on the expectation or fear of crime ("Is there any area right around here--that is, within a mile--where you would be afraid to walk alone at night?"). When these questions were crosstabulated with capital punishment, having been robbed or threatened with a gun and fear of the neighborhood were revealed to be unrelated to capital punishment,and having been burglarized was associated with opposing capital punishment (see Table 18). This finding is not surprising considering that criminal victimization is highest among groups that tend to oppose capital punishment--blacks, the young, and low-income earners (Executive Office of the President, OMB, 1967; U. S. Department of Justice, 1974).

Next, the association between methods of crime control and capital punishment was examined. The General Social Surveys include three questions relating to crime control. In 1972, 1973, and 1974,the General Social Survey asked, "In general, do you think the courts in this area deal too harshly or not harshly enough with criminals?" In 1973 only, it asked, "Are there any situations you can imagine in which you would approve of a policeman striking an adult male citizen?" <u>If yes or not sure</u>: Would you approve if the citizen:. . . . Was being questioned as a

TABLE 18

ASSOCIATION OF CRIME RELATED ITEMS TO CAPITAL PUNISHMENT

Source[a]	Variable	Final Model[b]	
	A. Criminal Victimization		
GSS73	Threatened with gun	d = 0	
GSS73, GSS74	Robbed	d = 0	
GSS73, GSS74	Fear to walk alone	d = 0	
GSS73, GSS74	Home burglarized	d = .115	σ = .035
	B. Crime Control		
GSS72, GSS73, GSS74	Courts		
	Too easy vs. about right	d = -.243	σ = .016
	Too harsh vs. about right	d = .101	σ = .010
GSS73	Police Hit Citizen	d = -.125	σ = .025
	(Base = Disapprove of hitting)		
GSS73	Police Hit Murder Suspect	d = -.093	σ = .048
	(Base = Disapprove of hitting)		

[a]GSS = General Social Survey conducted by National Opinion Research Center.

[b]Analysis was conducted in same manner as in previous tables.

suspect in a murder case?" Here, rating courts as too lenient was strongly associated with supporting capital punishment, and both approving of a policeman striking an adult male in general and of a murder suspect in particular was also associated with supporting capital punishment (see Table 18).

The association between both dissatisfaction with the courts and the greater approval of physical coercion by police can be seen in part as evidence of greater concern over crime control by those who favor capital punishment. Or, to put it another way, tougher courts, more persuasive policemen, and capital punishment are all seen as means of dealing with the crime explosion. This finding is consistent with the relationship reported earlier between political ideology and capital punishment. Liberals are concerned about social justice and conservatives about social control. To deal with social problems in general (the "roots" of crime), liberals favor programs of social amelioration. To conservatives, crime is caused by criminals whose punishment should be swift, sure, and stern. In sum, although there is no evidence of a relationship between criminal victimization and capital punishment, there is strong support for the proposition that support for capital punishment is associated with a concern about crime control.

The second proposition, that concern about crime is related to the level of crime, might well be accepted as axiomatic, but as one bit of proof it is worth noting that while the crime rate rose from 2,423 in 1965 to 4,775 during the first six months of 1974, the proportion considering the courts too lenient climbed from .575 to .842.[10]

Accepting the model as substantiated, we can now consider what is probably the major determinant of the change in attitudes on capital punishment--the rate of change in the murder rate. The homicide rate per 100,000 population fell from 7.1 in 1936 to 4.5 in 1963 and rose to

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[10]The crime statistics are from the Uniform Crime Reports of the Federal Bureau of Investigation. The figures on criminal justice are from Adams (1975).

9.8 in the first half of 1974;[11] The level of opposition to capital punishment rose from .36 in 1936 to .53 in 1966 and then fell to .34 in 1974, a directly inverse relationship. The change in the murder rate does not account for such fluctuations as the drop in opposition in 1953 or the zig-zag from 1966 to 1971, but it does explain nicely the "long swings" from 1936 to 1966 and from 1966 to 1974. In light of this, the change in the murder rate should be considered as a basic determinant of the change in public opinion on capital punishment since 1936.

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[11] Rates from 1936 to 1972 are in Executive Office of the President, Office of Management and Budget, 1973. Rates for 1973 and 1974 are from the <u>Uniform Crime Reports</u>.

APPENDIX 1

USAGES AND QUESTION WORDING[a]

	Wordings	Surveys[b]	Dates
A.	Are you in favor of the death penalty for murder?	AIPO	4/36
		AIPO59	11/36
		AIPO105	11/37
B.	In some countries, a person found guilty of murder is never sentenced to death but is given a long prison term. In most states in this country, a murderer is given the death sentence. Which do you think is the better sentence for a person found guilty of murder in the United States - a long prison term or death?	AIPO397	5/47

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[a]The list here includes only questions asking general approval or disapproval of the death penalty for murder or unspecified serious crimes. Other questions dealing with the death penalty are listed in Erskine, "The Polls: Capital Punishment," pp. 290-307. In addition to the Erskine article the following sources were used to compile this appendix: Survey Data Trend Analysis: An index to Repeated Questions in U.S. National Surveys Held by the Roper Public Opinion Research Center (Williamstown, Ma.: Roper Public Opinion Research, 1975); Hugo Adam Bedau, ed., The Death Penalty in America: An Anthology (Chicago: Aldine, 1964), pp. 231-257; Louis Harris, "Majority of Americans Now Favor Capital Punishment," The Harris Survey, June 11, 1973, p. 1-2;XINDEX, the data archival program of the Social Change Project, National Opinion Research Center; and Gallup Opinion Index, (November, 1974) pp. 3,5.

[b]AIPO = American Institute of Public Opinion (Gallup); Roper = The Roper Organization, Inc.; SRS = Survey Research Service, National Opinion Research Center; HARRIS = Louis Harris and Associates, Inc.; GSS = General Social Survey, National Opinion Research Center; SRC = Survey Research Center, Institute for Social Research.

Wordings	Surveys	Dates
C. Are you in favor of the death penalty for persons convicted of murder?	AIPO522	11/53
	AIPO562	3/56
	AIPO588	8/57
	AIPO625	2/60
	AIPO704	1/65
	AIPO729	5/66
	AIPO746	5/67
	AIPO774	1/69
	AIPO839	10/71
	AIPO846	2/72
	GSS72	3/72
	AIPO860	11/72
	GSS73	3/73
D. Do you think people who are convicted of the worst crimes, like murder, should be executed, or do you think the heaviest penalty given anyone should be life imprisonment?	ROPER	2/58
E. Do you think that having a death penalty for the worst crimes is a good idea or are you against the death penalty?	SRS760	10-11/64
F. Some states have abolished capital punishment - executing persons who commit a murder - and have substituted life imprisonment instead. Do you favor or oppose capital punishment?	Harris	7/66
G. Do you believe in capital punishment (death penalty) or are you opposed to it?	Harris	1969
	Harris	9/70
	Harris	6/73
H. The death penalty for serious crimes should be abolished entirely? 1. Strongly Agree 2. Mildly Agree 3. Mildly Disagree 4. Strongly Disagree	SRC233[c]	1/73
I. Do you favor or oppose the death penalty for persons convicted of murder?	GSS74	3/74

[c]All surveys have the adult population as their base except for SRC233 which covers employed persons only.

Wordings	Surveys	Dates
J. Suppose that on election day, November 5, you could vote on key issues as well as candidates. Please tell me how you would vote on each of these 14 propositions. Proposition 2: I favor the death penalty for persons convicted of murder. I oppose the death penalty for persons convicted of murder.	Gallup	10/74

APPENDIX 2

QUESTIONS RELATING TO THE REASONS AND CONDITIONS FOR SUPPORTING OR OPPOSING CAPITAL PUNISHMENT[a]

Date	Survey[b]	Questions	Responses
2/68	AIPO	A. Now, on another subject... Do you have any conscientious or religious scrupples against the death penalty?	
		Yes.............34%	
		No..............65%	
		Don't Know...... 1%	(1504)
		IF YES, ASK: Here are three statements. Please read them and tell me which comes closest to your views on the death penalty.	
		1. If I were a juror on a murder case, I would never under any circumstances vote for the death penalty, no matter how horrible the crime........................18%	
		2. If I were a juror on a murder case, I would vote for the death penalty only if it were a horrible murder and a most terrible murderer.........................7%	
		3. If I were a juror on a murder case, I would vote for the death penalty only very reluctantly, if there were no mitigating circumstances.......................6%	
		Don't Know............................3%	
		34%	

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[a]The sources are Hans Ziesel, Some Data on Juror Attitudes Toward Capital Punishment (Chicago: Center for Studies in Criminal Justice, University of Chicago Law School, 1968), pp. 7-9, Louis Harris, "Majority of Americans Now Favor Capital Punishment," The Harris Survey, (June 11, 1973), pp. 1-3, and Louis Harris "Through Public Favors Death Penalty, Most Would Use it Sparingly," The Harris Survey, (June 14, 1973), pp. 1-2.

[b]AIPO = American Institute of Public Opinion, Harris = Louis Harris and Associates, Inc.

Date	Survey	Questions	Responses
6/73	Harris	B. Do you believe in capital punishment (death penalty) or are you opposed to it?	
		Believe in	59%
		Opposed	31%
		Not Sure	10%
			(1537)
		C. Do you feel that the death penalty is more effective (a better deterant) or not more effective than (READ LIST) in keeping other people from committing such crimes as murder?	
		Life sentences with possible parole	
		More effective	56%
		Not more effective	32%
		Not Sure	12%
		Life sentences without parole	
		More effective	57%
		Not more effective	29%
		Not Sure	14%
		D. Now, I'd like to read you some statements other people have made about why they support capital punishment. For each one would you tell me if it represents your own view completely, fairly well, only slightly, or not at all?	
		Capital punishment is more effective than other penalties in keeping people from committing crimes.	
		Reflects own view	61%
		Does not	33%
		Not Sure	6%
		A government which cannot execute criminals is going to become weak and lose the respect of the people.	
		Reflects own view	49%
		Does not	42%
		Not Sure	9%

Date	Survey	Questions	Responses

D. Continued

The Bible is right when it preaches "an eye for an eye and a tooth for a tooth."

Reflects own view..............40%
Does not.......................49%
Not Sure.......................11%

Someone who has committed a terrible crime such as murder is an animal and deserves to be executed.

Reflects own view..............41%
Does not.......................51%
Not Sure....................... 8%

E. Suppose it could be proven that your satisfaction that the death penalty was no more effective than long prison sentences in keeping other people from committing crimes such as murder, would you be in favor of the death penalty or would you be opposed to it?

Favor..........................35%
Oppose.........................48%
Not Sure.......................17%

F. Do you feel that <u>all</u> persons convicted of (READ LIST) should get the death penalty, that no one convicted of (ITEM ON LIST) should get the death penalty, or do you feel that whether or not some convicted of (ITEM ON LIST) gets the death penalty should depend on the circumstances of the case and the character of the person?

First degree murder

All............................28%
No one.........................16%
Depends........................53%
Not Sure....................... 4%

Date	Survey	Questions	Responses
		G. Suppose you were being considered as a possible juror for a trial where if the person were convicted of the crime he would automatically get the death penalty. If the job of the jury were just to decide whether or not the person was guilty, which statement on this card best describes how you would feel in advance of trial?	
		If guilt were proven, I could always vote guilty even though the defendant would automatically receive the death penalty...........	39%
		I could not say in all cases, even if guilt were proven, that I would vote guilty, knowing the defendant would automatically receive the death penalty...........	33%
		I could never vote guilty, even if guilt were proven, knowing the defendant would automatically receive the death penalty...........	16%
		Not Sure........................	12%

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A CASE STUDY IN AMERICAN SOCIAL CHANGE: PARTY IDENTIFICATION, 1952-1972

D. Garth Taylor

March 1974

This paper was part of a series entitled "A Survey Metric Model of Social Change." Appreciation and thanks are due to a number of persons: Karen Newman Gaertner shouldered the thankless task of initially retrieving the data; John Fry wrote computer programs without which this would have been a lost cause; and James A. Davis engaged in discussions from which this effort benefited greatly.

Trend Analysis for Party Identification in Regions, Cohorts, and Educational Groups--Zero-Order Data

The current interest in trend analysis has produced a number of projects for the study of change over time. Since Duncan's article for The Russell Sage Conference on Social Indicators (Duncan, 1969), there have been numerous projects funded to retrieve and replicate questions from earlier studies. Methodologies are being developed to treat time as a substantive variable in the analysis of change in qualitative data. The research reported here is part of one of those projects and the techniques employed are some of those new methodologies. We have chosen an almost prosaic substantive area--party identification--one that has been handled annually in reports stemming from analyses of the University of Michigan Survey Research Center's series of election studies starting in 1948. We propose to take data from all the SRC studies since 1952 and to trace the growth of the segment of the population that identifies with neither of the major political parties--the problematic Independent sector. Our data come from responses to a question repeated on all the SRC studies. The exact question wording is as follows:

> Generally speaking, in politics do you usually think of yourself as a Republican, a Democrat, an Independent, or what? (If Republican or Democrat) Would you call yourself a strong (R) (D)? or not very strong (R) (D)? (If Independent or other) Do you think of yourself as closer to the Republican or Democratic party?

The response categories were:

SRC Response Category	Recoded for Present Analysis
Strong Democrat Not very strong Democrat	Democrat
Independent Democrat Independent Independent Republican	Independent
Strong Republican Not very strong Republican	Republican
Other, Minor Party, Apolitical, Refused, NA	Excluded

As we will see, most substantive statements about the proportional representation of Republicans and Democrats make little sense unless one also considers the increasing weight which must begiven the non-party-identified sector. The first step is to determine some general contour to the phenomenon we shall explore. When feasible, our method will be to look at the relative sizes of the Democratic or Republican constituencies, not only as they compare to each other, but compared to the Independent category as well. In many cases, we will trace these ratios over time and will attempt to determine how much gain or loss of membership in either of the major parties is due to changes in the composition of the Independent group and how much is actual crossover from one party to another.

Two of the goals of this paper involve determining trends of social change in the recent past, if possible, and making projections into the near future of what we would expect to occur if roughly the same social circumstances were to obtain in, say, 1974 as obtained in the preceding ten or fifteen years.

In estimating trend equations, it seems to be a fact of life that the unique situations, crises, and personalities of any single year will be glossed over in the minimization of the squared residuals. There is a trade off between (a) using all the data you have which would preserve enough detail to be relevant to individual years, and (b) not using so much data that you lose track of meaning.

Substantively, there are four time spans that should be examined. First, there is the whole time period: when possible, we should attempt to use all the data and talk about changes over the last 22 years. It may be, however, that certain processes that we are currently experiencing were not set in motion until 1960, the early Kennedy-Johnson years. Thus, 1960 to the present would be a second time span to examine. There is a third time span of interest, from 1964 to the present. The 1964 campaign has been described as a "critical election" (Converse, 1965) and a "time of greatly increased ideological constraint" (Nie, 1974). It may be that certain relationships and trends were not established until that time. Finally, regional strategies and different styles of campaign appeal were inaugurated in the 1968 campaign, which may have slowed the erosion of party strengths or may have created new alignments, suggesting a fourth time span of interest. In order to keep this paper to a manageable length, we propose not to examine each time span for each set of controls presented. Instead, we will pursue the time honored strategy of examining the data for linearity and presenting those linear trends that make sense, subject to the substantive and statistical constraints mentioned above.

The first illustration of the technique is presented in Figure 1. Figure 1 has three parts: part (a) shows the proportion of Republican voters to Independents as a function of time; part (b) shows the proportion of Democrats to Independents over time; and part (c) shows how the ratio of

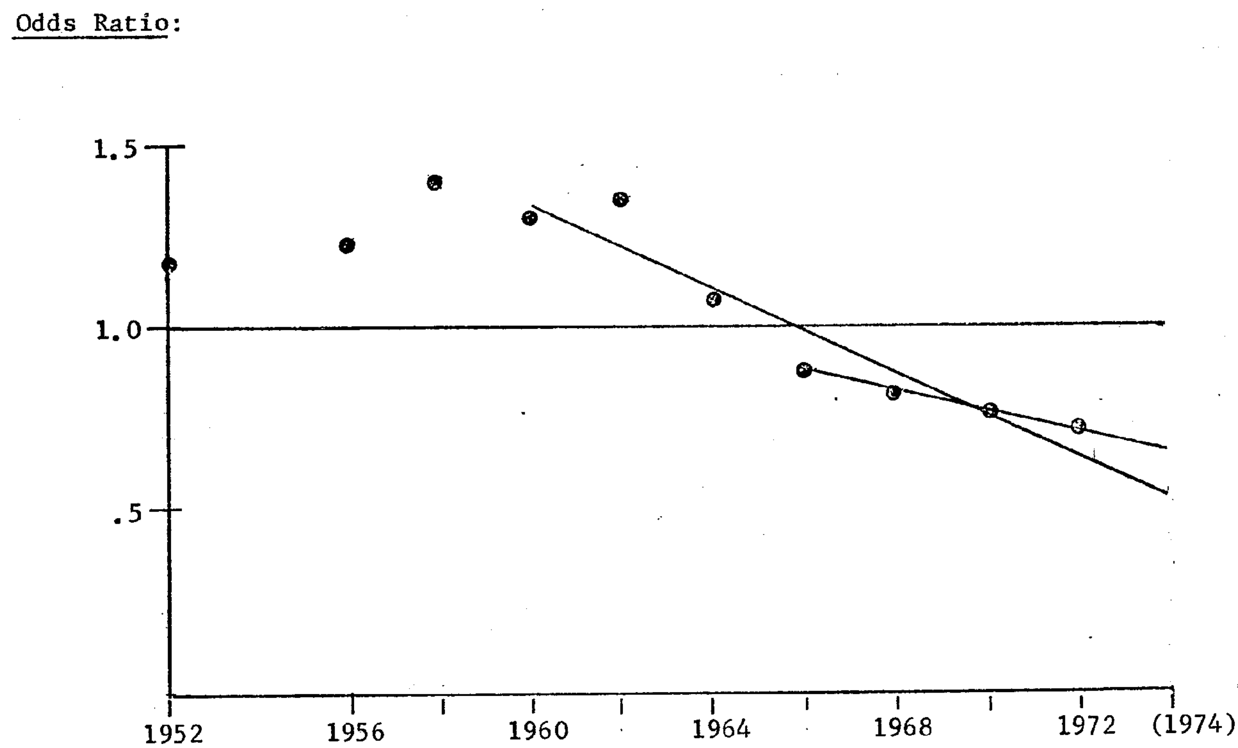
Republicans to Democrats changed in the national elections of the last two decades. Examining Figure 1, we see that both the Democratic and the Republican parties have been steadily losing strength to the Independent category. Over recent years there may have been a slight increase in the proportion of Republicans to Democrats, but the impression from Figure 1 is that this is because the Republicans have been losing people at a slower rate, although the absolute level of identification with either party is declining.

Looking at the data in Figure 1, for example, an interesting social indicator might be the rate at which the major parties are losing people. For the Democrats, the 1950s show a lot of "bounce," and a trend does not seem to assert itself until the early 1960s. It appears that the losses for Republicans have been fairly monotonic since 1956. Since 1960, the ratio of Republicans to Independents has been declining at the rate of .057 points a year. Fitting a least squares line to the data in Figure 1 part (a) gives the equation:

$$\text{Proportion Rep/Ind} = 1.33 - .057 * (\text{year of study} - 1960) \qquad (1)$$

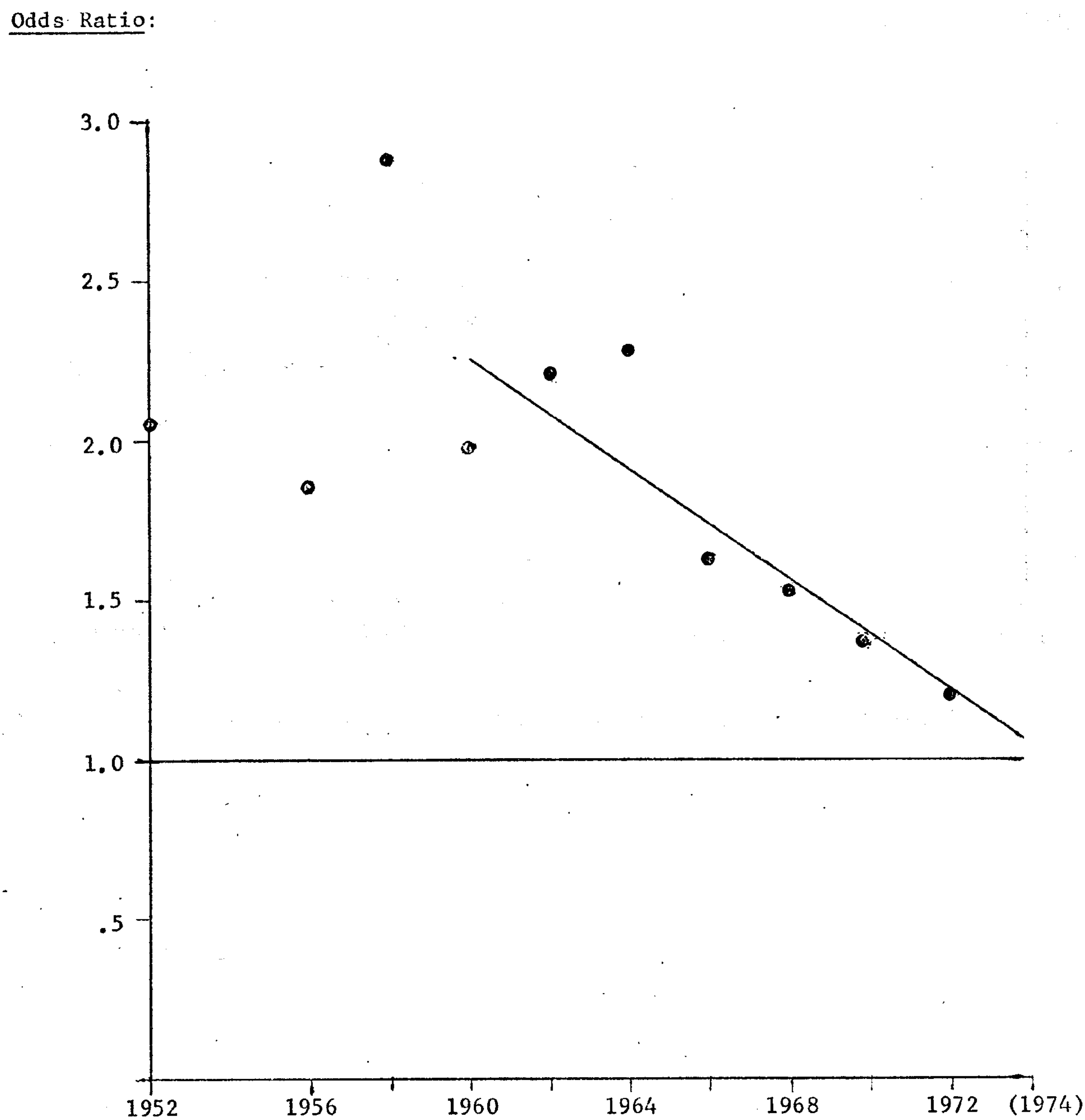
This is the regression of the proportion of Republicans to Independents on time. It says, in English, that the proportion of Republicans to Independents equals 1.33 minus .057 times the quantity (the year the study was done minus 1960). It is interesting to note that, using this equation for 1974, we would predict the proportion of Republicans to Independents to be .532. This may be too liberal an estimate. In Figure 1, we have actually fitted two trend equations, one since 1960 (equation 1, above) and another using data from 1966 to 1972. In the latter case, the slope is less negative and the predicted value for the ratio of Republicans to

Figure 1.--Regressions of Ratios of Political Parties over Time



(a) Total Number of Republicans to Total Number of Independents

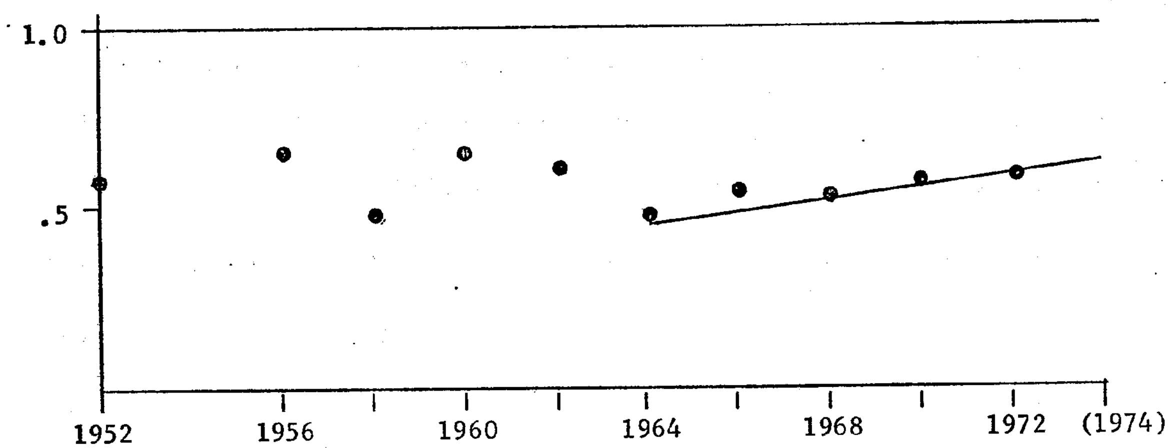
Figure 1.--(Cont.)



(b) Total Number of Democrats to Total Number of Independents

Figure 1.--(Cont.)

Odds Ratio:



(c) Total Number of Republicans to Total Number of Democrats

Note: When the fitted regression lines are solid lines, as in Figure 1 and in many subsequent graphs, it means that the slopes were calculated using data from all years between the end points of the line. We point this out because later in the report we will be interested in trends calculated using data from only those years when there was no presidential election; these equations will be represented by a dashed line (see, for example, Figure 3).

Independents is .654. We know of no criterion that would tell us which trend is the real thing, i.e., which one is right. Part of the purpose of this report is to raise just this sort of question and, hopefully, to lay some substantive and methodological ground rules for our own study of social change.

A similar analysis of the data in Figure 1, part (b), suggests that the Democrats have been losing strength, compared to the Independents, at the rate of .085 units a year. The trend equation is:

$$\text{Proportion Dem/Ind} = 2.25 - .085\ (\text{year of study} - 1960) \qquad (2)$$

This rate is actually greater than the rate of Republican losses. The predicted value for 1974 is 1.07.

Part (c) of Figure 1 shows a great deal of stability. We are inclined to say that the proportion of Republicans to Democrats has been fairly constant over the last two decades at around .57. Substantive reasons, however, lead us to suspect that the apparent upswing since 1964 is not just the result of irregularities of sampling procedure. The slope during this period is .013. It may be that this apparent increase is due to the differences between the rates (slopes) at which each party is losing strength: since the Republicans are losing more slowly than the Democrats, they show a net increase in proportional terms. This trend is apparent in many social groups, as we shall see when we introduce control variables.

Cohort Analysis

There has been considerable debate about the effects of cohort and aging on party identification (Cutler, 1969, Klecka, 1971). For purposes of this analysis, we have defined three cohorts and have traced their patterns of party identification. A brief review of the literature did not suggest any "right" way to group cohorts, or even any particular way that most researchers would agree upon. The cohorts in this report are defined as follows:

1) The Older or World War I Cohort: those born before 1907. Members of this cohort reached age 16 in 1922 or before.

2) The Middle or Inter-War Cohort: those born between 1907 and 1923, socialized in the decades between World War I and World War II.

3) The Younger or World War II/Cold War Cohort: those born 1924 and later.

The data for the cross-tabulation of cohort by party by year are presented in Table 1. This table gives some idea of the absolute number of cases we are talking about in our discussion of proportions. The results for plotting proportional party identification against time are fairly inconclusive for the old and middle cohorts; there is so much bounce that any linear fit would have a standard error several times larger than the slope. We do find that the general trend observed in our discussion of Figure 1 holds for both the old and the middle cohorts. If we collapse year into two categories (before and after 1965), instead of using all ten, the trend becomes more apparent.

Table 2 presents the cross-classification of party identification by year for the older cohort when year is dichotomized (i.e., collapsing the data in Table 1). Looking only at the data for Republicans and Independents (the top two rows of Table 2), we can determine how much the proportion of Republicans to Independents changed over the two time periods by computing the cross-product ratio, using equation (3).

$$\frac{528 * 448}{1106 * 283} = .755736 \qquad (3)$$

TABLE 1

CROSS-TABULATION OF COHORT, PARTY IDENTIFICATION, AND YEAR OF STUDY

Year of Study	Cohort								
	Old			Middle			Young		
	Party Identification								
	Demo-cratic	Inde-pendent	Repub-lican	Demo-cratic	Inde-pendent	Repub-lican	Demo-cratic	Inde-pendent	Repub-lican
1952	324	156	249	366	166	167	135	79	56
1956	232	112	212	333	164	193	188	129	96
1958	313	76	170	302	102	144	190	102	81
1960	186	73	161	230	127	139	183	104	95
1962	167	49	152	228	85	112	199	134	98
1964	234	62	162	333	141	141	381	211	146
1966	126	66	92	211	103	103	240	187	120
1968	200	63	117	261	152	151	373	326	172
1970	144	78	103	250	118	142	371	360	186
1972	180	76	136	312	168	181	544	618	294

Source: SRC Presidential Series.

TABLE 2

COLLAPSED VERSION OF TABLE 1 FOR THE OLD COHORT ONLY

Party	1952-1964	1966-1972
Republican	1,106	448
Independent	528	283
Democratic	1,456	647

For most of this report we will work with ratios and cross-product ratios. These are easy to calculate, not far removed from the data, and can be easily normed to the Q statistic by the following formula:

$$\frac{\text{Ratio} - 1}{\text{Ratio} + 1} = Q \qquad (4)$$

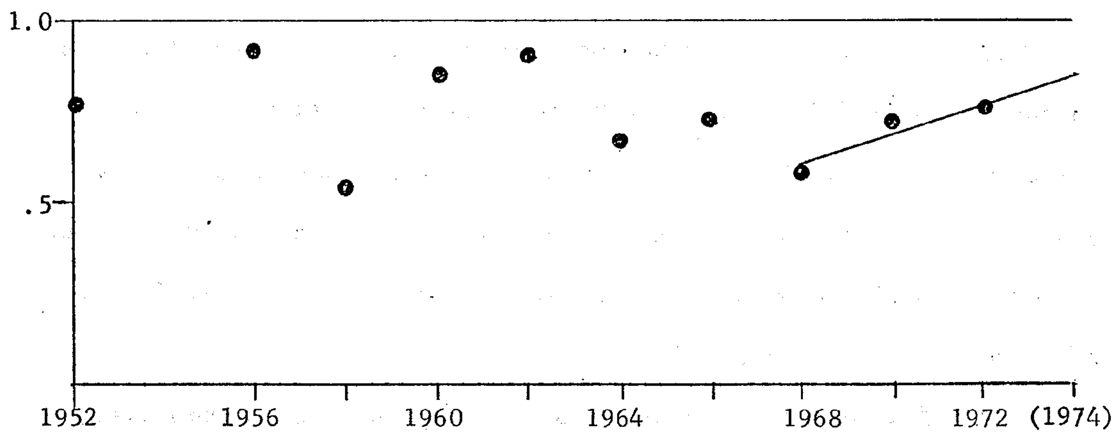
Using this formula, Yule's Q for the cross-product ratio of Republican to Independent in Table 2 is -.139, a weak negative correlation, indicating that the proportion Republican to Independent in the old cohort is negatively associated with time, or, put another way, that the old cohort tends to feel less identification with the Republican Party, to the benefit of the Independent category, over time.

Other collapses of the data in Table 1 may be made to show changes in proportion from (a) Democratic to Independent for the old cohort, (b) Republican to Independent for the middle cohort, and (c) Democratic to Independent for the middle cohort. Table 3 shows the correlations (cross-product ratios) for each of these ratios and time, and their value when normed to Q. The Q's are all negative, further evidence for an across-the-board decrease in party identification. Moreover, comparing the magnitudes of the correlations suggests that (1) the older cohort is deserting the Republican Party much faster than the middle cohort (which may not be changing at all), and (2) both cohorts seem to be deserting the Democratic Party at about the same rate.

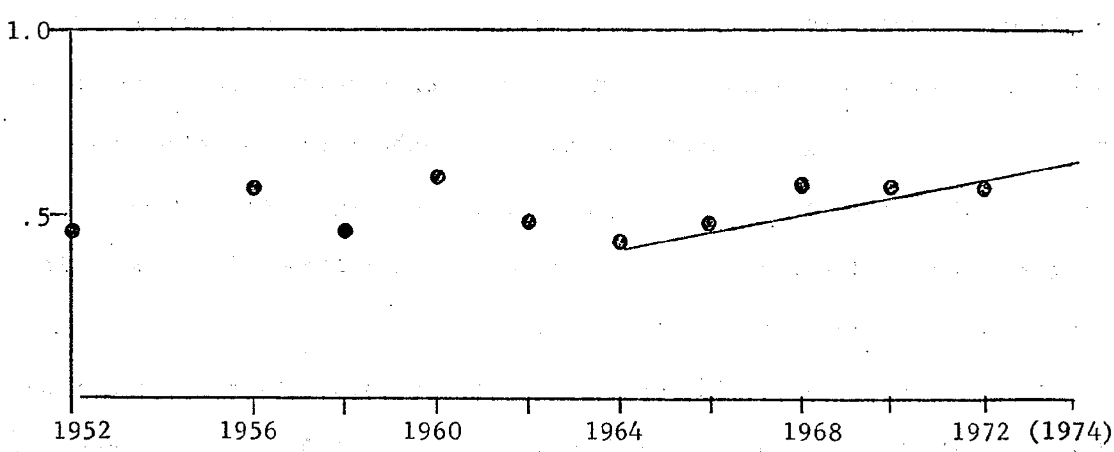
In the discussion of Figure 1 we noted a possible trend of the proportion of Republicans to Democrats increasing since 1964. Figure 2 confirms the possibility. The data in Figure 2 show that the proportion of Republicans to Democrats has been climbing slowly for the middle cohort since 1964

Figure 2.--Regressions of the Ratio of Republicans to Democrats on Time for Older and Middle Cohorts

Odds Ratio:



(a) Older Cohort



(b) Middle Cohort

and more noticeably for the older cohort since 1968. Figure 3 presents the data for the young cohort; this trend is also apparent for that group.

TABLE 3

ODDS RATIOS AND Q'S FOR ASSOCIATIONS BETWEEN PARTY IDENTIFICATION AND TIME

Cross-Tabulation	Cohort	
	Old	Middle
Republican/Independent * year	Odds ratio = .756 (Q = -.139)	Odds ratio = .934 (Q = -.034)
Democratic/Independent * year	Odds ratio = .829 (Q = -.093)	Odds ratio = .837 (Q = -.089)

Table 4 presents a smmmary of the slopes, intercepts, and predicted values in 1974 for the cohort trends in party identification which we have just discussed. Since all three slopes are positive, it is possible to attribute the trend to an "aging" effect--that is, as each cohort becomes older it also attains a higher proportion of Republicans to Democrats. However, the greater incidence of Independent identification could also be considered an aging effect, since it is omnipresent as well. Consequently, we must be chary of any simple equation of aging and conservatism.

TABLE 4

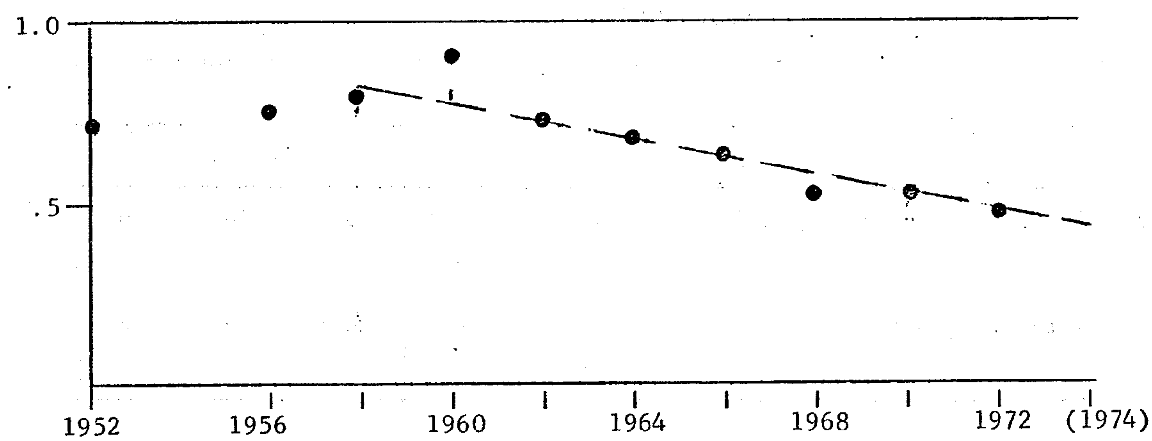
MAJOR PARTY IDENTIFICATION TREND DATA FOR THREE COHORTS

Cohort	Slope	Intercept	Time Interval	Predicted Value for 1974
Old . . .	.043	.605	1968 - 1972	.861
Middle .	.02	.449	1964 - 1972	.646
Young . .	.016	.414	1964 - 1972	.572

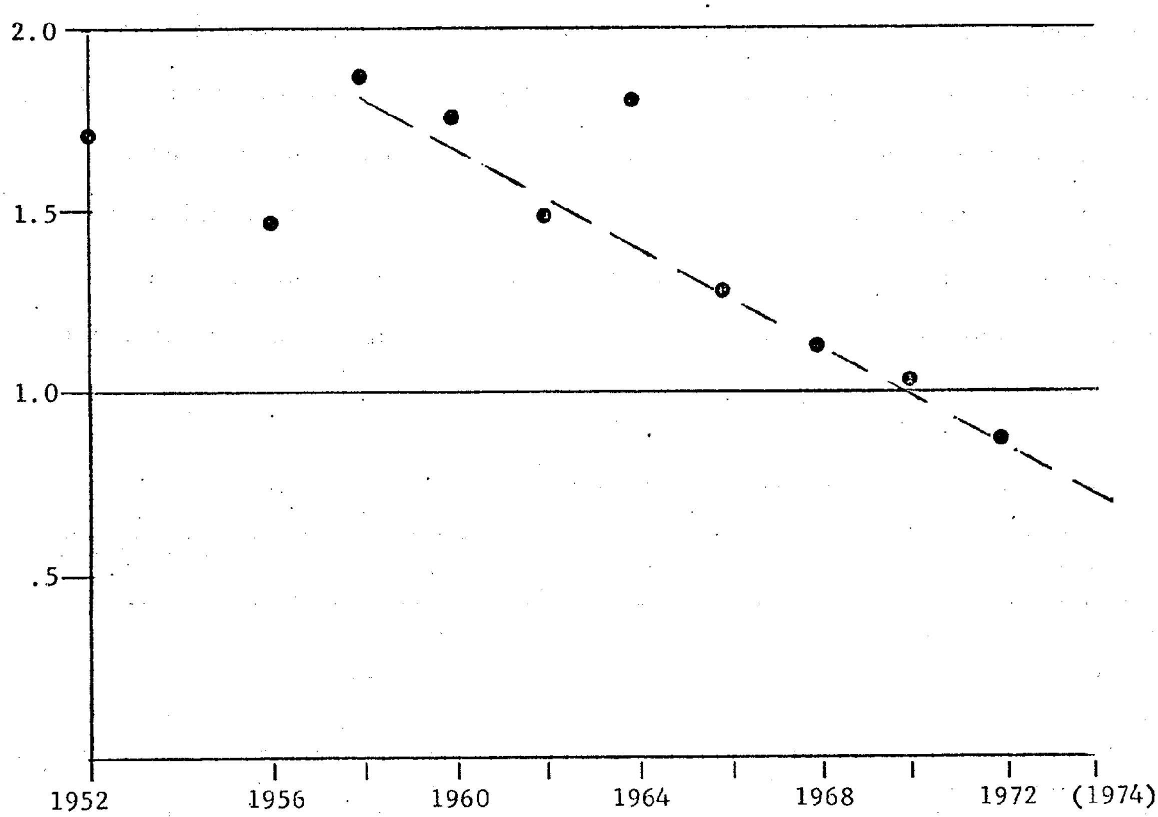
Note: Different time intervals have been used for the different cohorts. In this case we have not presented an exact replication of measurement procedures, to allow for trends that seemed more "real" to us after inspecting the data.

Figure 3.--Plots and Regression Lines for Ratios of Party Identification in the Young Cohort

Odds Ratio:

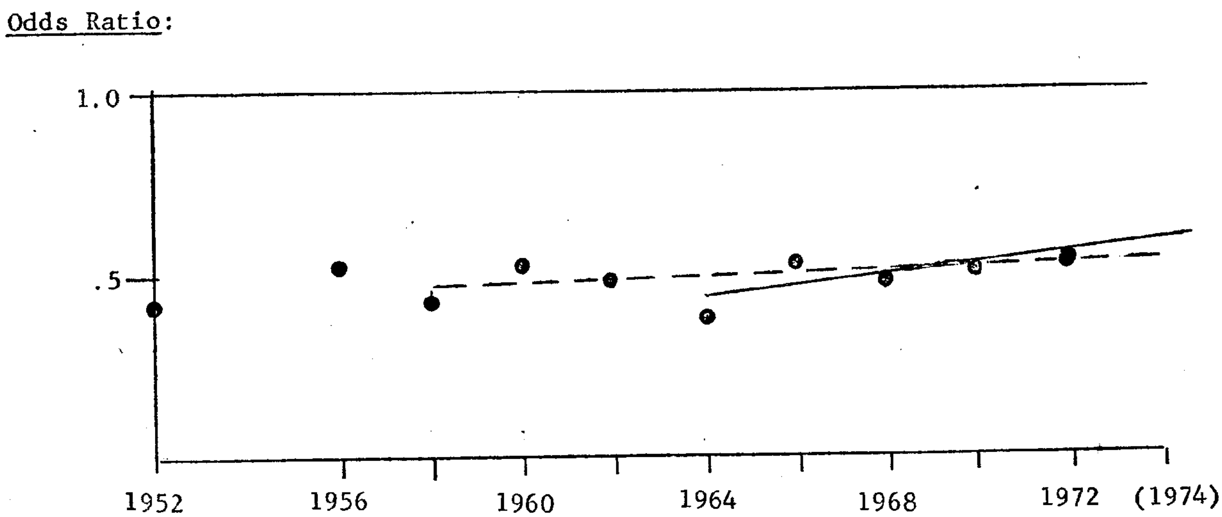


(a) Proportion Republican to Independents, non-Presidential Election Years



(b) Proportion Democratic to Independents, non-Presidential Election Years

Figure 3.--(Cont.)



(c) Proportion Republican to Democratic, non-Presidential Election Years, and Since 1964 (Solid Line)

Note: The dashed line indicates that the least-squares line was fitted to data from non-presidential years only.

So far we have not discussed Independent identification in the young cohort. The data in the first two parts of Figure 3 are especially receptive to an across-time treatment. First, there is a linear trend that is more pronounced in non-presidential years. There is some theoretical justification for considering non-presidential years as more sensitive to long-term changes in the electorate (see Campbell in Campbell, et al., 1966). We will therefore fit trend lines for the data at four-year intervals, starting with 1958. This trend is particularly interesting because in 1972 there were, for the first time, more Independents than either Republicans or Democrats in the young cohort. The results from fitting least squares trend lines to the data in Figure 3 for non-presidential years are presented in Table 5. It is interesting that, using the off-year statistics, we still predict a slow increase in the proportion of Republicans to Democrats, although the slope and predicted values for 1974 are not as large as those presented in Table 4.

TABLE 5

DATA FROM LEAST SQUARES REGRESSIONS OF RATIOS OF PARTY IDENTIFICATION FOR THE YOUNG COHORT

Ratio	Slope	Intercept	Time Span	Predicted Value in 1974
Republican/ Independent	-.023	.809	Non-presidential series	.44
Democratic/ Independent	-.067	1.82	Non-presidential series	.741
Republican/ Democratic	.006	.445	Non-presidential series	.538

Perhaps the way to describe the difference between the two projections we have made for 1974 is to make the following kind of statement: There are at least two trend components that will help determine the ratio of Republicans to Democrats among the young cohort in 1974. One is the slope of about .02, which has described this ratio since 1964. The other component is the more long-term trend, using data from all the years in which there were no presidential elections. The slope in this case is about .01. If the first component is "stronger" in 1974, we predict that the observed ratio will be near .572. On the other hand, 1974 is a non-presidential year, and may be more accurately predicted by the off-year equation, giving a value of .538. Or it may be that both predictions are off base. The problem, in principle, is to incorporate more parameters in the model of prediction.

We will summarize our discussion with Table 6, which presents the slopes, intercepts, and ratios that we have found to be important for a description of change in party identification among the different cohorts. Table 6 is the type of table that we will present for each control variable introduced. The data from these summary tables form an abbreviated reader's guide to social change in party identification in the past two decades.

Given the data in Table 6, the political analyst needs one more set of facts to make gross predictions about the absolute numbers of Democrats, Republicans, and Independents in the near future. Each of the trend statements must be weighted by the proportion of the total population that each cohort is expected to represent. Analysis reported elsewhere (Davis, et al., 1974) indicates that, in comparing the old and middle cohorts, the proportion of old to middle has been steadily declining. In fact, this ratio is very accurately represented by the following equation:

$$\text{Ratio of old/middle for U.S.} = .99 - .02 * (\text{year of study} - 1952) \quad (5)$$

Starting in 1952, there were just as many members of the old cohort as of the middle cohort in the SRC sample. But this ratio has been declining at the rate of 2 points a year, so that in 1974 we predict that the proportion of old to middle will be about .55.

TABLE 6

SUMMARY OF PARTY IDENTIFICATION TREND DATA

Party Identification	Old	Middle	Young
Republican/ Independent	time span: pre-1965 vs. post-1965 O.R. = .76 (Q = -.14) regression is nonlinear	time span: pre-1965 vs. post-1965 O.R. = .93 (Q = -.03) regression is nonlinear	time span: pre-1965 vs. post-1965 O.R. = .69 (Q = -.19) time span: non-presidential election years slope = -.023 intercept = .81
Democratic/ Independent	time span: pre-1965 vs. post-1965 O.R. = .83 (Q = -.09) regression is nonlinear	time span: pre-1965 vs. post-1965 O.R. = .84 (Q = -.09) regression is nonlinear	time span: pre-1965 vs. post-1965 O.R. = .61 (Q = -.24) time span: non-presidential election years slope = -.067 intercept = 1.8
Republican/ Democratic	time span: pre-1965 vs. post-1965 O.R. = .91 (Q = -.05) regression time span = 1968-1972 slope = .043 intercept = .61	time span: pre-1965 vs. post-1965 O.R. = 1.12 (Q = .06) regression time span = 1964-1972 slope = .02 intercept = .45	time span: pre-1965 vs. post-1965 O.R. = 1.13 (Q = .06) time span: non-presidential election years slope = .006 intercept = .45 time span: 1964-1972 slope = .016 intercept = .41

When the same type of analysis is done on the ratio of members of the young to middle cohorts over time, the data are most accurately described by an exponential regression:

$$\text{Ratio of young/middle for U.S.} = .41 * e^{((.08)*(\text{year of study}-1952))} \qquad (6)$$

This curve can be loosely described as increasing over time with a positive acceleration.

In considering the data in Table 6, then, we are saying that the middle and young cohorts should be given more weight in determining the absolute numbers of Democrats, Republicans, or Independents in any political forecast. There is a precise way of taking the information from equations (5) and (6) and the information from Table 6 and combining them in such a way that, for any sample size in any year, we could predict the number of people who would identify themselves as belonging to one of the three parties. This technique is described in Davis (1974), and we will not develop the model here.

For other types of analysis, it may be desirable to control for the changing cohort composition in the population and for the different patterns of party identification in each cohort when examining the effects of other control variables. This would be done by partial correlation techniques. We will present ways of analyzing partial relationships between predictor variables and party identification in the second part of this report. For now we will concern ourselves with the overall trends that set the fabric for the later discussion.

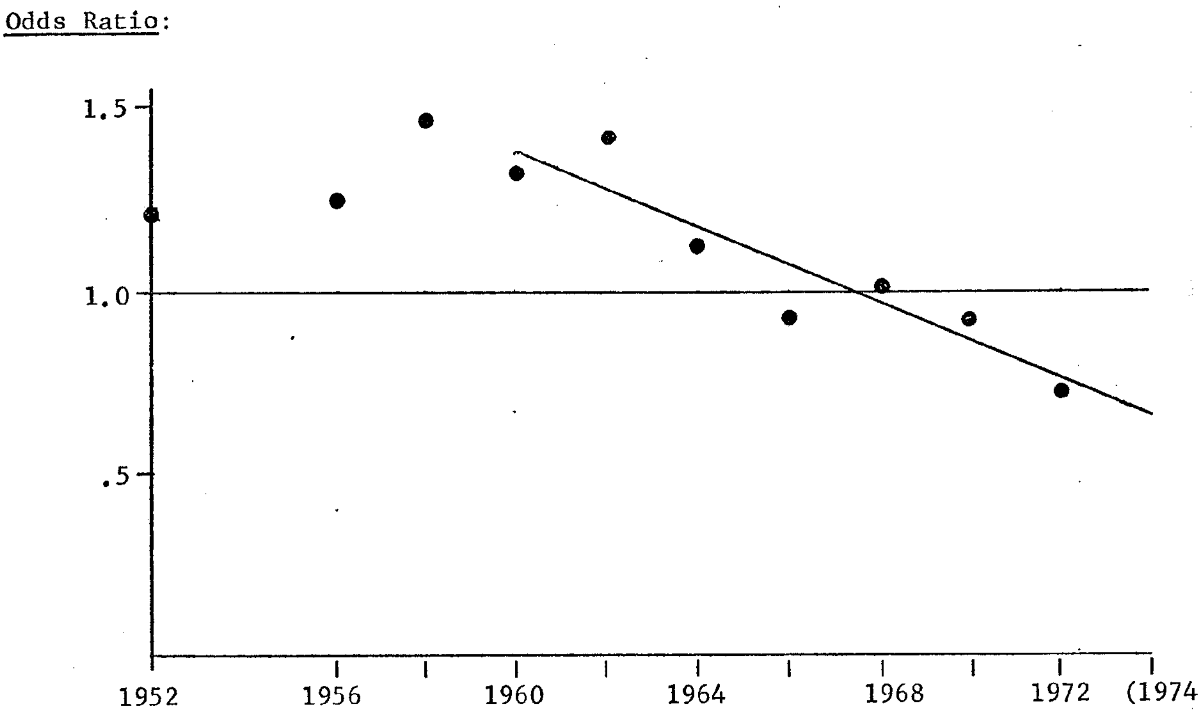
Region Analysis

We turn now to the second variable in our general model of demographic controls--region. We have dichotomized this variable into (1) South, which includes states described as border states in the usual SRC classification, and (2) non-South, which includes everything else.

The same patterns that characterized the regular erosion of party identification in the three cohorts also seem to occur in the non-southern states. The plot is given in Figure 4. A decline in identification with either party since 1960, and an increase in the proportion Republican to Democrat since 1964, are the conclusions we must draw from the data. The absolute frequencies of the cross-tabulation of region by party by year are presented in Table 7, and the slopes, intercepts, and other minutiae from Figure 4 are given in Table 8. The results here bear speculation from two perspectives.

First, we may legitimately ask how much of the change observed in regions is due to the different cohort composition of the regions. From analysis of the SRC data which has been reported elsewhere (Davis, et al., 1974), investigation has shown (1) older cohorts tend to be more "southern" in any specific year, and (2) over time, there is a tendency for the population to move to the South, which applies to all cohorts with approximately equal strength. In determining whether the region of one's residence affects the likelihood of one's party choice, it would be desirable to control for the changing cohort composition of that region over time. Part II will attempt to treat this question more fully.

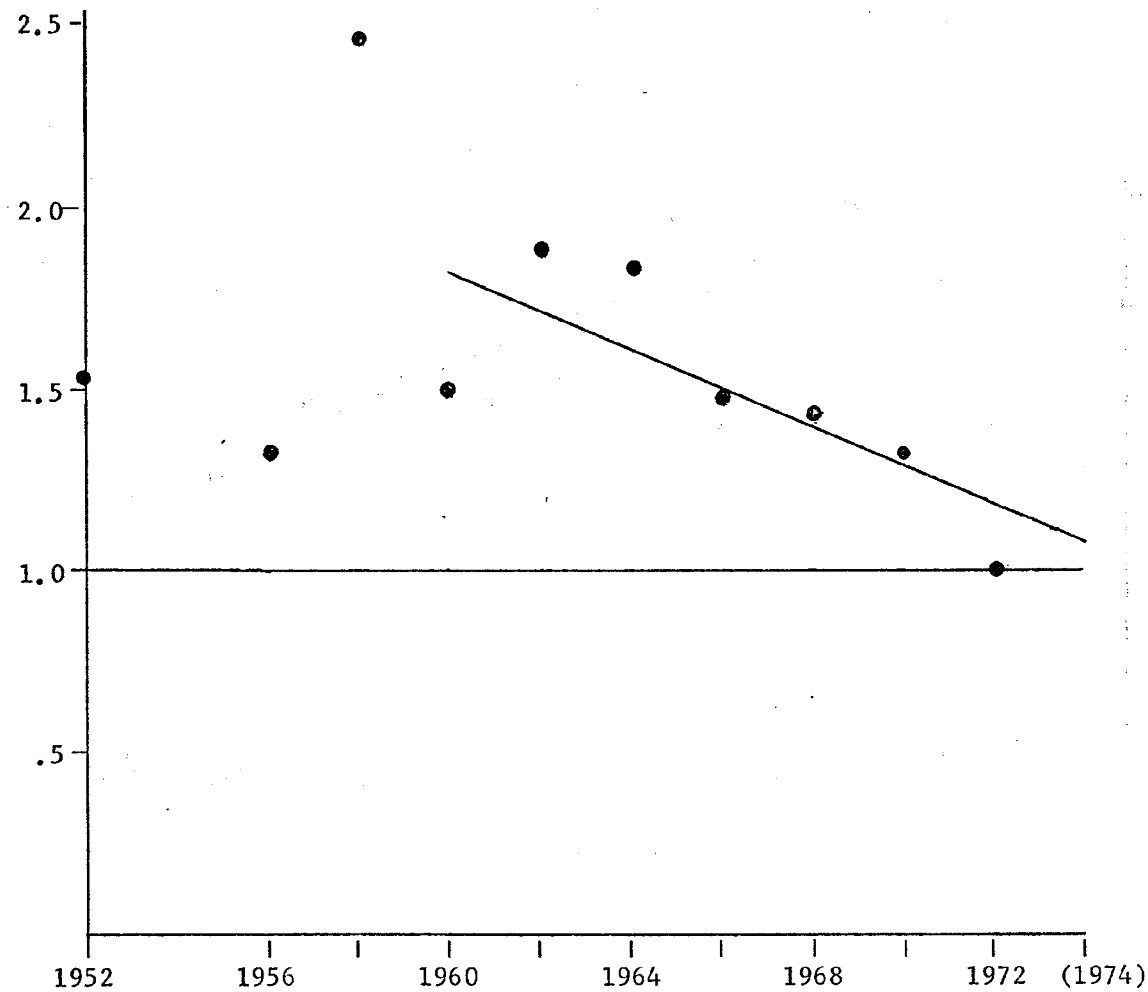
Figure 4.--Plots of Regression of Ratios of Party Identification in the Non-Southern States



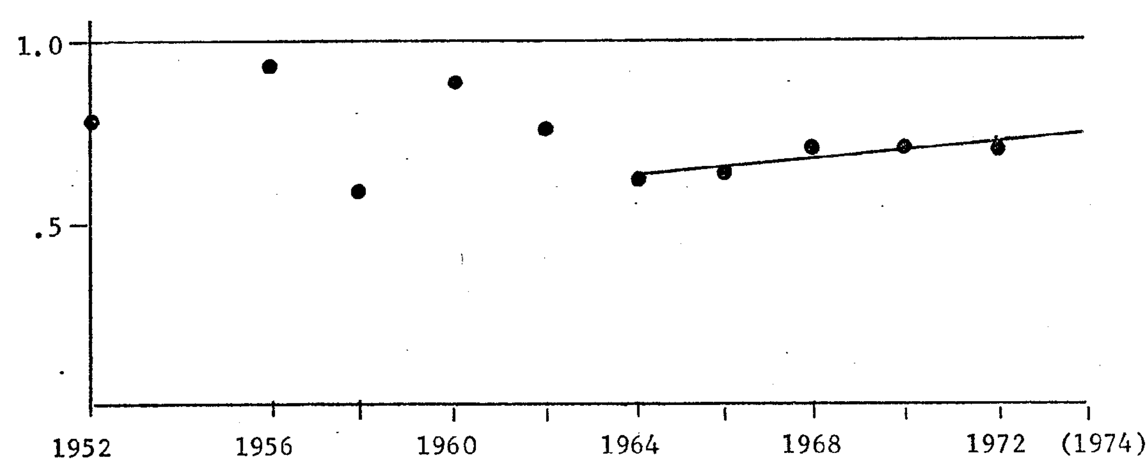
(a) Republican to Independent

Figure 4.--(Cont.)

Odds Ratio:



(b) Democrat to Independent



(c) Republican to Democrat

TABLE 7

CROSS-TABULATION OF REGION, YEAR OF STUDY, AND PARTY IDENTIFICATION

Year of Study	Non-South			South		
	Democrat	Inde-pendent	Republican	Democrat	Inde-pendent	Republican
1952	512	331	405	313	70	67
1956	450	334	419	303	71	82
1958	540	218	321	265	62	74
1960	343	227	302	256	77	93
1962	354	188	266	240	80	96
1964	595	322	365	353	92	84
1966	381	260	246	196	96	69
1968	523	364	367	311	177	73
1970	472	353	331	290	203	100
1972	618	615	444	418	247	167

Source: SRC Election Series.

TABLE 8

PARTY IDENTIFICATION TREND DATA IN THE NON-SOUTHERN STATES

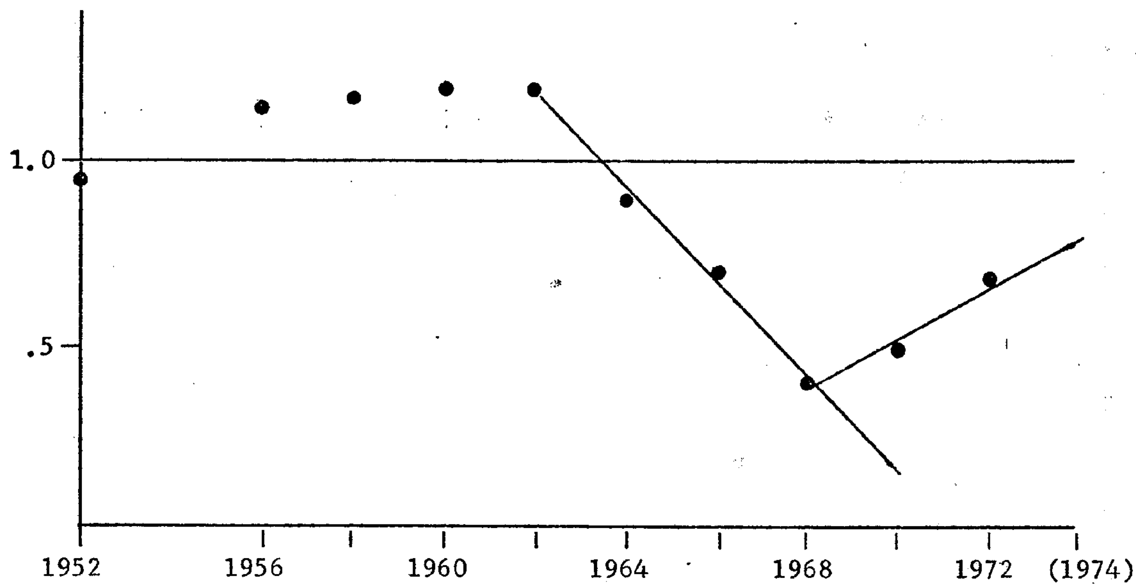
Party Identification	Ratio			
	Slope	Intercept	Time Span	Predicted Value in 1974
Republican/Independent	-.052	1.38	1960-1972	.655
Democrat/Independent	-.054	1.82	1960-1972	1.07
Republican/Democrat	.013	.623	1964-1972	.756

Secondly, the trends are different in the South, which should not come as a shock. The patterns of party identification show some rather striking changes. Interestingly, the changes are all in the same direction as observed in the non-southern states; they are simply more striking magnifications of these trends. Figure 5 shows the regression of the relevant ratios on time. Most spectacular is the decline in the proportion of Democrats to Independents. This ratio drops at the rate of .17 points a year over the 20-year span. The upward turn in 1972 may signify a new trend, or it may be only an idiosyncratic "bounce" much like the deviation for 1964.

Another interesting turn of events is depicted in parts (a) and (c) of Figure 5. Between 1956 and 1962, the Republicans showed a small but stable edge over the Independents. The mean ratio of Republican to Independent for this period is 1.19. Because of the precipitous decline in identification with the Democratic Party, the proportion of Republicans to Democrats was rising during this period at the rate of .024 points a year [part (c)]. But in 1962, the ratio of Republicans to Independents also began to drop at the rate of .13 units a year, almost as large as the loss in the Democratic Party [part (a)]. The net result of these shifts in party identification was that, in 1964, the proportion of Republican to Democrat was .21 points less than would have been expected on the basis of the trend in the preceding eight years (Table 9). In 1968, the Republican representation in the South seems to have taken another strategic swing, this time back up. At this point the ratio of Republicans to Independents begins to approach 1.00, the predicted value for 1974 is .79, and the proportion of Republicans to Democrats also begins to rise. Depending on the equation we use, the predicted proportion of Republicans to Democrats in 1974 will be between .41 and .49.

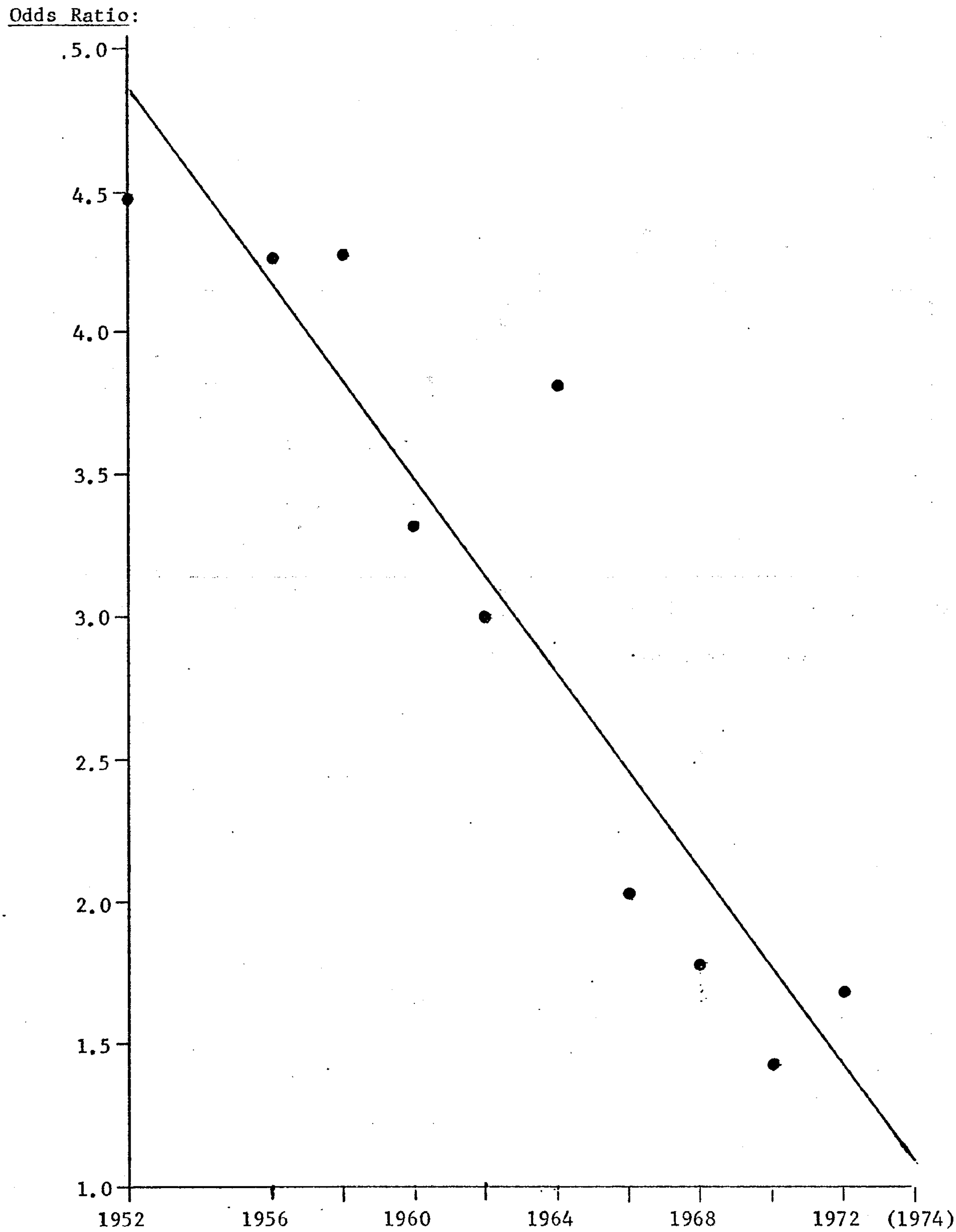
Figure 5.--Plots of Regression of Ratios of Party Identification in the Southern States

Odds Ratio:



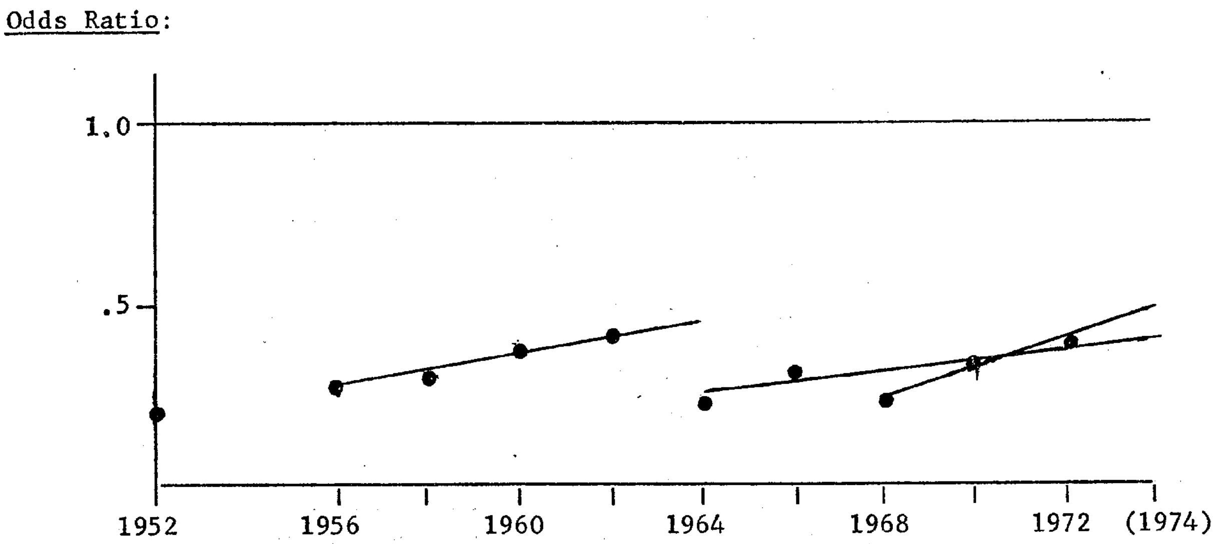
(a) Republican to Independent

Figure 5.--(Cont.)



(b) Democrat to Independent

Figure 5.--(Cont.)



(c) Republican to Democrat

TABLE 9

MEASURES RELEVANT TO DEPICTING PARTY PATTERNS IN THE SOUTH, 1952-1972

Time Span	Measures
	(a) Proportion Republican to Independent
1956-1962	stable, mean = 1.19
1962-1968	intercept = 1.19 slope = -.128 predicted value in 1970 = .172
1968-1972	intercept = .395 slope = .066 predicted value in 1974 = .791
	(b) Proportion Democratic to Independent
1952-1972	intercept = 4.86 slope = -.172 prediction to 1974 is uncertain
	(c) Proportion Republican to Democratic
1956-1962	intercept = .257 slope = .024 predicted value in 1964 = .446
1964-1972	intercept = .251 slope = .016 predicted value in 1974 = .409
1968-1972	intercept = .244 slope = .041 predicted value in 1974 = .491

It may be worth commenting on why, in Table 9, we hedge on the prediction for the proportion of Democrats to Independents in the South in 1974. As we have noted, we are not entirely secure in believing that the trend that characterized the period from 1952 to 1968 will continue, or even that it applies to the 1972 data (although we did include this point in the equation). One interpretation of the data in Figure 5 is that the

South is becoming more like the rest of the country in its pattern of party identification. If all the predictions implied in this graph and in Figure 4 were to come true in 1974, the result would probably be less regional heterogeneity of political party membership than has been the case for some time. Table 10 presents the expected values for 1972 and 1974 for the ratios we are talking about. The bottom two rows show the two regions becoming more nearly alike; the top row shows that, if anything, the South is expected to become more Republican than the non-southern parts of the United States.

TABLE 10

EXPECTED VALUES OF PARTY IDENTIFICATION RATIOS IN 1972 AND 1974 FOR SOUTHERN VS. NON-SOUTHERN STATES IN THE U.S.

Party Identification	1972		1974	
	Non-South	South	Non-South	South
Republican/Independent .	.76	.66	.66	.79
Democrat/Independent . .	1.17	1.42	1.07	1.09
Republican/Democrat . .	.73	.38-.41	.76	.41-.49

Of all the graphs we have looked at so far, the data for the South have shown the steepest slopes and the most abrupt turns. This type of pattern characterizes many groups that have been focal points of political change in the last decade or so. These are groups that the major parties have made special efforts to recruit. The South is a particular case in point since the voter registration drives in the early 1960s brought an increased identification with the Democratic Party, while since 1964 there have been increasing attempts by the Republican Party to enlarge its own base of power in the same areas. Another key group that has been a focal point of political attention is the well educated, who are known to show higher levels of political knowledge (Converse, 1965) and political participation. Groups like these, which for one reason or another are the focus of more intense political activity, show a trend in political identification that in its general pattern reflects the overall trends in the society. However, the ups and downs in these more focal groups show a much higher bounce and more sensitivity to characteristics of individual elections. This will become more apparent when we consider patterns of identification for different educational groups.

Educational Group Analysis

From analysis of the demographic model reported above, we have developed trend equations showing that over the last 20 year, while southerners are less likely to finish high school than non-southerners, southerners who do finish high school are more likely to go to college. Similarly, while men are less likely to finish high school than women, men who do finish high school are more likely to go to college. The same is true for the comparison between the old and middle cohorts. Members of the older cohort are less likely to have completed high school, but those that did show a greater tendency to have also gone to college. The only exception to this pattern of relationships is the comparison between the young and the middle cohorts. For all 20 years, members of the young cohort were more likely than those of the middle cohort to have completed high school. In 1952, members of the middle cohort were more likely to have gone to college, but 1952 to

1972 were years in which members of the young cohort were still in school. This gap between cohorts narrowed, disappeared, and finally inverted, so that now the young are nearly twice as likely to have gone to college, controlling for region and sex.

In the case of education, then, we have the result that, in the last 20 years, the young have been experiencing a quite different process of change than have the other cohorts. This difference in patterns of change between cohorts seems to hold for the analysis of other variables besides education.

We have already observed in the discussion of the relation between cohort and party identification that the old and middle cohorts showed a nonlinear pattern that could only be described with a very general dichotomy of time into years before and after 1965. The young cohort showed a movement in the same direction as the older two cohorts but with fewer idiosyncrasies (errors of estimate) for each year. The trend could be characterized as linear, and much more regular than the corresponding movements for the older cohorts. This suggests several hypotheses: are younger cohorts more ideological, are they just better educated, is their orientation to politics less bound to particular parties, platforms, and personalities? We will not attempt to answer all of these questions directly in this presentation. We do hope, however, to provide a concrete base for their consideration at a later time.

In predicting ratios of party identification for educational groups, we will make much more use of estimating slopes for non-presidential years only. The relation between the ratios and education is much less perfidious in the off years. Table 11 shows the data for the cross-tabulation of education by party identification by time. For the present analysis, education was collapsed into three categories: less than 12 years (less than high school graduate), 12 years (high school graduate), and college-educated (beyond high school graduation). The party identification ratios for these three categories are plotted against time in Figures 6, 7, and 8.

TABLE 11

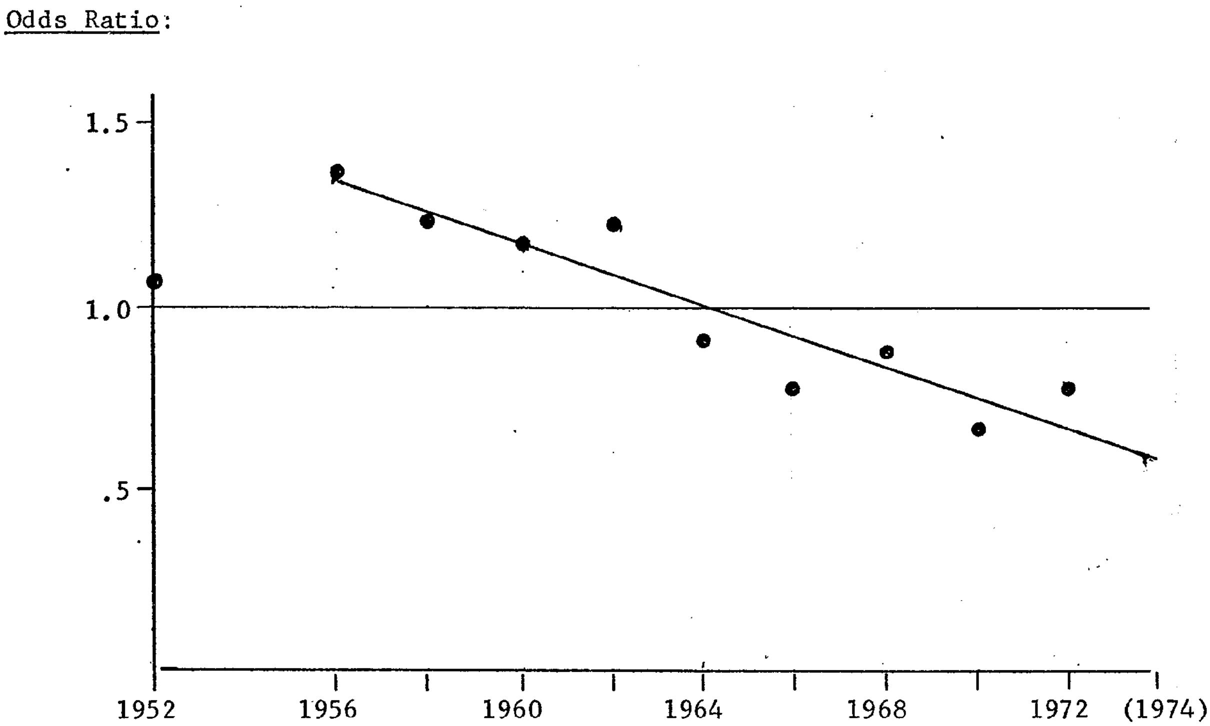
CROSS-TABULATION OF EDUCATION, PARTY, AND YEAR OF STUDY

Year of Study	Less than High School Graduate			High School Graduate			College-Educated		
	Party								
	Demo-cratic	Inde-pendent	Repub-lican	Demo-cratic	Inde-pendent	Repub-lican	Demo-cratic	Inde-pendent	Repub-lican
1952	553	229	245	184	98	131	88	74	96
1956	407	173	239	226	151	140	120	81	122
1958	461	136	171	210	89	115	126	55	109
1960	321	141	165	182	95	102	96	68	128
1962	308	114	141	166	83	108	120	71	113
1964	500	157	142	278	137	161	170	120	146
1966	293	140	111	176	129	103	108	87	101
1968	430	158	138	259	178	148	145	205	154
1970	375	195	129	242	210	156	145	151	146
1972	467	266	208	328	311	190	241	285	213

Source: SRC Election Series.

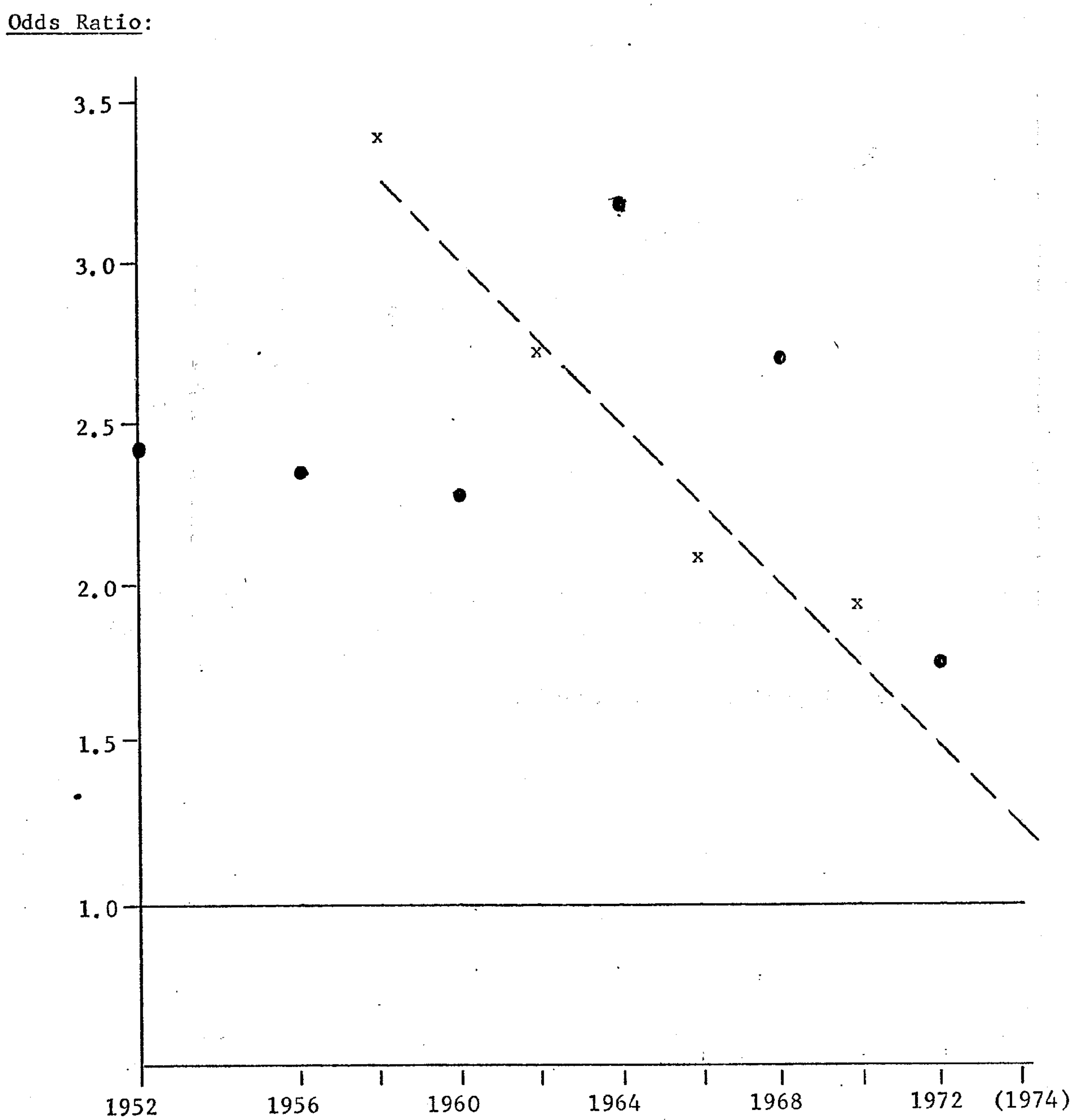
All three groups show a negative slope for ratio of Republicans to Independents. The ratio varies between -.032 and -.055 for the two less-educated groups, depending on the time series used (Table 12). The college-educated show a much steeper slope, between -.087 and -.094. This means that the relation between proportion of Republicans to Independents and time is specified by (interacts with) the level of education one is talking about.

Figure 6.--Plots of Regression of Ratios of Party Identification for Less than High School Graduates



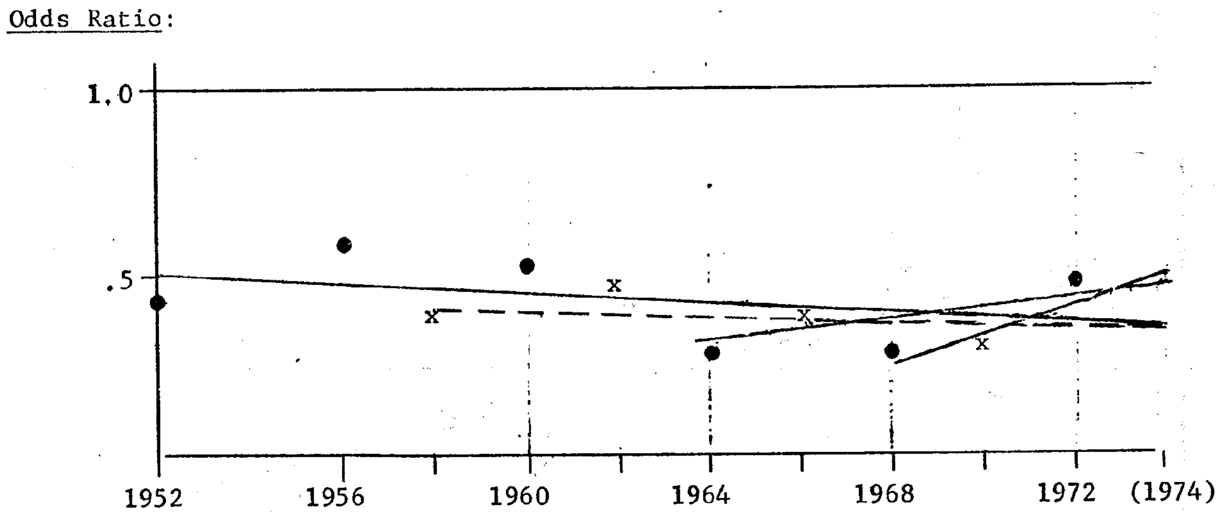
(a) Republican to Independent

Figure 6.--(Cont.)



(b) Democrat to Independent

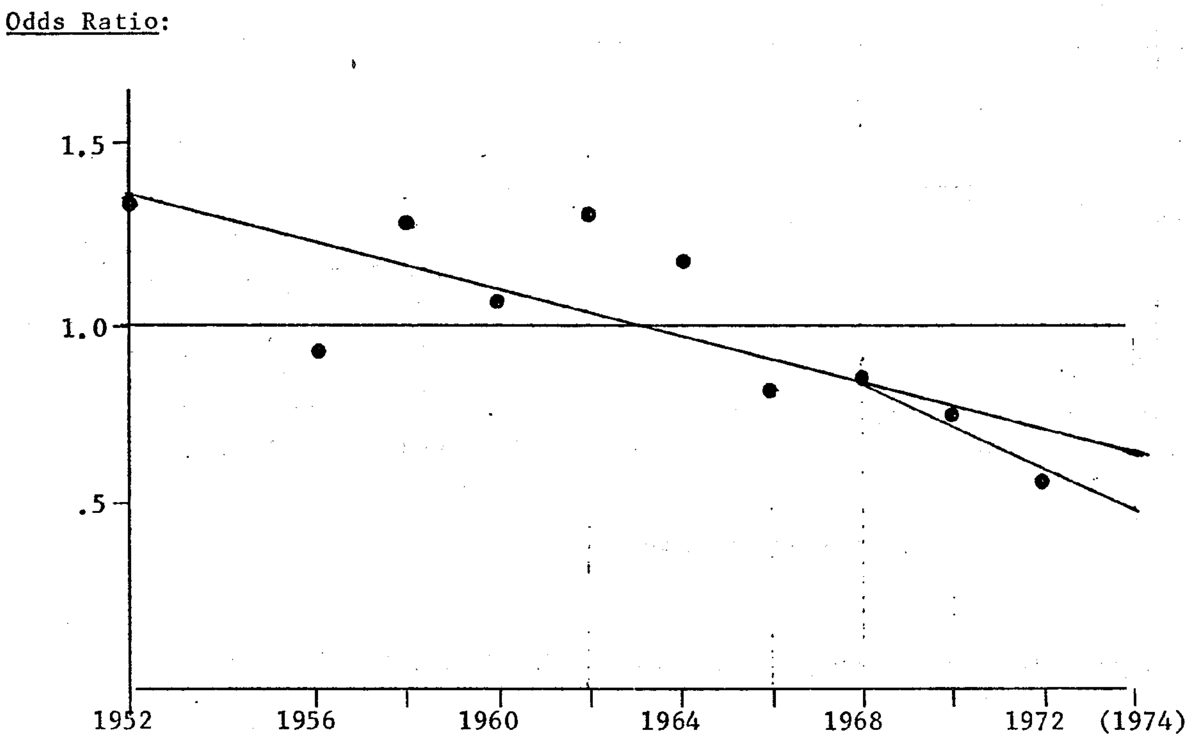
Figure 6.--(Cont.)



(c) Republican to Democrat

Note: In this and subsequent figures, "x" indicates off-year data points.

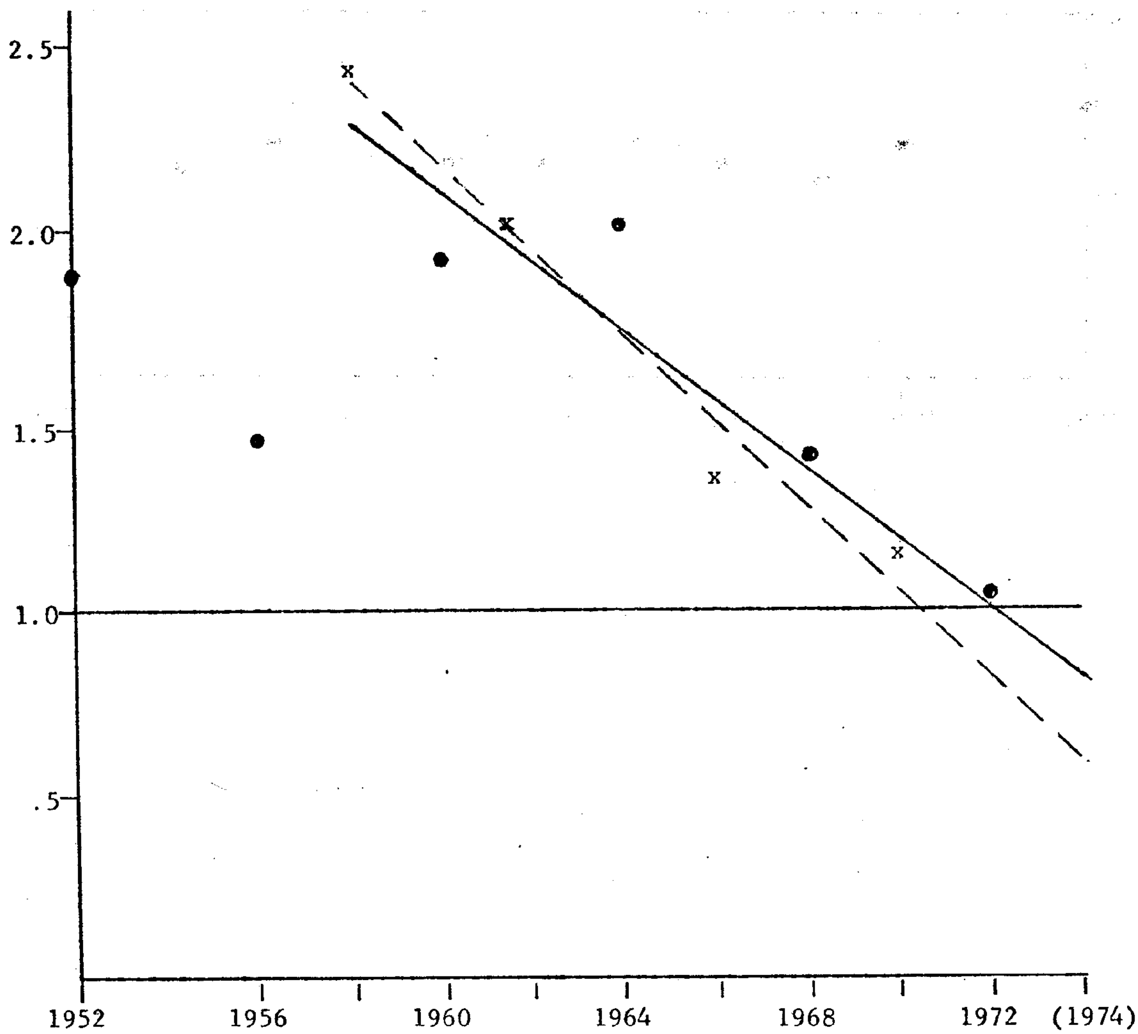
Figure 7 --Plots of Regression of Ratios of Party Identification for High School Graduates



(a) Republican to Independent

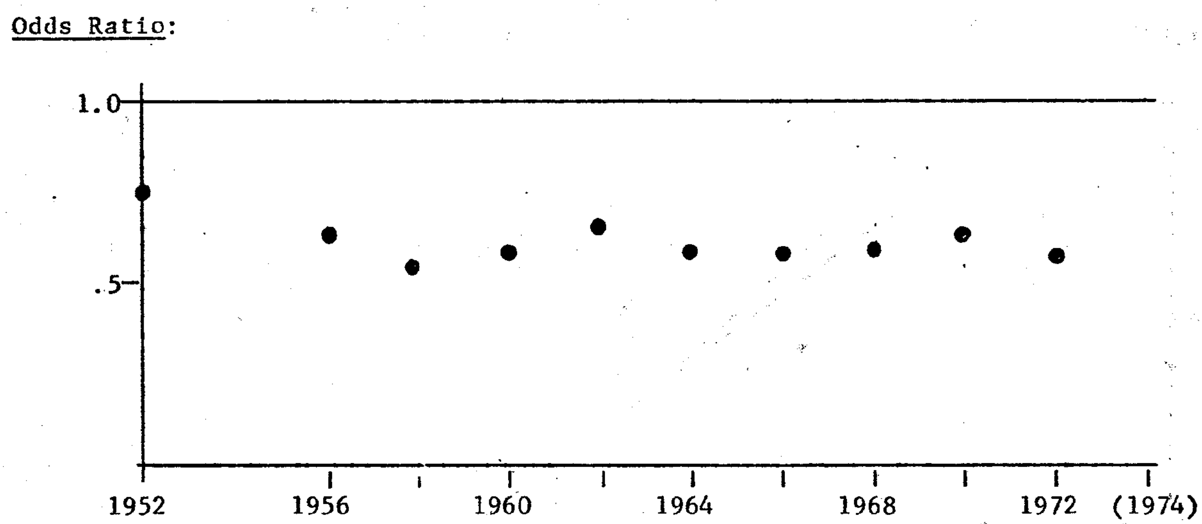
Figure 7.--(Cont.)

Odds Ratio:



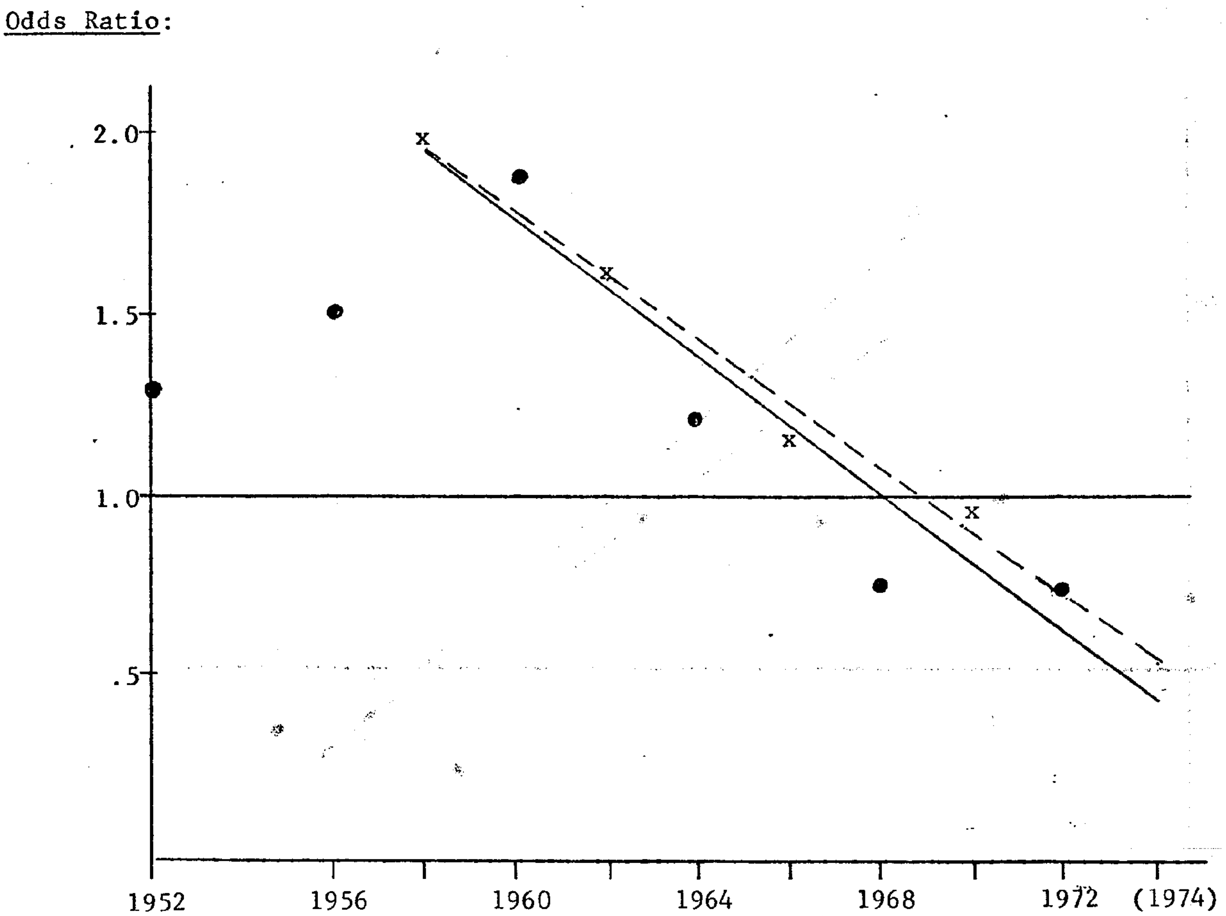
(b) Democrat to Independent

Figure 7.--(Cont.)



(c) Republican to Democrat

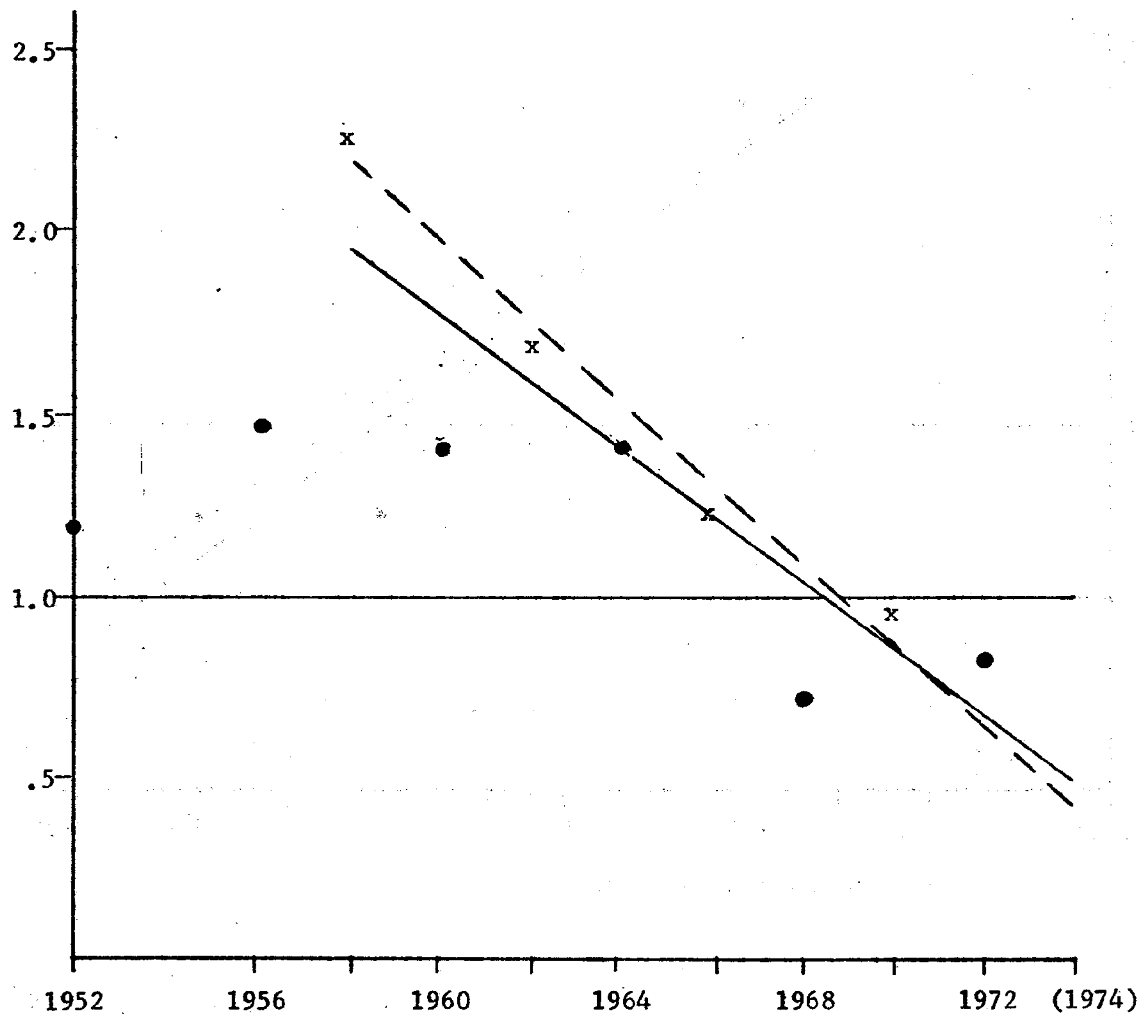
Figure 8.--Plots of Regression of Ratios of Party Identification for College-Educated



(a) Republican to Independent

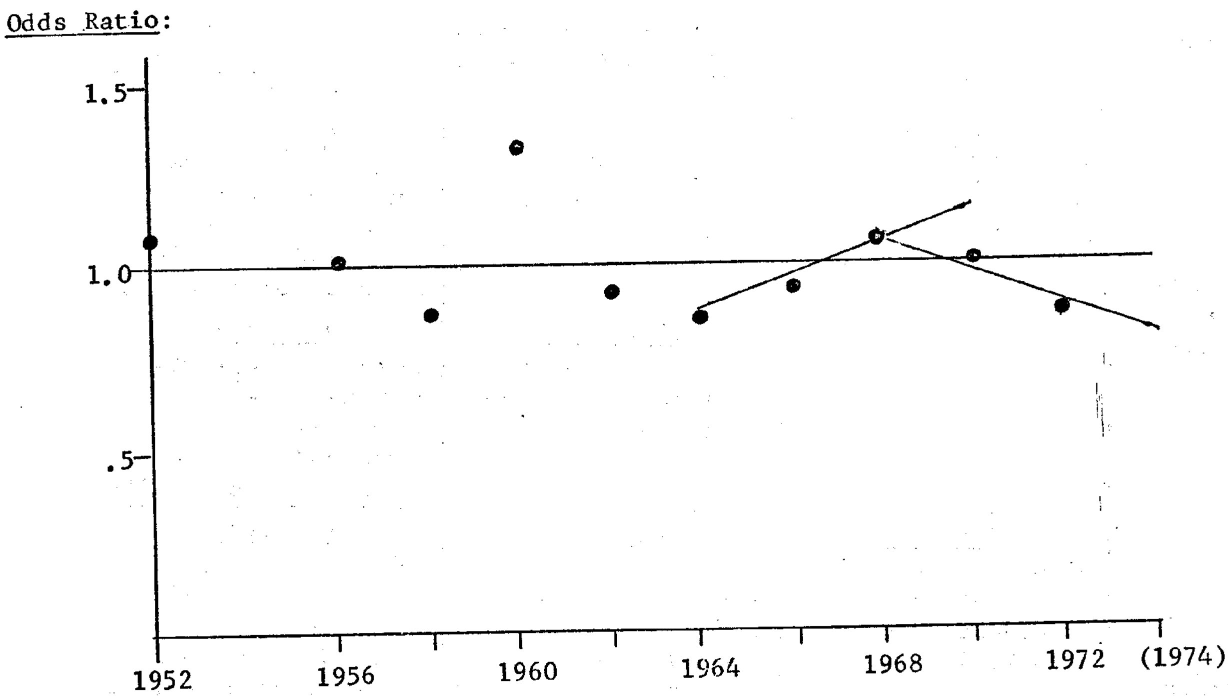
Figure 8.--(Cont.)

Odds Ratio:



(b) Democrat to Independent

Figure 8.--(Cont.)



(c) Republican to Democrat

TABLE 12

MEASURES RELEVANT TO DEPICTING PARTY PATTERNS IN THE THREE EDUCATIONAL GROUPS

Ratio of Party Identification	Educational Groups		
	Less than High School	High School Graduate	College-Educated
Republicans to Independents	<u>1956-1972</u> Slope = -.044 Intercept = 1.34 Predicted value in 1974 = .571	<u>1952-1972</u> Slope = -.032 Intercept = 1.35 Predicted value in 1974 = .653 <u>1968-1972</u> Slope = -.055 Intercept = .839 Predicted value in 1974 = .508	<u>Off-Year</u> Slope = -.087 Intercept = 1.95 Predicted value in 1974 = .558 Standard error = .082 <u>1958-1972</u> Slope = -.094 Intercept = 1.95 Predicted value in 1974 = .441 Standard error = .156
Democrats to Independents	<u>Off-Year</u> Slope = -.125 Intercept = 3.28 Predicted value in 1974 = 1.27	<u>Off-Year</u> Slope = -.113 Intercept = 2.42 Predicted value in 1974 = .61 Standard error = .129 <u>1958-1972</u> Slope = -.095 Intercept = 2.33 Predicted value in 1974 = .827 Standard error = .178	<u>Off-Year</u> Slope = -.111 Intercept = 2.21 Predicted value in 1974 = .435 Standard error = .113 <u>1958-1972</u> Slope = -.092 Intercept = 1.97 Predicted value in 1974 = .49 Standard error = .259
Republicans to Democrats	Mean = .415 <u>Off-Year</u> Slope = -.004 Intercept = .411 Predicted value in 1974 = .348 Standard error = .054 <u>1952-1972</u> Slope = -.007 Intercept = .49 Predicted value in 1974 = .337 Standard error = .086 <u>1964-1972</u> Slope = .014 Intercept = .297 Predicted value in 1974 = .441 <u>1968-1972</u> Slope = .031 Intercept = .309 Predicted value in 1974 = .4946	Mean = .603 <u>1952-1972</u> Slope = -.003	Mean = 1.0 <u>1952-1972</u> Slope = -.007 <u>1964-1968</u> Slope = .051 Intercept = .85 Predicted value in 1970 = 1.16 <u>1968-1972</u> Slope = -.045 Intercept = 1.07 Predicted value in 1974 = .806

The college-educated also show a higher intercept (1.95) than do the two less-educated groups (1.34), which means that, in the early years, there was a two-variable relationship between education and proportion of Republicans to Independents, with the college-educated showing more party loyalty. At some point, however, because of the differences in slope, the lines crossed. There was no relation between education and loyalty that year, and for years after that the relation was reversed. Table 12 shows that the ratio of Republicans to Independents for the college-educated is expected to be between .441 and .56 in 1974. The less than high school graduates are expected to identify slightly more strongly: .571. The high school graduates are expected to be even more Republican; the expected ratio from Table 12 is .653.

In reporting the trend for the college-educated, we made use of both types of trend lines: since 1958, and non-presidential election years. For many analyses, the off-year regression gives a considerably lower standard error of the estimate. We suspect that there are at least two reasons why this should be so. The first derives from the standard reference from the political science literature, where it is believed that off-year identification is a more valid and reliable estimate of a person's party preferences (Campbell, 1966). If this is true, then ratios or correlations based on response to these items should also show a less random pattern in the non-presidential years, or at least they should show a relationship much closer to the "true" value.

The second reason we might expect a lower average error in the non-presidential series is that, as a completely fortuitous result of our research design, the mean year in the non-presidential series is 1964

(4 data points), while the mean for the presidential series is 1962 (6 data points). Or, to put it differently, the presidential series has 3 points before 1960 and the non-presidential series has only one. It has been observed and reported elsewhere (Davis, et al., 1974) that it is very likely that the Survey Research Center became much more accurate in its sampling and technical procedures with each successive survey it fielded in this particular series. This means that the early years, substantive considerations aside, will be expected to show more variance in the estimation of any parameters. The data points we are using for our off-year election series involve fewer surveys done during the time when there is the greatest variance in the measurement device (the early years), while the whole series is more evenly spaced. For this reason alone we would expect less average error in the non-presidential regression estimates.

We have used off-year equations for all three educational groups in estimating the change in the proportion of Democrats to Independents. All three groups seem to be decreasing at about the same rate, between -.092 and -.125. The intercepts are vastly different, ranging from 3.28 for the lowest educated group to 2.21 for the college-educated. This means that although the educational groups decline about the same amount in the proportion of Democrats to Independents from one year to the next, a rank order is still preserved among those groups, with the less-educated groups always being more likely to identify themselves as Democrats.

The graphs for the ratio of Republicans to Democrats show almost no trend over time: one is probably most correct to predict the overall mean for any given year. Table 12 shows that these means are related to education, with the lower-educated more likely to be Democrats and the college-educated equally likely to be Democratic or Republican, although in recent years they are actually most likely to be Independents.

The group consisting of less than high school graduates shows, at best, a curvilinear trend: with each passing year, the slope for the regression becomes slightly more positive; therefore, the more we consider short-term rather than long-term trends in this ratio, the higher value we predict for it in 1974. This is shown in the lower left-hand cell of Table 12, where we have fitted data for four different time spans: 1952 to 1972, 1964 to 1972, 1968 to 1972, and non-presidential election years. The off-year trend gives a prediction closest to the full 20-year equation. The presentation of the four time spans shows that although the ratios in any given year may be volatile, there are various ways of breaking down the data to winnow out the change, if any, that they describe. Describing Figure 6, part (c), we would say that, generally, the ratio of Republicans to Democrats for the less than high school educated has been stable at around .415 for the years 1952 to 1972. On the other hand, there are indications that this ratio is rising (slowly, to be sure) in recent years, and that in 1974 we may expect values from .441 to as high as .495 for this ratio.

In contrast, part (c) of Figure 8 illustrates the fits and starts which characterize key groups. The ratio of major party identification among the college-educated seems cyclic, or possibly a sine wave tilted down slightly. Aside from an abnormally large value in 1960 (1.33 in Figure 8), this ratio seems to fluctuate around 1.00, its mean, with possibly a tendency in later years to lean toward the Democratic side of the graph. The trend itself, rather than being random, appears to exhibit much of the same variety as the patterns reported in Figure 5 for the ratios for the South.

Partial Associations and Interactions between the Democratic Variables and Party Identification

As advertised, this part of the report will examine the relationships that remain among the variables in the analysis after everything else has been controlled. These relationships fall into two categories: significant and non-significant. Goodman's technique of testing effects for significance within a framework of hierarchical modeling was used to determine which effects in our data we would consider non-random (Goodman, 1972). We used a stepwise procedure in building the model, which is described in another of Goodman's articles (Goodman, 1971). This means that we first built a model to explain the changes in all the control variables (education, sex, cohort, region, time). Various findings from this model have been reported in Part A. Once the effects that adequately describe the independent or control variables were measured, we tested the dependent variables (party identification) by allowing the controls to interact in all ways possible and by only testing the significance of those effects involving the dependent variable.

Using this procedure, we found that it was necessary to include the following effects to make the model fit the data:

Two-Variable Effect

(Party, Sex)	The ratios for party are not the same for men and women, all other things held constant.

Three-Variable Effects Not Involving Education

(Party, Year, Cohort)	The association between party and cohort is not the same in all years, all other things held constant.
(Party, Year, Region)	The association between region and party is not the same in all years, all other things held constant.

(Party, Cohort, Region)	The association between region and party is not the same in all cohorts, all other things held constant.

Three-Variable Effects Involving Education

(Party, Year, Education)	The association between education and party is not the same in all years, other things held constant.
(Party, Cohort, Education)	The association between education and party is not the same in all cohorts, all other things held constant.
(Party, Region, Education)	The association between education and party is different in different regions, net of all other effects.

All effects were significant at the .01 level, using the chi square likelihood ratio statistic, with the Pearson goodness-of-fit chi square as a check against small cell sizes.

The Two-Variable Effect

The most surprising finding was the sex effect. Our review of the literature had not led us to expect it, and previous analysis had shown the partial correlation between sex and preference for either Republican or Democratic Party to be zero (the partial odds ratio for this test was 1.007). The data show that the expected ratio of Republicans to Democrats is the same for both sexes once the effects of age, region, and education have been taken out. The sex effect is significant because after all controls are introduced, men are much more likely to identify themselves as Independents than women are. Table 13 shows the observed ratios of Republicans and Democrats to Independents for men and women for the ten studies. These are zero-order data, unadjusted for differences in age or education, which may have some effects (although the model shows these to be non-significant). There is a good-size discrepancy, with men more likely to be Independents in most years. The partial correlation between sex (male vs. female) and ratio Republican to Independent is .725, which is about what we would get if we took the average male ratio and divided it by the average female ratio. In terms of Yule's Q, the association between sex and proportion Republican to Independent is -.159, a low negative correlation, indicating that men are more likely to be Independents.

TABLE 13

DATA FOR THE HYPOTHESIS THAT MEN ARE MORE LIKELY THAN WOMEN TO CLASSIFY THEMSELVES AS POLITICALLY INDEPENDENT

Year of Study	Republican to Independent			Democrat to Independent		
	Female	Male	Difference (F-M)	Female	Male	Difference (F-M)
1952	1.39	.99	.40	2.33	1.8	.53
1956	1.56	.95	.61	2.07	1.66	.41
1958	1.61	1.23	.38	3.69	2.16	1.53
1960	1.69	.99	.70	2.57	1.5	1.07
1962	1.62	1.08	.54	2.35	2.09	.26
1964	1.24	.93	.31	2.62	1.97	.65
1966	.95	.81	.14	1.7	1.53	.17
1968	.84	.78	.06	1.7	1.35	.35
1970	.85	.68	.07	1.5	1.22	.28
1972	.81	.61	.20	1.42	.97	.45

The partial correlation between sex and the other ratio, Democrats to Independents, is .721. Given what we know from the literature about the transmission of party identification from father to son to son's wife, the findings presented here provide a further interesting twist. No matter what party, the proportion of men who identify with it will be 25 per cent less than the proportion of women. The indications from Table 13 are that the differences between the sexes are becoming smaller in the more recent years, and the association may not be significant in the near future if this trend continues. It appears, then, that there may be a slight interaction between time and the partial correlation between sex and party identification. This was found to be non-significant by the hierarchical modeling procedures, but for the record we may note that, using just the data since 1966, we obtain the following partial correlations, both of which are closer to 1.0:

Republican to Independent by Sex, 1966-1972 = .783

Democrat to Independent by Sex, 1966-1972 = .741

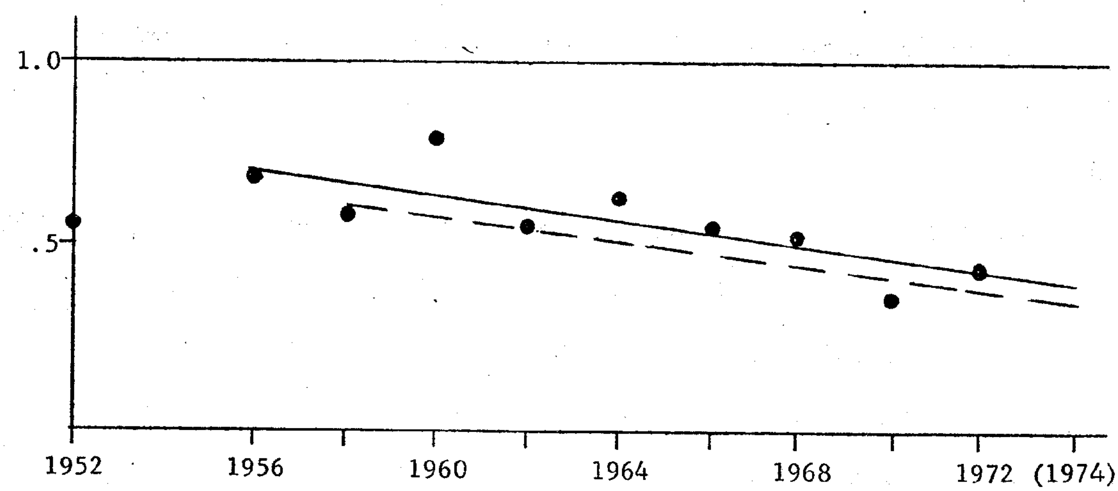
In summary: although the trend does not test to statistical significance, its relative monotonicity and substantive interest lead us to suggest that although men are more likely to identify themselves as Independents, this is somewhat less the case in the more recent years.

Interactions Not Involving Education

In Part A, we discussed the effects of cohort and region on the predicted values for party identification. We presented the zero-order data partly to discover the general contours of the trend we hope to explain and partly to elaborate the techniques we will use to incorporate time into the discussion of social change. What we did not do was examine the effects of cohort or region after the effects of all but the predictor variables were removed from the data. The sex effect was easy

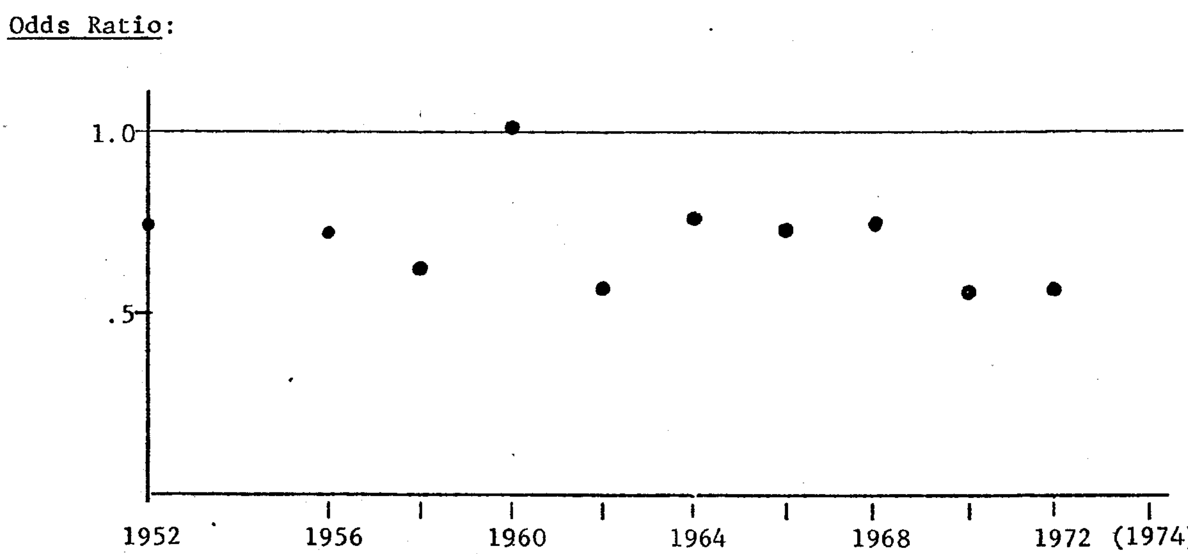
Figure 9.--Regression of the Partial Correlation between Cohort and Party Identification, Comparing the Young and Middle Cohorts

Odds Ratio:

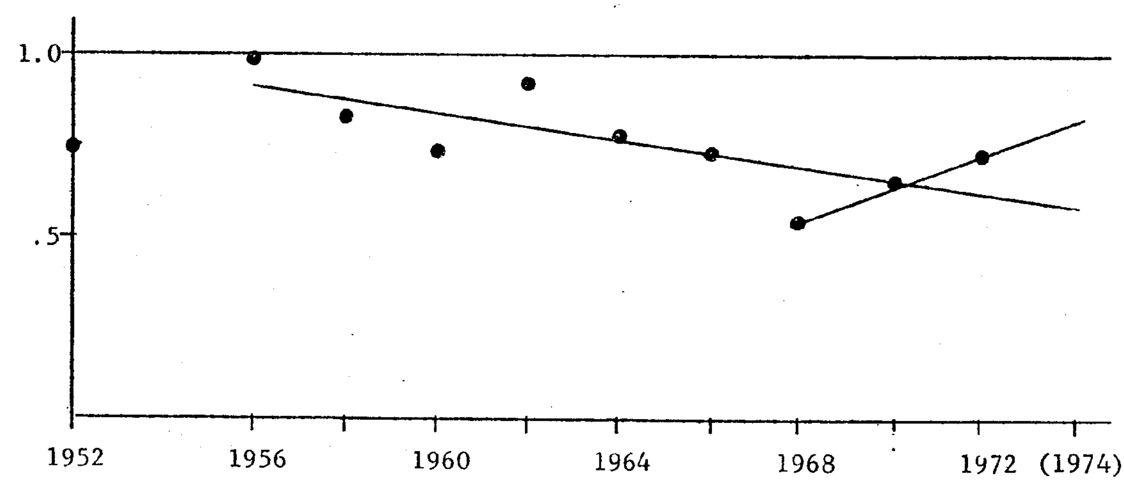


(a) Republican to Independent

Figure 9.--(Cont.)



(b) Democrat to Independent



(c) Republican to Democrat

other variables (e.g., region), the plot shows the opposite pattern: correlations are clearly sharper during the years of national elections. We will note this effect whenever it occurs, for it shows some promise for developing theoretical positions about when certain types of issues or identifications will be more salient than others.

At any rate, the off-year trend line is declining .016 points a year. If we use all the data since 1956, we predict a regression of -.018 points a year. The expected value for this partial correlation in 1974 is between .351 and .389. This means that, with all other things held constant, the younger cohort is becoming "Independent" faster than the middle cohort, so that the partial association between party identification (Republican vs. Independent) and cohort (young vs. middle) is becoming inreasingly negative. For the expected values in 1974, we are talking about Q's in the range of -.44 to -.48. The importance of this technique of presentation is that we have (a) summarized data from several tables presented in Part A in a way that (b) controls for the effects which we observed in all the tables of Part A.

The second part of Figure 9 has no trend lines drawn in. That is because both the off-year and the total slopes have absolute values less than .01. This means that whatever systematic differences we observed between the young and the middle cohort in identification with the Democratic Party are accounted for by the other variables in the model. Thus, we would expect that the regular rate of increasing Independent identification in the young cohort will be explained by one of the variables yet to be analyzed (region and education). This figure shows the same problem we noted earlier of a seemingly non-random spread between the average off-year correlation and the average presidential year correlation. Pooling all data, we get an average overall partial correlation of .70, while for the off-years only, the average of the partials is .62. This means that in off years, other things held constant, either (1) the young cohort is more likely than usual to claim no major party identification, or (2) the middle cohort is more likely to claim Republican identification (or both). We will not present the data to analyze this particular issue, although the tables in Part A suggest that the first choice is most likely.

Part (c) of Figure 9 suggests that the young and middle cohorts started out with about the same proportions of Republicans to Democrats in each, but that over the 20-year period, the young have increasingly become identified with the Democratic Party (net of other effects of increasing education or a geographic shift South, which we know characterize the young cohort). The slopes and predicted values for the total and the off-year series are almost exactly the same, the correlation has been declining .02 points a year, and the expected value, using the long-term trend, is .60.

Since 1968, however, there is reason to doubt the accuracy of this trend prediction. Using the shorter time span gives a predicted value of .82 for the partial correlation, which is almost exactly the value observed in the late fifties. In other words, after a period of increasing differentiation, the two cohorts are again becoming more alike, at least with respect to preferences for political parties. The data for this part of the analysis, as well as for the old cohort, are presented in Table 14.

The older cohort showed considerable "bounce" when we examined the zero-order ratios in Part A. A pattern does not become absolutely clear,

TABLE 14

REGRESSION OF PARTIAL CORRELATIONS BETWEEN PARTY IDENTIFICATION AND COHORT

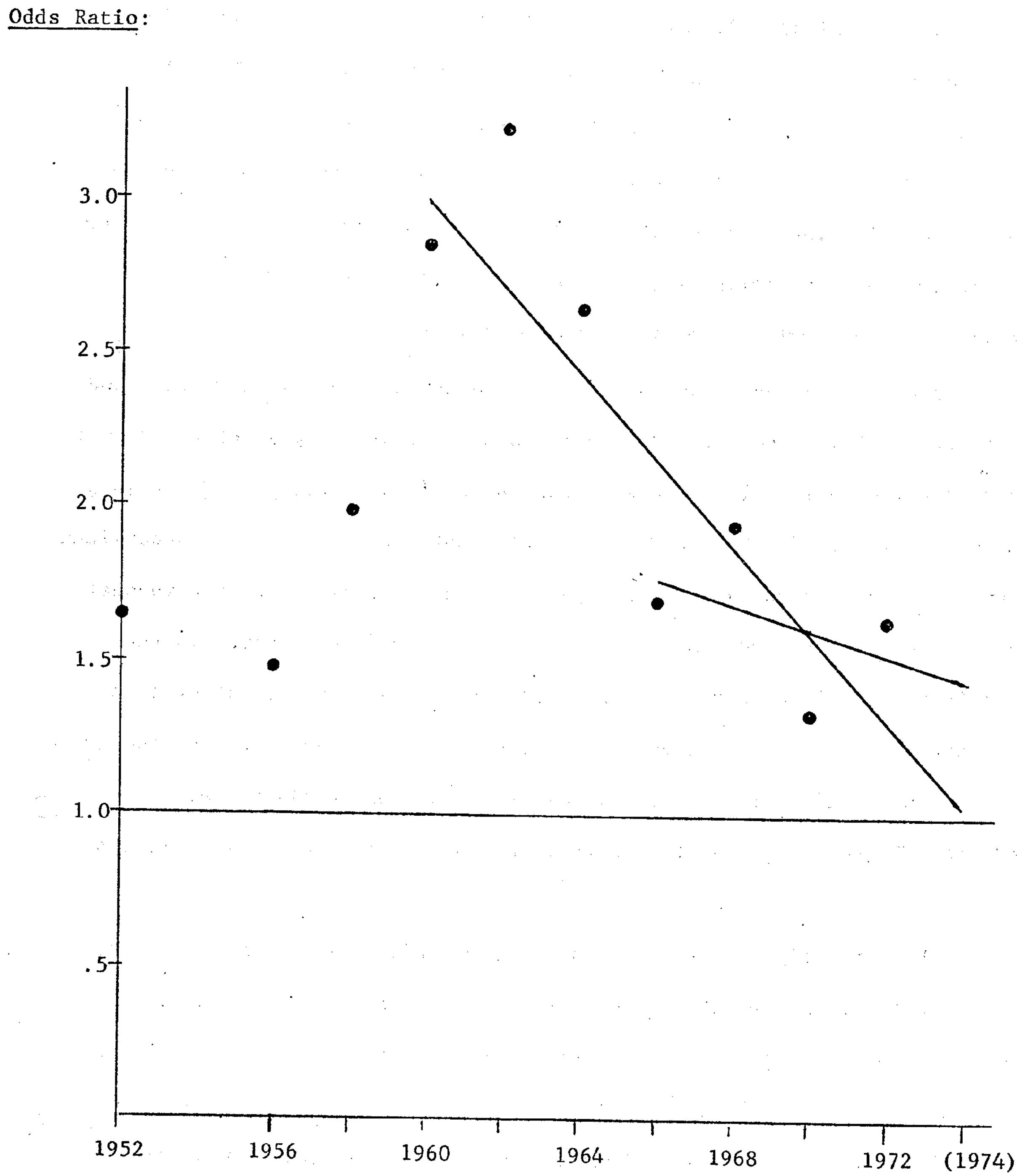
Party Identification	Cohorts Compared	
	Young/Middle	Old/Middle
Republicans to Independents	<u>Off-Year</u> Slope = -.06 Intercept = .606 Predicted value in 1974 = .351 <u>1956-1972</u> Slope = -.018 Intercept = .706 Predicted value in 1974 = .389	<u>Average Partial Correlation</u> 1952 - 1958: 1.72 1960 - 1964: 2.92 1966 - 1972: 1.66 <u>1960-1972</u> Slope = -.146 Intercept = 3.08 Predicted value in 1974 = 1.03 <u>1966-1972</u> Slope = -.041 Intercept = 1.78 Predicted value in 1974 = 1.45
Democrats to Independents	<u>Off-Year</u> Slope = 0 Mean = .62 <u>1952-1972</u> Slope = -.01 Mean = .70	<u>Average Partial Correlation</u> for Presidential Years 1962, 1966, 1970 = .96 <u>Off-Year since 1962</u> Slope = -.023 Intercept = 1.06 Predicted value in 1974 = .78 <u>1958-1972</u> Slope = -.05 Intercept = 1.38 Predicted value in 1974 = .615 <u>1960-1972</u> Slope = -.017 Intercept = 1.22 Predicted value in 1974 = .987
Republicans to Democrats	<u>Off-Year</u> Slope = -.017 Intercept = .891 Predicted value in 1974 = .614 <u>1956-1972</u> Slope = -.017 Intercept = .911 Predicted value in 1974 = .597 <u>1968-1972</u> Slope = .043 Intercept = .562 Predicted value in 1974 = .82	<u>1966-1972</u> Slope = -.08 Intercept = 1.91 Predicted value in 1974 = 1.28

but some regularities do emerge when the effects of other variables are removed and the ratios compared with those for the middle cohort. The graph is presented in Figure 10. All of the slopes in parts (a) and (b) of Figure 10 are negative. These data show that, contrary to conventional wisdom, the older cohort has been de-identifying with major political parties at a rate faster than the middle cohort. The net effect of this trend has been that since 1966, the older cohort has been becoming more like the middle cohort in its party preferences [the slope for part (c) is negative and the magnitude of the partial odds ratio is approaching 1.0].

Putting Figures 9 and 10 together, we may say that if current trends continue, it will become very difficult in a few years to predict a person's party affiliation if all you know is that person's age [all part (c) values are approaching 1.0]. Furthermore, the de-identification with the Republican Party seems to be associated with a person's age; the older and the younger cohorts are becoming Independents faster than the middle cohort. On the other hand, the slopes for the Democratic Party defection are either less conclusive (Figure 10) or nonexistent (Figure 9), so we suggest that the trend of de-identification with the Democratic Party is not nearly as much associated with a voter's age as it is with other factors (which we will discuss below).

The next effect we will examine is the interaction between region, party, and year. So far the discussion of the effect of region on party preference has suggested that the southern states have shown basically the same pattern of Independent identification as other parts of the country, except that the South is more sensitive to the idiosyncrasies of particular elections and candidates than is the case in other parts of the country.

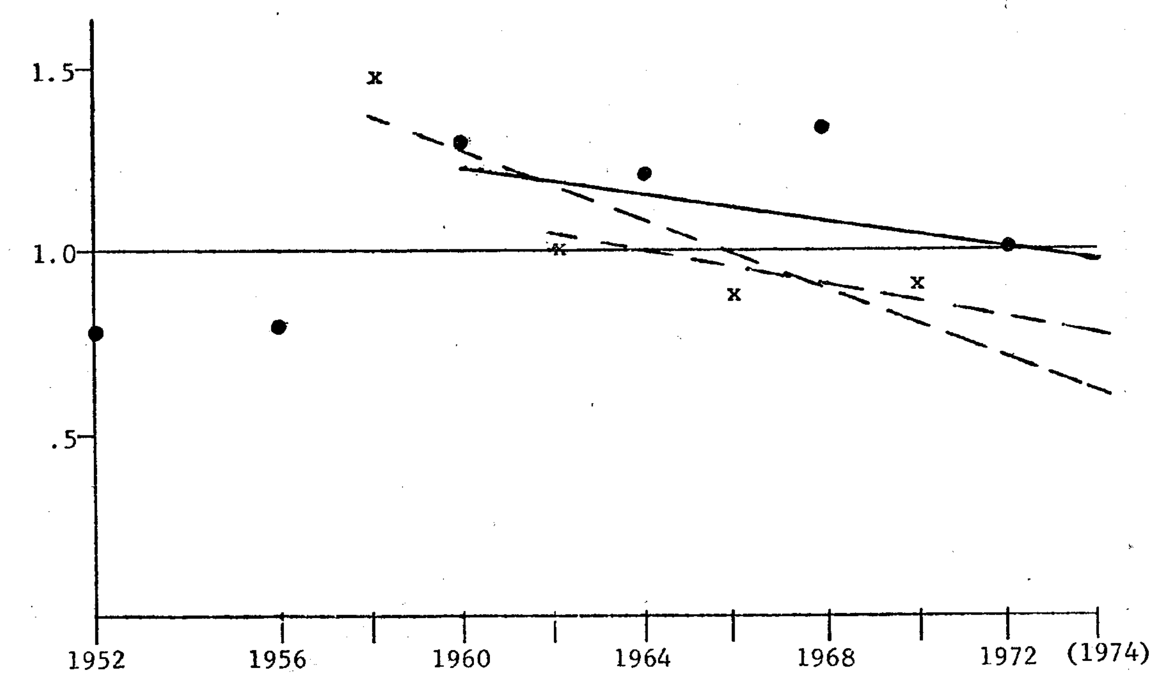
Figure 10.--Regression of Partial Correlation Between Cohort and Party Identification, Comparing the Old and Middle Cohorts



(a) Republican to Independent

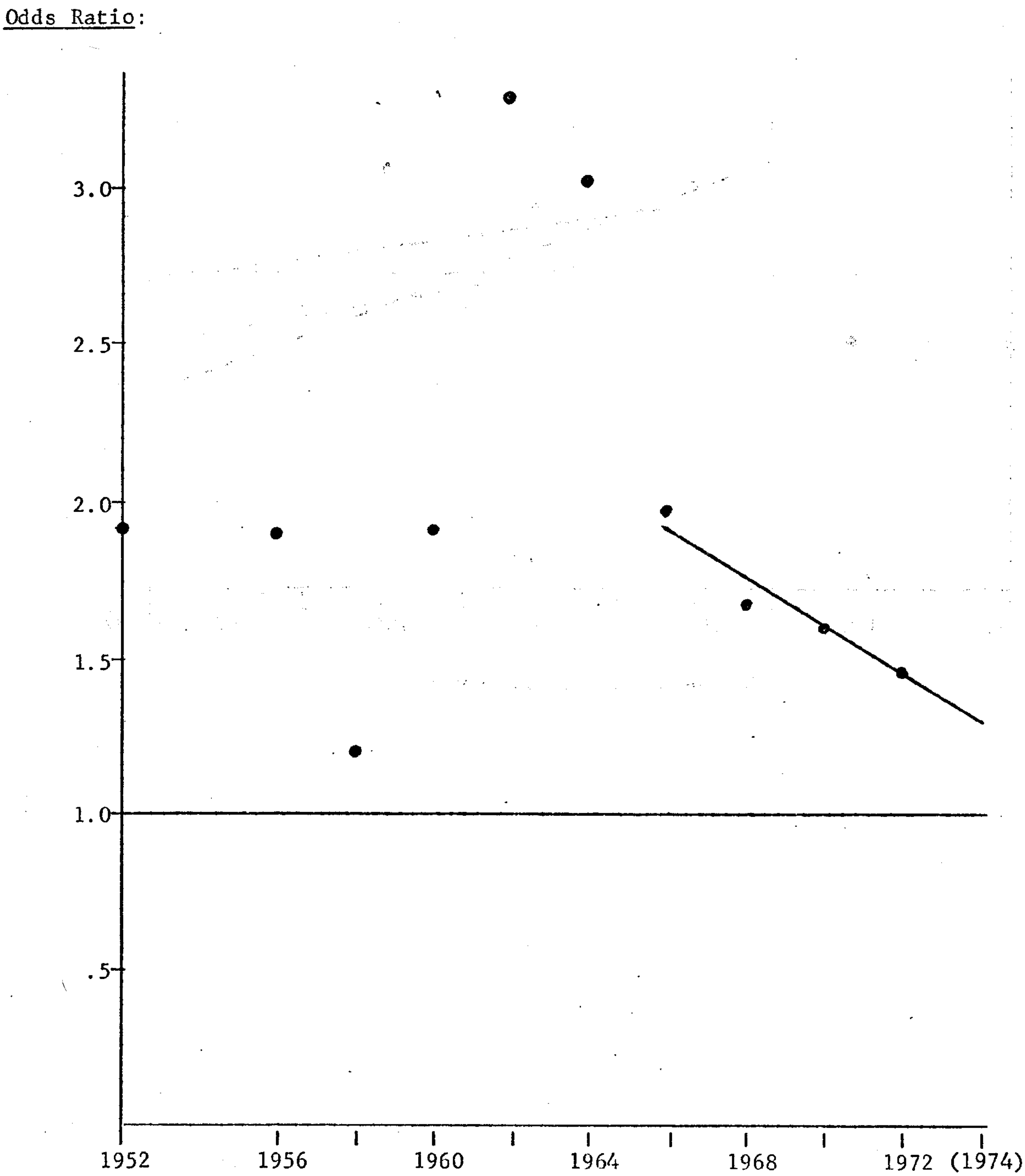
Figure 10.--(Cont.)

<u>Odds Ratio</u>:



(b) Democrat to Independent

Figure 10.--(Cont.)



(c) Republican to Democrat

This, at least, is the finding derived from the zero-order data presented in Part A.

We have also observed that there are complex interactions between region and the other control variables in the analysis (cohort and education). Thus far, we have no way of knowing how much of the change we have reported in the South is due to unique regional effects and how much is due to a more spurious relation between region and other variables known to independently affect party identification. We should emphasize that the "unique" regional effects that we will explore in this analysis are only unique with respect to the other control variables in our analysis. We will, in fact, suggest further controls that might be introduced to explain the apparent regional effects which we will describe.

In Part A, we reported that the proportion of Republicans to Independents was steadily declining in both regions, but that there was a steeper slope in the non-southern states; consequently, the net effect is that the Republicans appear to be gaining strength in the South. Table 15, part (a) presents the ratios of Republicans to Independents in the two regions for the years 1958 to 1972. These are the ratios for which the trend lines in Figures 4 and 5 were calculated. The third row of Table 15 15-(a) is the ratio of the entries in the first two rows. It is a second-order odds ratio and is a measure of the association in each year between region and proportion Republican to Independent. The impression from the figures here is that in 1958, the two regions were very similar in their proportions, then they underwent increasing differentiation between 1964 and 1968, and since 1968 have again been becoming more alike.

TABLE 15

ZERO-ORDER RATIOS OF PARTY IDENTIFICATION IN THE TWO REGIONS

Region	Year of Study							
	1958	1960	1962	1964	1966	1968	1970	1972
	(a) Republican to Independent							
South	1.2	1.2	1.2	.91	.72	.41	.49	.68
Non-South . . .	1.5	1.3	1.4	1.1	.95	1.0	.94	.72
Ratio .	.8	.92	.86	.83	.76	.41	.52	.94
	(b) Democrat to Independent							
South	4.3	3.3	3.0	3.8	2.0	1.8	1.4	1.7
Non-South . . .	2.5	1.5	1.9	1.8	1.5	1.4	1.3	1.0
Ratio .	1.7	2.2	1.6	2.1	1.3	1.3	1.1	1.7

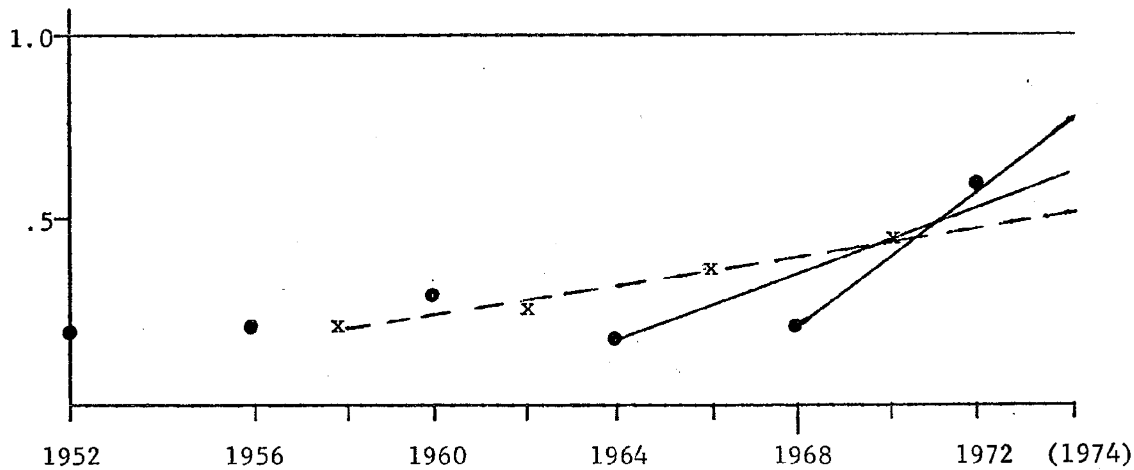
Region	(c) Republican to Democrat					
	1962	1964	1966	1968	1970	1972
South	.4	.2	.4	.2	.3	.4
Non-South . . .	.75	.61	.65	.70	.70	.72
Ratio .	.53	.33	.62	.29	.43	.57

A similar table of partial correlations between region and party identification would show how much of this trend of massification to differentiation back to massification (Glenn, 1967) is due to changing educational patterns, cohort mortality, and how much of the trend is uniquely regional.

Figure 11 shows a plot of these partial correlations over time and gives a somewhat different picture from the zero order correlations in Table 15. Three different trend lines were fitted: off-year, since 1964, and since 1968. In all three cases, the trends show a regular linear increase in the partial odds ratio. Since 1958, the data show that after all other effects in our table are removed, the South and the

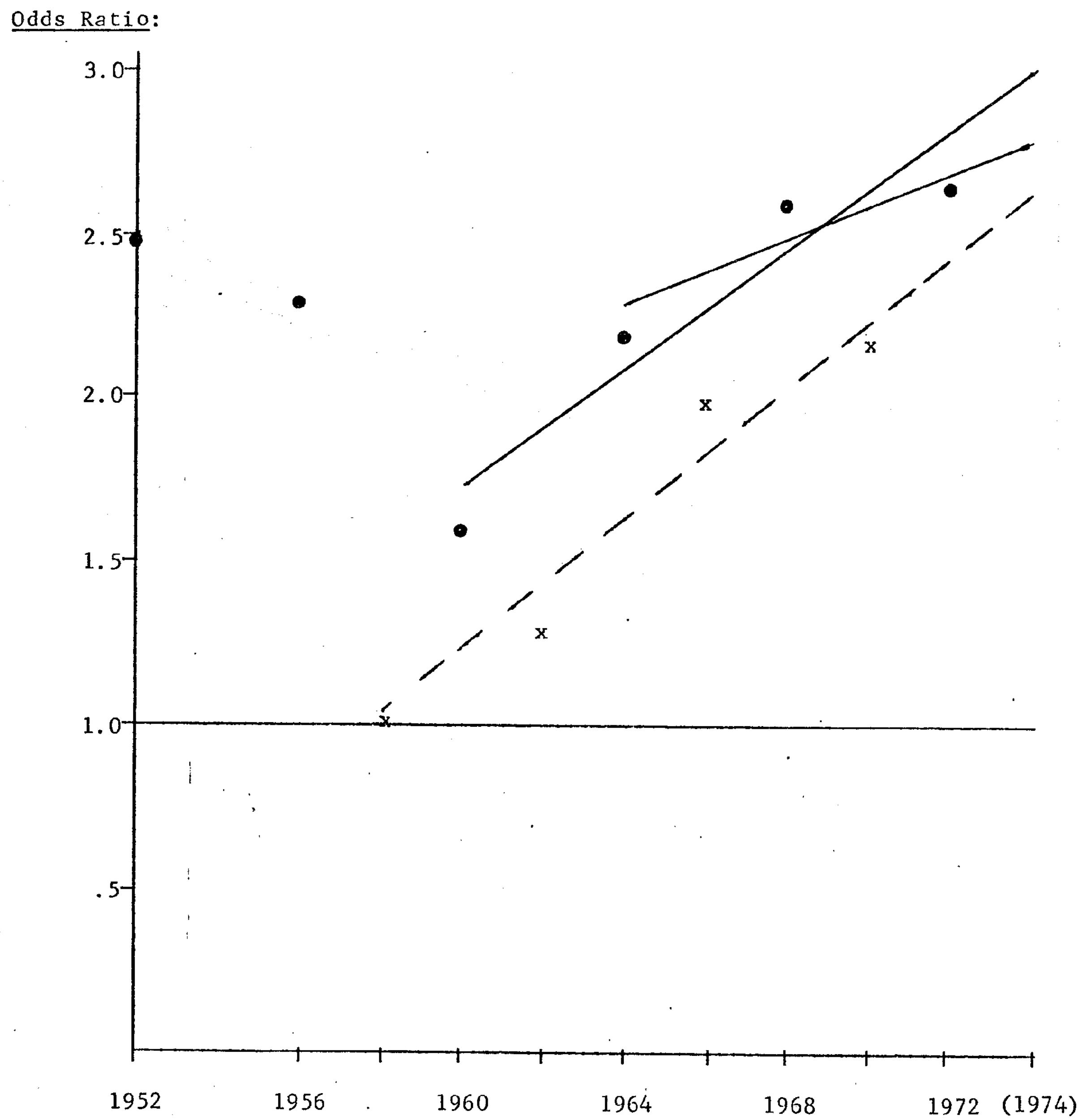
Figure 11.--Regression of Partial Correlation between Region and Party Identification

Odds Ratio:



(a) Republican to Independent

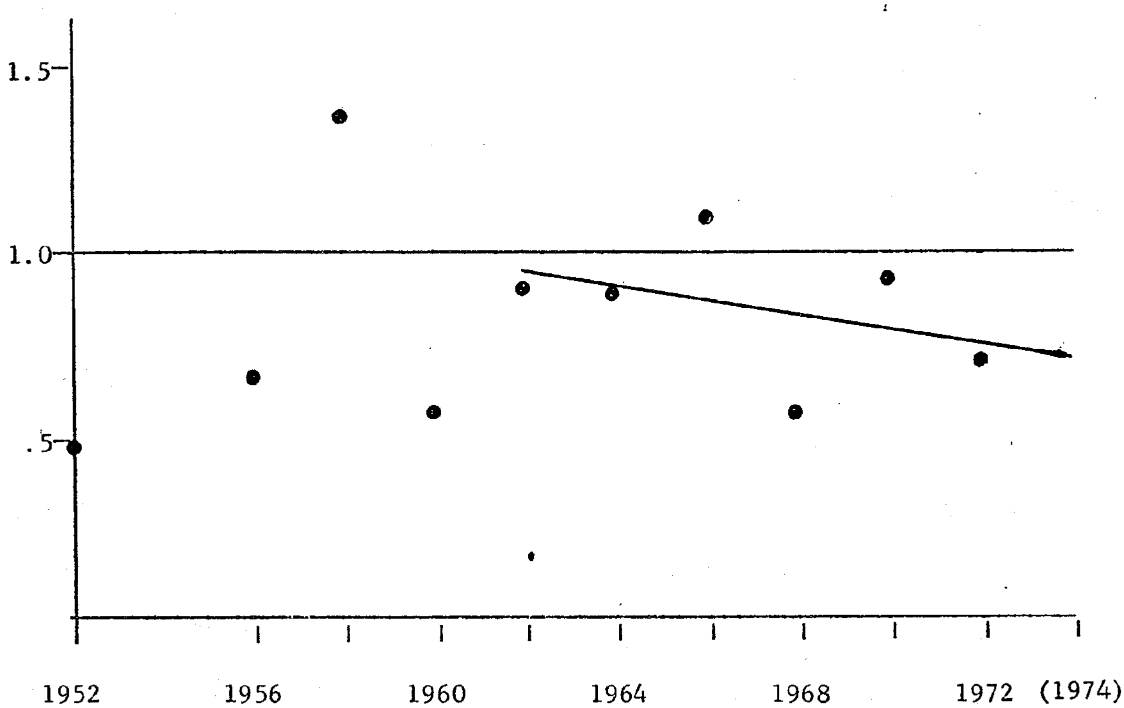
Figure 11.--(Cont.)



(b) Democrat to Independent

Figure 11.--(Cont.)

Odds Ratio:



(c) Republican to Democrat

North have been becoming much more alike in their proportions of Republicans to Independents. Since the ratios are all less than one and converging on one, we know that the cause of this linear change is either that the South is becoming more Republican, or that the North is becoming more Independent, once all other effects are controlled. The discussion in Part A suggests that some of both processes are occurring, the net result being that the South and the non-South regions are becoming increasingly difficult to distinguish in terms of the proportion of Republicans to Independents.

Table 16 gives the slopes, intercepts, and predictions for the trend lines in Figure 11. We predict that in 1974 the partial correlation between region and proportion Republican to Democratic will be between .52 and .79, depending on how recent a trend we wish to consider. The problem with the more recent trends, of course, is that (a) they are based on few observations, and (b) we expect much more erratic behavior in any short series of adjacent years because of the idiosyncrasies of specific elections. It may be that the slopes for the trend lines for any short series will fluctuate around some long-term "true" value. The best measure that we have been able to unearth for this true value is the off-year regression. If this were the case, our interpretation of Figure 11-(a) is that in recent years, the partial correlation has been rising at an abnormally large rate, and that political events may evolve in such a way as to reduce the slopes in recent years back to a value near the off-year slope of .02. The picture of change we are depicting is a general trend of homogeneity between regions with cyclical perturbations that appear either to accelerate or retard this movement.

TABLE 16

REGRESSION OF PARTIAL CORRELATION BETWEEN REGION AND PARTY IDENTIFICATION

(Region = South vs. Non-South)

Partial Correlation	Measures
Region by Proportion of Republicans to Independents	Overall Mean = .232 Off-Year Slope = .02 Intercept = .21 Predicted value in 1974 = .523 1964-1972 Slope = .05 Intercept = .189 Predicted value in 1974 = .636 1968-1972 Slope = .093 Intercept = .239 Predicted value in 1974 = .797
Region by Proportion of Democrats to Republicans	Off-Year Slope = .099 Intercept = 1.046 Predicted value in 1974 = 2.637 Presidential Years Slope = .0885 Intercept = 1.742 Predicted value in 1974 = 2.98 1964-1972 Slope = .051 Intercept = 2.295 Predicted value in 1974 = 2.806
Region by Proportion of Republicans to Democrats	Mean 1962-1966 = .966 Mean 1968-1972 = .7394 1962-1972 Slope = -.0198 Intercept = .952 Predicted value in 1974 = .714

The importance of the partial correlational technique for this analysis of trends in regional homogeneity should become clearer, since the conclusion from the trend in partial correlations in Figure 11 is somewhat different from the conclusion we drew earlier about the differences between the regions. Our earlier finding, based on discussion of the zero-order correlations between region and proportion of Republicans to Independents, was that regions were much more similar in the fifties and early sixties than in the late sixties, when an apparent differentiation was occurring. By 1970, however, these differences were again disappearing. It now appears that the similarities before the mid-sixties were a spurious result of the different cohort and educational compositions of the two regions, which were more pronounced in the early years of the series. Examining **only** the marginals, one would surmise that, in the later sixties, the Republicans in the South were suddenly beginning to identify with the Independent Party. A more detailed appraisal of the situation, presented in Figure 11, shows that once cohort and educational effects are put aside, the South always had a much lower expected proportion of Republicans to Independents, and that it was **only** the nature of the distribution of cohorts, education, and patterns of migration that was keeping the Republican Party "alive" in the South in the early years. Once the process of cohort succession had begun to work itself out in the middle sixties, and its implications in terms of the distribution of education across regions began to be felt, the zero-order tables began to show a decline in Republican identification. Any strategy to regain the marginal losses to the Republican Party in the South, then, would not only involve decreased political activity in the South, but also a reorientation by the politicians in terms of whom they perceived as their audience.

The changes in regional identification with the Democratic Party show another interesting turn of events. The reader may recall the precipitous decline in the proportion of Democrats to Independents recorded for the South in Part A. The zero-order odds ratios for this decline, as well as for the decline in the non-southern states, are reported in part (b) of Table 15. The ratio of the two regional odds ratios in the third row of this table shows a consistent positive association: the South has always tended to have a higher proportion of Democrats to Independents and, although the ratios for both regions have been declining over time, this association was stronger in 1972 than it had been in the previous six years. Judging from the zero-order associations in this row, we might guess that the relation between region and the proportion of Democrats to Independents would show a curvilinear relation over time, with a tendency for relationships to be more pronounced in the presidential election years. In fact, the partial correlations for this time period, plotted in part (b) of Figure 11, do not show this relationship. What we have instead is a beautiful covariance structure with partial correlations constantly increasing over time and a pronounced tendency for sharper correlations in the non-presidential years. Once other variables are controlled, identification with the Democratic Party is a phenomenon that is becoming increasingly differentiated by region. In 1974, the trend equations predict that once effects of cohort and education are controlled, the ratio of Democrats to Independents in the South will be from two and one-half to three times as great as the ratio in the non-southern states.

This is a puzzling result, since the hypothesis from Part A would be that, since the ratio for the South was declining faster than that for the non-South, the correlation between region and Democratic identification would, if anything, become more negative.

We suspect that this regional differentiation is caused by the fact that the pattern of de-identification with the Democratic Party in the non-southern states is more strongly related to education and cohort variables than in the southern states. Consequently, controlling for the effects of these variables will tend to "wash out" the effect of region in the amount of skew the non-southern states will contribute to the partial correlation. Living in the North appears to affect party identification because younger and more well-educated people live in the North and these people are tending to classify themselves as politically Independent. De-identification in the South, on the other hand, appears to be more of an across-the-board effect that is not affected by the controls we have introduced.

A simple examination of the slopes of Figure 11 should give a clue to the third turnabout we will report concerning the regional effect on the changing proportion of Republicans to Democrats in 1952 to 1972. The data reported in Part A indicate that there were usually between one-fourth and one-half as many Republicans as Democrats in the South in these years. Since this was nowhere near the ratio for the North, there tended to be a healthy zero-order association between region and major party identification. These zero-order odds ratios are reported in Table 15-(c). The trend seems essentially random, with a dip in 1968, and all values norm to significantly negative Q's.

The plot of the partials in Figure 11 tells a somewhat different story. Between 1962 and 1966, the average partial odds ratio is .97. This means that after the effects of the other variables are controlled, there is essentially no difference between the regions in preference for either the Republican or the Democratic Party. In the years 1968 to 1972, the average correlation is .74, a decline of 23 points. Once the effects of cohort and education are controlled, the ratio of Democrats to Republicans is about 25 per cent greater in the South than in the non-South. Moreover, this is an effect that has materialized since 1962. One possible explanation for this effect is that the well-documented rate of increased political participation by black voters in the South is a trend that is differentially beneficial to the Democratic Party and that would not be controlled by a partial correlation over cohort, sex, and education.

To summarize the discussion thus far of regional effects over time: The regions are becoming more alike in their preference for the Republican Party as opposed to the Independent, but vastly different in their preference for the Democratic Party. The net effect is that, controlling other variables (which affect the absolute numbers of Republicans or Democrats in an area), unique regional effects, which were absent in the early sixties, are reasserting themselves to the disadvantage of the Republican Party.

The second regional effect we will discuss is the finding from the hierarchical analysis that the partial correlation between region and party identification was not the same in all three cohorts. If we were to present an Analysis of Variance layout, we might say that each region involved a somewhat different treatment in terms of the correlation it produced between cohort and party identification. Alternatively, we could say that each cohort shows a different pattern of party identification, and furthermore that the pattern for each cohort in the South is not the same as the pattern in the

North. Since we have just examined an interaction from the point of view of region as the specifying variable, we will present this part of the analysis in terms of the different effects experienced within each cohort.

To get a perspective on the partial correlations that will be the substance of this part of the presentation, it is perhaps best to follow the same procedure we have used all along: look first at the ratios of party identification; from these ratios determine the zero-order correlation; and, finally, compare this zero-order with the partial correlation. Table 17 presents the means of the odds ratios over the full 20-year span for our party comparisons within each category of cohort and region. Table 17 also presents the ratios of these means, which are the approximate measures we will use for the average zero-order correlations between region and party in each cohort.

TABLE 17

MEAN RATIOS OVER 20-YEAR PERIOD FOR EACH COHORT AND THE RATIO OF THESE MEANS

Comparison	Cohort								
	Old			Middle			Young		
	Mean Non-South	Mean South	Ratio South/ Non-South	Mean Non-South	Mean South	Ratio South/ Non-South	Mean Non-South	Mean South	Ratio South/ Non-South
Republican to Independent	1.98	1.59	.80	1.2	.967	.81	.73	.52	.71
Democrat to Independent	2.27	4.17	1.84	1.79	3.54	1.98	1.24	2.12	1.71
Republican to Democrat	1.0	.387	.387	.69	.276	.4	.6	.266	.44

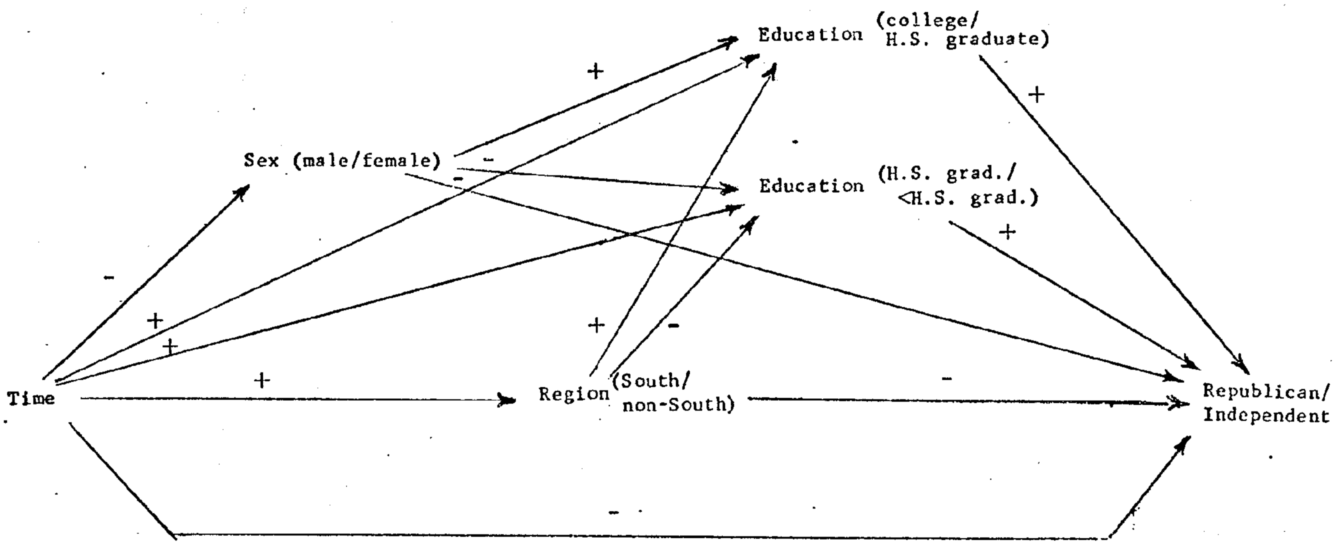
The data show (a) the proportion of Republicans to Independents is consistently higher in the non-southern states, (b) the proportion of Democrats to Independents is consistently higher in the southern states, and (c) there are practically always fewer Republicans than Democrats, with this phenomenon more pronounced in the South. What the zero-order data do not show is the slightest trace of an interaction between region and cohort. The correlations in any row seem pretty much the same no matter which cohort is being examined. This means that controlling for education and year will have different effects on the correlation between region and party depending upon which cohort we are discussing. We can expect that in some cases this control will act to "explain" the zero-order relationship, in other cases the control variables will actually suppress a stronger regional effect, while in yet other cases the controls will not change the relation at all.

How would controlling education and year explain a correlation between party and region? To illustrate, let us examine the correlation between region and the ratio of Republicans to Independents in the old cohort. The zero-order odds ratio is about .80. We know from previous discussion that there has been a trend in the last 20 years of a lower and lower proportion of Republicans to Independents in the older cohort. Furthermore, as mentioned in Part A and extensively documented elsewhere (Davis, et al., 1974), the older cohort has been moving South at a fairly constant rate over the last 20 years. The first effect is a time-party relationship and the second a time-region relationship. We know from demographic sources that differential mortality tends to raise the overall levels of education in older cohorts, and documentation in Part A shows that more education is correlated with a greater predicted proportion of Republicans to Independents.

We also know that time tends to increase the proportion of women to men in an older cohort, and that this will directly affect the dependent variable. The increased proportion of women will also have an indirect effect through its influence on the educational levels of the cohort. The article just cited shows that decreasing the number of men in the older cohort will tend to raise the proportion of high school graduates to less than high school graduates in the older cohort (men are less likely than women to finish high school in this cohort), but it will decrease the proportion of college-educated to high school graduates (men who do graduate from high school are more likely than women to go to college in any cohort). To give some idea of the complexity of the interrelation of all these effects, Figure 12 presents a path diagram summarizing the argument that controlling for all the prior variables might alter the relation between region and proportion of Republicans to Independents.

It turns out that controlling for the variables in the model does change the relation. The partial correlation for this comparison is given in Table 18. The partial odds ratio indicates that once the demographic changes and educational levels have been taken into account, there is practically no difference between regions in the proportion of Republican Party identification in the old cohort. The controls in the model do very little, however, to account for the regional differences in the two younger cohorts, where the partials are almost exactly the same as the zero-order relationships (the first row in Table 18). For younger voters, then, the region of one's residence is an important variable in determining whether or not one will identify with the Republican Party. This is apparently not so in the older cohort. The data in the second row suggest exactly the opposite

Figure 12.--Causal Model for the Effect of Control Variables on the Relation between Region and Proportion Republicans to Independents in the Old Cohort



pattern for Democratic Party identification: among the old cohort, after all other effects have been controlled, southerners are about twice as likely as non-southerners to choose the Democratic Party over an Independent identification. The cohort comparison suggests that this regionalism is declining for the younger cohorts, where there seems to be a weakening of the tradition of Democratic identification for younger cohorts in the South.

TABLE 18

PARTIAL CORRELATION BETWEEN REGION AND PARTY IDENTIFICATION FOR THREE COHORTS, PARTIALED OVER SEX, EDUCATION, AND YEAR

Partial Odds Ratio	Cohort		
	Old	Middle	Young
Region* by Republican/ Independent	.940 (Q = -.03)	.798 (Q = -.11)	.724 (Q = -.16)
Region* by Democrat/ Independent	2.05 (Q = .34)	1.83 (Q = .29)	1.38 (Q = .16)
Region* by Republican/ Democrat	.456 (Q = -.37)	.461 (Q = -.37)	.527 (Q = -.31)

*Region is categorized South (high category) vs. Non-South (low category).

The first two rows of Table 18 show linear trends in the relationship between cohort and the correlation between region and party identification. The trends go in the opposite direction, however, depending upon the party in question. This is the interaction found to be significant in the hierarchical model. The third row of the table shows that there is no interaction between cohorts in the partials between region and major party identification.

This is a difficult interaction to explain, and the zero-order data shed little light on the matter. The deviant cell in the table of partial correlations (Table 18) is the first partial for the old cohort. If this were around .75, it would be possible to say that the main effect in the table is the declining tendency for the South to be described as uniquely Democratic. This appears to be a case where controlling the other variables had two effects: (1) suppressing the regional effect in the older cohort and (2) helping to explain the regional effect in the younger cohort. The zero-order data suggest that the regional effects are about the same when, in fact, they seem to be operating quite differently, depending on one's age and social circumstances. The net result of this is that the regions are also becoming more alike in their distribution of Republicans to Democrats in successively younger cohorts (the younger cohorts are closer to 1.0).

The .94 in the upper left-hand cell of Table 18 does not simplify things. One possible explanation is that the tendency toward southward migration (which applies with approximately equal strength to all cohorts) may be disproportionately attracting older Republicans to the South. It is not unreasonable to expect that the members of the older cohorts, by and large beyond the years of labor force participation, are drawn to the South most often for reasons of health, retirement, and the like. The forces attracting the younger cohorts would have more to do with the opportunities afforded by the increasing industrialization and urbanization in the South. We are suggesting that these reasons for migration may operate in such a way as to bring a greater than "expected" number of older Republicans, while the attractions for the younger cohorts would be uncorrelated with party preference. This dynamic would have the effect of depleting the supply of Republicans in the old cohort in the North and inflating the supply in the South. A possible hypothesis here is this: if region of upbringing were controlled, the partial correlation between region and proportion of Republicans to Independents in the old cohort would be much more similar to the correlation in the other age groups.

Interactions Involving Education

The recent literature on social indicators and social change tends to place a great deal of importance on the changes in levels of education over the past 20 years. From a macrosocial standpoint, increased levels of education are often expected to account for much of the marginal shift in survey items ranging from tolerance to happiness. For the questions in this paper, it has been suggested (Converse, 1965; Campbell, et al., 1964) that higher levels of education are prerequisites for heightened states of "ideological awareness" in the electorate. Ideological awareness is supposed to run generally on a liberal-conservative (or possibly, a Democratic-Republican) continuum, and it might therefore be hypothesized that changing patterns in party identification are tied to rising levels of education. Specifically, if education promotes ideological awareness, and political parties are the social manifestations of these ideologies, then one might hypothesize that party identification is less random among the better educated. As it stands, though, we have no hypothesis about whether education makes any difference in the political party one actually identifies with.

Glenn (1973)argues that class patterns have been associated with preference for the Republican or Democratic party. Education is often used as the surrogate measure for social class, and until recently, more education was associated with a greater propensity to identify with the Republican Party. The gist of Glenn's argument, however, is that in the most recent elections, the traditional class patterns (and hence educational patterns) in voting have been on the decline in areas outside the South.

Given the data at our disposal, a reasonable hypothesis might be that the correlation between education and party identification has been changing outside the South. Stated formally, we are hypothesizing an interaction between time, region, education, and party identification. We tipped our hand (in the introduction to this part of the report) when we listed the effects necessary to fit the model to the data and no four-variable interaction was among them. When we tested the significance of this four-variable effect alone, the chi square goodness-of-fit statistic had a p value of .034--close, but as we said, not necessary to fit a model. It may be that we are using a broader definition of "South" than was used by Glenn. Our southern category (described in Part A) includes those states usually classified as border states in the SRC coding. This was done to preserve cell sizes large enough to allow us to make reasonable estimates of parameters. It may be that a more restrictive categorization of "South" would show a more lively interaction. Since our findings by and large support Glenn's, we will not dwell on this point.

In this report,we find that the relation between party and education is specified by:

a) Time: "Class" differences do seem to be disappearing over time, but the effect is the same in both regions once the other effects are controlled.

b) Cohort: The young are not following the patterns of their predecessors; the college-educated in this group are about equally split between Independents and Republicans, in contrast to the strong preference for the Republican Party among the college-educated in the older cohorts.

c) Region: Once trends associated with cohort and time are controlled, education has very little association with party preference in the South, while the education effects in the non-southern regions are generally stronger.

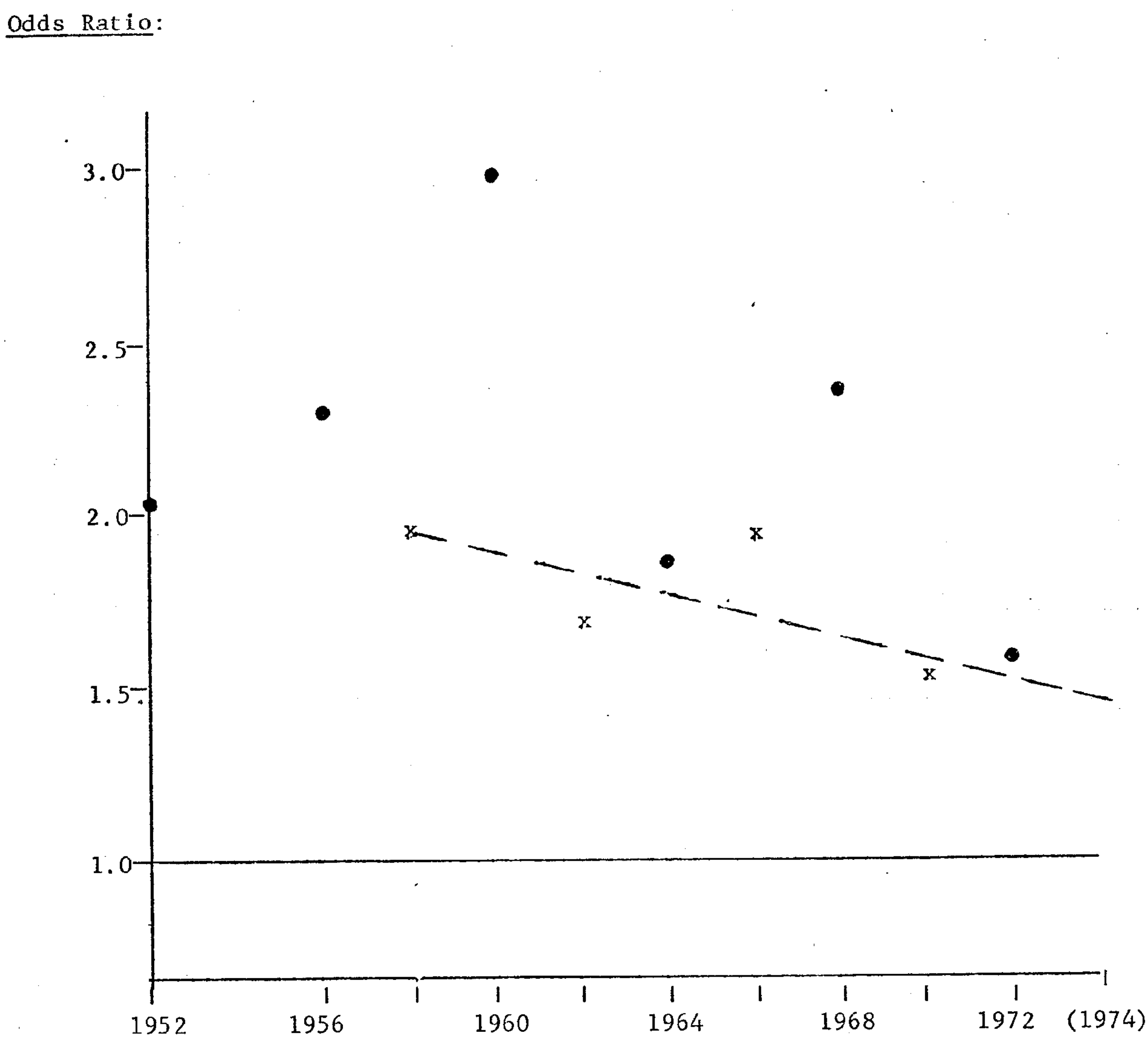
Figure 13 shows the partial correlations between education and party preference for the 20 years of the series. Most values are well above 1.0, indicating that, whichever dichotomy of education is used, the "higher" category always tends to be more Republican after other effects are controlled. The off-year regressions indicate that there is a tendency for the partials to approach 1.0 over time. The slopes and predictions for the fitted trends from Figure 13 are in Table 19.

TABLE 19

REGRESSION OF PARTIAL CORRELATIONS BETWEEN EDUCATION AND PARTY PREFERENCE

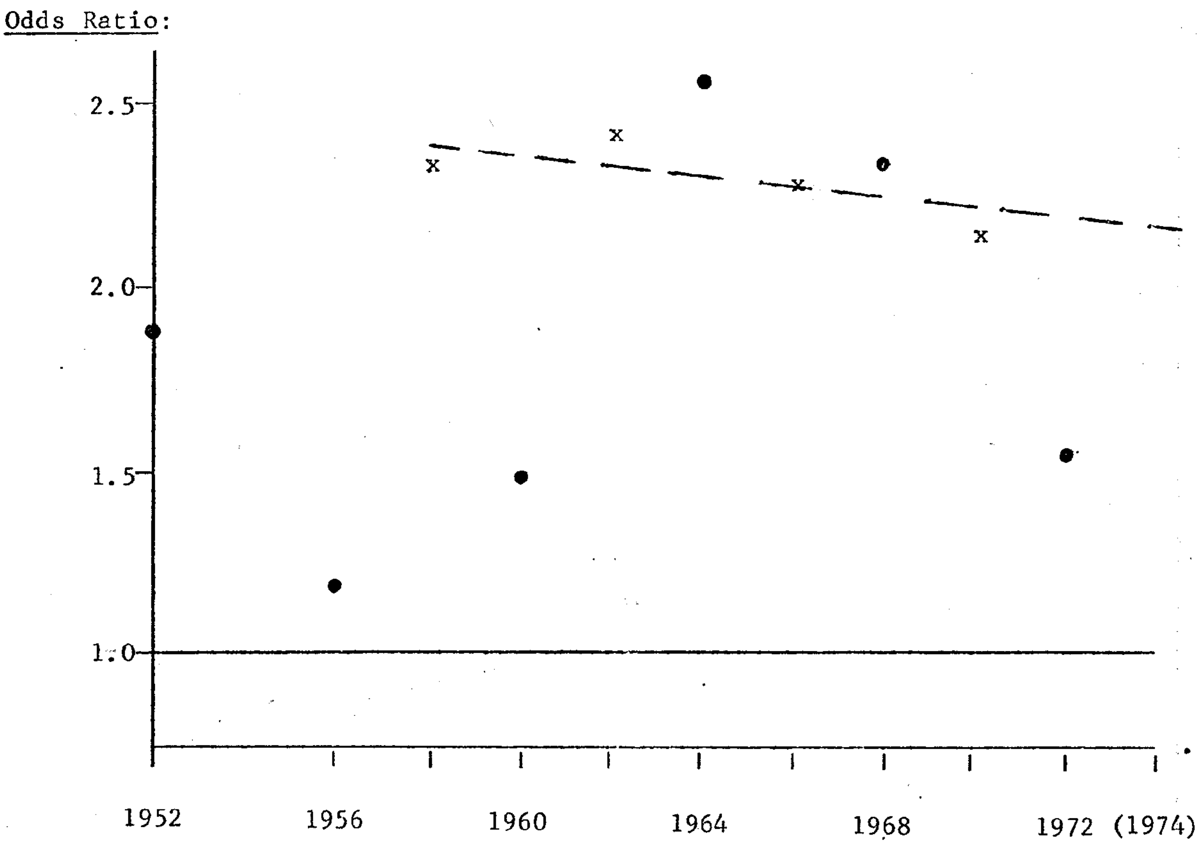
Ratio of Party Preference	Education Dichotomized as:	
	College-Educated/ High School Graduate	High School Graduate/Less than High School Graduate
Republican to Democrat	Mean = 2.02 Mean, presidential years only = 2.19 Off-Year Slope = -.029 Intercept = 1.94 Predicted value in 1974 = 1.47	Mean = 2.02 Off-Year Slope = -.016 Intercept = 2.39 Predicted value in 1974 = 2.17

Figure 13.--Partial Correlations between Education and Party Identification--Republican/Democrat



(a) College Educated vs. High School Graduate

Figure 13.--(Cont.)



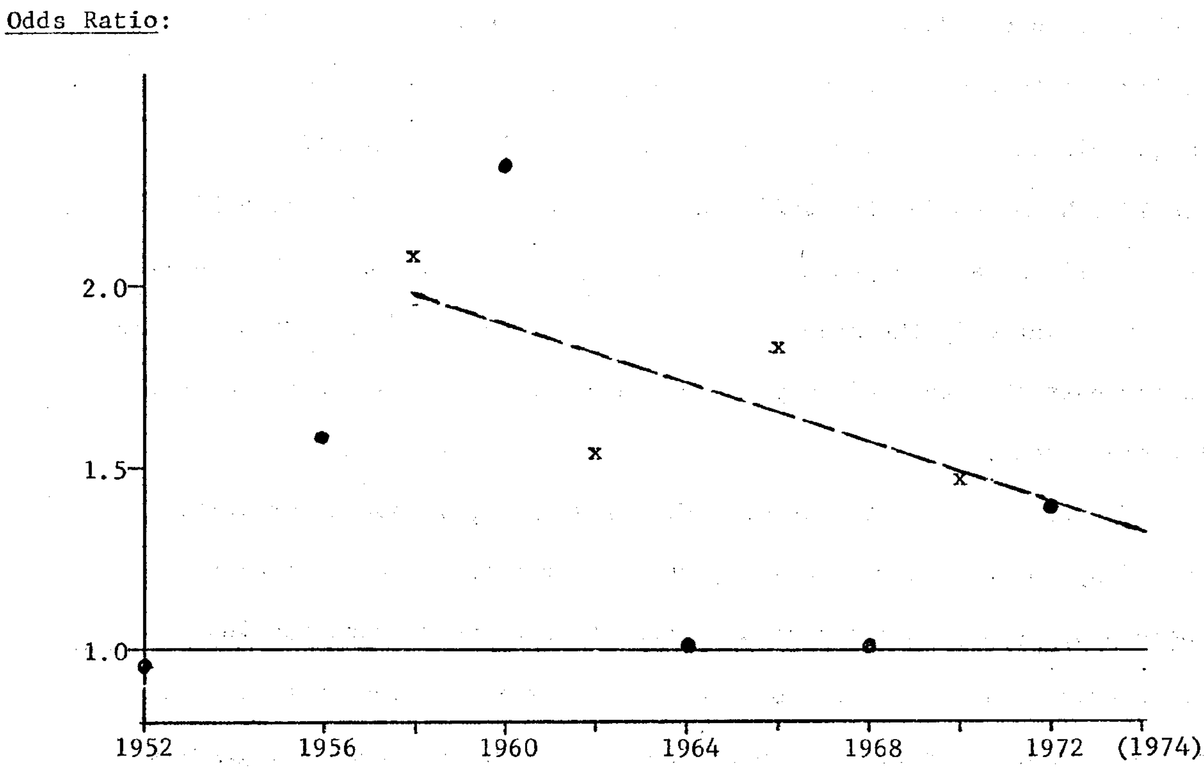
(b) High School Graduate vs. less than High School Graduate

An important aspect of Figure 13 is the miserable fit that would be obtained if we were to include the presidential years in the equation. The off-year points do seem to describe a linear pattern that is broadly generalizable to the other points on the graph. However, the points for the major election years are all above the trend line in part (a) of Figure 13 (the means for the different series are compared in Table 19) and the presidential year points for part (b) seem to wander perfidiously. Anyone analyzing only the major elections since 1964 would report a whopping trend for part (b), but this may not be an accurate representation of the real social trend.

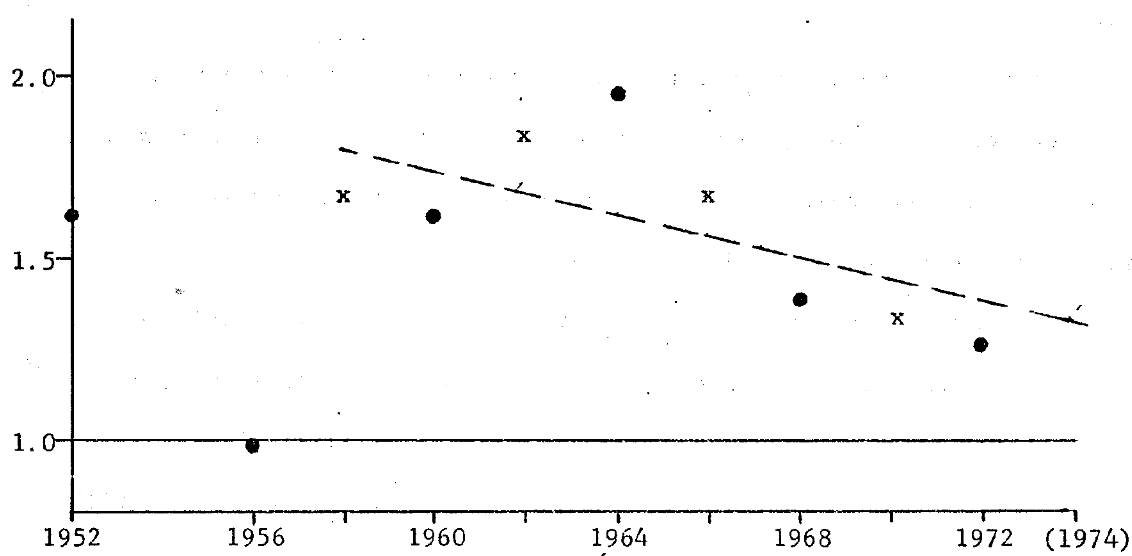
We believe the data are most conservatively, if not accurately, described by the off-year equations, which show a slow decline (.02 to .03 points per year) in the partial correlation between education and party identification. Since education is the variable closest to social class in our model, we derive support for the recent hypotheses suggested by Glenn (1973), although the trend does not appear to be specified by region.

If we examine the preference for major parties relative to the Independent category, we gain further insight into the reasons for this finding. Figure 14 shows that, for every year in the non-presidential series, the partial between education and proportion Republican to Independent declines three to four points. That is, once the other variables have been controlled, the proportion of Republicans to Independents is tending to become the same in all categories of education. Since the predicted values in 1974 for both partial odds ratios are 1.32, we still expect a small net correlation between education and party, on the order of a partial gamma equal to .15. Slopes and intercepts for this figure are in Table 20.

Figure 14.--Partial Correlations between Education and Party Identification--Republican/Independent



(a) College-Educated vs. High School Graduate



(b) High School Graduate vs. less than High School Graduate

TABLE 20

REGRESSION OF PARTIAL CORRELATIONS BETWEEN EDUCATION AND PROPORTION OF REPUBLICANS TO INDEPENDENTS

Ratio of Party Preference	Education Dichotomized as:	
	College-Educated/ High School Graduate	High School Graduate/Less than High School Graduate
Republicans to Independents	Mean = 1.51 <u>Off-Year</u> Slope = -.04 Intercept = 1.96 Predicted value for 1974 = 1.32	Mean = 1.53 <u>Off-Year</u> Slope = -.031 Intercept = 1.81 Predicted value for 1974 = 1.32

Cohort and region do not enter into this interaction by year. This suggests that the trend of yearly decline holds across all categories of cohort and region. Previous discussion has suggested that the overall levels of correlation between education and party ought to be different for different cohorts and regions. This is not an inconsistent finding. It is analogous to an Analysis of Covariance model in which each cell of the region by cohort table would have a different intercept for the correlation between education and party. Across time, the partial in each cell would lose about .035 points a year. In any given year the differences between regions and cohorts would be preserved since all would be declining at the same rate, but after 20 years the correlations in all cells would be somewhat smaller than in the beginning.

So far we have seen that the partial correlation between education and major party preference has been declining. Figure 14 suggests that one reason for this may be that it is becoming increasingly difficult to distinguish between Republicans and Independents on the basis of education alone. If we turn to Figure 15, we see that this might be all that is happening. Over time, the partial correlation between education and preference for Democrats to Independents seems nonlinear for the first comparison in the figure and random for the second. During off years, the proportion of Democrats to Independents tends to have a slight negative association with education. In presidential years, many of the collegians apparently become Independents; the correlations become a lot more negative in part (a) of Figure 15 and nothing happens in part (b).

The net result of the education effects is that:

a) The correlation between education and proportion Republican is positive, but is declining. One might say that social class is becoming less a predictor of Republican identification.

b) The correlation between education and proportion Democrat is negative, but doesn't seem to be doing much over time. The class/party correlation seems weak but stable, especially in non-presidential years.

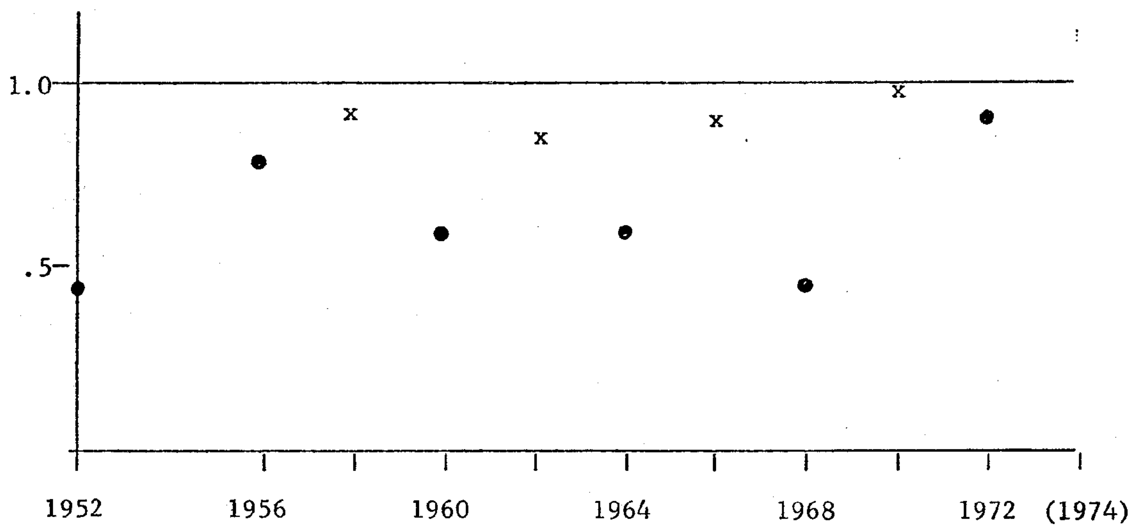
c) The partial correlation between education and major party identification can be viewed broadly as the ratio of the partial for Republicans to Independents divided by the ratio of Democrats to Independents. Since the top half of this ratio is getting smaller and the bottom half is staying the same, the effect over time is that the partial between education and major party identification is declining. It may be too optimistic, however, to say that the meaning of this trend is a decline in the class base of party identification.

We have set the stage but not really raised the curtain on the results that elaborate the second interaction involving education. By examining the relation between cohort, region, and our dependent variable, it is possible to throw some light on the theoretical issues that led us to trichotomize education the way we did.

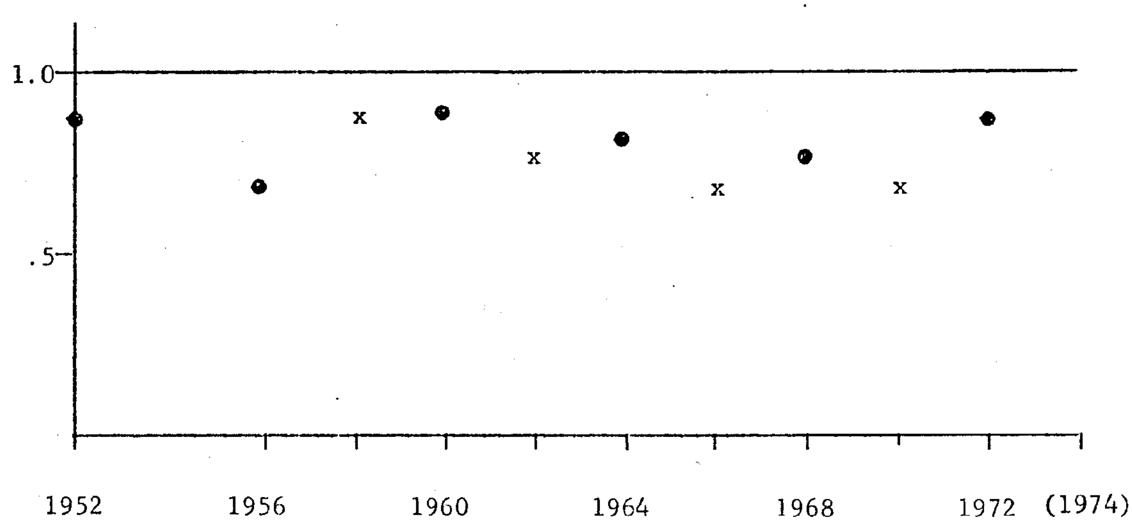
A survey of demographic data (Davis, 1963) suggested that the meaning of high school graduation has changed somewhat since the early years of

Figure 15.--Partial Correlations between Education and Party Identification--Democrat/Independent

Odds Ratio:



(a) College-Educated vs. High School Graduate



(b) High School Graduate vs. Less than High School Graduate

this century during which the older cohort was socialized. At that time, most of those who completed high school went on to college; the major social distinction was between those who completed high school and those who did not. Sometime between World War I and the end of World War II, the values and needs of American society changed such that most people were completing high school, but only a low (and fairly constant) proportion of them were going on to college. During this period there was a change in the meaning of the high school diploma; during the years of the middle cohort's socialization, and certainly by the Cold War, it was assumed that most people would be graduated from high school, and the major social distinction was between those who went on to college and those who did not.

In examining the partial correlations between education and party identification, we would expect the high school to less than high school distinction to be of greatest "salience" to members of the older cohort, and less covariance in party identification between the college and high school distinction. In the two younger cohorts we would expect that the more salient distinction would be between the college and the high school educated.

Table 21 presents the data for this hypothesis. The first row shows that, no matter the cohort, more education is associated with a preference for the Republican Party over the Democratic Party. The lowest and the highest association are both in the column for the old cohort. Moreover, the pattern in this cell supports the hypothesis. The distinction between graduation and non-graduation from high school is far more important in sorting the old cohort along party lines than is the college versus high school graduate distinction. For the middle cohort, the pattern is reversed, again supporting the hypothesis. The graduate/non-graduate difference is important, suggesting that the value of this distinction has been preserved, but the distinction between collegians and non-collegians has assumed primary importance in differentiating political faiths.

TABLE 21

PARTIALS BETWEEN EDUCATION AND PARTY WITHIN THE THREE COHORTS

Partial	Older Cohort	Middle Cohort	Younger Cohort
College-educated/High school graduate by Republican/Democrat	1.4 (Q = .17)	2.25 (Q = .38)	1.75 (Q = .27)
High school graduate/less than high school graduate by Republican/Democrat	2.52 (Q = .43)	1.74 (Q = .27)	1.66 (Q = .25)
College-educated/High school graduate by Republican/Independent	2.12 (Q = .36)	2.09 (Q = .35)	.92 (Q = -.04)
High school graduate/less than high school graduate by Republican/Independent	1.59 (Q = .23)	1.28 (Q = .12)	1.45 (Q = .18)
College-educated/High school graduate by Democrat/Independent	.93 (Q = -.03)	.56 (Q = -.28)	.81 (Q = -.11)
High school graduate/less than high school graduate by Democrat/Independent	.62 (Q = -.23)	.72 (Q = -.16)	.90 (Q = -.05)

Unfortunately, from one point of view, Table 21 also presents data against the hypothesis. Specifically, the data for the younger cohort do not show the same break for the correlations between education and Republican Party preference. Also, if we average the two coefficients in each cell in the first row, it appears that, on the whole, the correlation between education and party is lower for the young than for the other two cohorts. Looking down the third column, it appears that the correlations for the younger cohort are consistently lower than the corresponding entries for the other cohorts. These two findings may be related and may explain why the hypothesis does not hold for the younger cohort. In this case, there is a conflict between two social trends. The college/high school difference does not indicate party identification for the younger cohort any better than the high school/less than high school difference because education as a variable is not as salient among the young as it is in the older cohorts.

If the rules of the game have changed for the Cold War generation, then we can still graciously hold our hypothesis, with the minor addition of a restriction on the time period to which it applies. This would not be the first point in the analysis where we have argued that the young cohort is a special case to be treated with separate methods and hypotheses.

The data in Table 21 bear further scrutiny, for they may suggest further reasons for the pattern of ratios for the old and middle cohorts in the first row. The partial correlations between education and the proportion Republican to Democrat are surprisingly similar for the two older cohorts. This suggests that different patterns of identification with the Democratic Party must be creating the effect we observed in the first row. The third row does, in fact, show that the level of one's education interacts differently with Democratic Party identification, depending on one's cohort. In the old cohort, the college/high school distinction has little effect on the expected distribution of Democrats and Independents. However, the high school/less than high school distinction once again comes through with a negative correlation that is probably significant. Among the members of the old cohort, high school graduates are more likely to classify themselves as Independents than are those who never finished high school. Moving over one column in the table, the high school/less than high school effect remains for the middle cohort (as before), but now the important distinction for predicting the proportion of Democrats to Independents is the college versus high school graduate comparison.

To summarize this point, level of education has the same effect for the old and middle cohorts in predicting the ratio of Republicans to Independents. When it comes to predicting the ratio of Democrats to Independents, however, the high school graduate to less than high school graduate distinction is most important in the old cohort, and the college to high school distinction is most important in the middle cohort. This adds a further refinement to the above hypothesis. Cutting points along the continuum of education have different meanings for the old and middle cohorts with regard to the level of identification with the Democratic Party, but not the Republican Party. The combination of these two findings explains in some sense the result reported at the beginning of this discussion on the different partial correlations between level of education and major political party identification in the older two cohorts.

The final substantive presentation of this paper harks back to our earlier discussion of the characteristics of social life in the different regions of the United States. The effect to be explained is the finding from the hierarchical model that the partial correlation between education and party is not the same in the two regions. The interpretation of this effect is actually very straightforward. If the main distinction in southern politics is Democrat vs. other, we would expect that the decision to identify with either the Republicans or the Independents would be more random than in other areas of the country where there have been two functioning political parties for the last two decades.

The zero-order correlations in Table 22 show that, in the South, it is the high school to less than high school difference that is the better predictor of whether or not a voter will consider himself an Independent. This pattern is most similar to the pattern of partial correlations we observed for the older cohort. In the non-South, with no other controls introduced, it is the college versus high school distinction that most distinguishes between Republicans and Independents. This reinforces a previous observation: once effects of cohort are controlled, a high affinity between college education and Republican Party identification remains.

It is valid to ask the extent to which these effects are a result of a unique regional influence, with respect to the other variables in our model. The partial correlations for the same comparisons are presented in Table 23. Once differences of cohort and sexual composition over time have been controlled, the only uniquely regional effect seems to be that education does not affect Republican Party identification as much in the South as it does in the North. Consequently, education does not affect major party identification as much in the South, as is shown in the third row in the table.

A theory of massification of regional effects in party preference wodld require either that the North become less differentiated in its association between party and education, or, on the other hand, that the South adopt the more "class-oriented" approach to national politics and begin to have its educational elites form a stronger attachment to the Republican Party.

TABLE 22

ZERO-ORDER CORRELATIONS BETWEEN EDUCATION AND PARTY IDENTIFICATION IN THE DIFFERENT REGIONS

Correlation	Region	
	Non-South	South
College-educated/ school graduate by Democrat/Independent	.669 (-.20)	.82 (-.10)
High school graduate/less than high school graduate by Democrat/ Independent	.653 (-.21)	.65 (-.21)
College-educated/High school graduate by Republican/Independent	1.27 (.12)	1.09 (.05)
High school graduate/less than high school graduate by Republican/ Independent	.99 (0)	.66 (-.20)
College-educated/High school graduate by Republican/Democrat	1.90 (.31)	1.33 (.14)
High school graduate/less than high school graduate by Republican/ Democrat	1.52 (.21)	1.03 (.01)

TABLE 23

THE INTERACTION BETWEEN REGION, EDUCATION, AND PARTY

Partial Correlation	Region	
	Non-South	South
College-educated/High school graduate by Democrat/Independent	.75 (Q = -.14)	.78 (Q = -.12)
High school graduate/less than high school graduate by Democrat/ Independent	.80 (Q = -.11)	.81 (Q = -.11)
College-educated/High school graduate by Republican/Independent	1.93 (Q = .32)	1.35 (Q = .15)
High school graduate/less than high school graduate by Republi-can/Independent	2.06 (Q = .35)	1.12 (Q = .05)
College-educated/High school graduate by Republican/Democrat	1.37	1.11 (Q = .05)
High school graduate/less than high school graduate by Republican/ Democrat	1.50 (Q = .20)	.90 (Q = -.05)

Summary

This report is part of a series of studies attempting to measure the real and apparent changes in American society in the last two decades. We have used party identification as a dependent variable because (1) there is a large body of literature against which our findings can be checked, and (2) it was expected that fairly pronounced changes that were related to each variable in the model had been occurring.

There are two directions in which this study could be extended. The first would be to put together a general model that would predict the long-term changes in the levels of party identification based on the parameters we have identified. The problem with this approach is that the model would almost assuredly never give accurate predictions in any specific year, especially if it were a major election year. The second direction would be to take changes in party identification as one case, one observation if you will, in the broader empirical examination of changes in American life. In this vein, we have oriented much of our discussion to problems of massification versus differentiation, persisting sexual differences, the changing meaning of education in the society, and the tendency for the society to drift into new political and ideological alignments. As such, this study is a groundbreaker for our own project, since it anticipates many of the problems of trend analysis and measurement that will be encountered when other dependent variables are examined.

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VOLUNTARY ORGANIZATIONAL MEMBERSHIP

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Introduction

The literature on organizational membership is of two main varieties. First, are the stratification or community organization theorists who generally explain differences in organizational membership as attributable to differences in educational levels, occupational categories, and other measures of socioeconomic status. The early work of Komarovsky (1946), and, I think, Hyman and Wright (1958, 1971), to some extent fall under this heading. The second main approach to organizational membership comes under the literature on aging. Perhaps the best summary of this approach is in Riley, et al. (1972, Vol. 1). Here, the main effects are the correlations between aging and general indicators of social integration, such as happiness, health status, labor force participation, voting behavior, and the like. These two approaches are blended in some of the current literature on political participation in which both socioeconomic and social-psychological determinants of participation are considered (Campbell, et al., 1964).

In this report, we will attempt to address ourselves to both approaches. The educational differences in organizational membership are fairly well known.[1] We will assess the importance of socioeconomic determinants of organizational membership by examining the extent to which they "explain" the educational differences noted above. Age differences in organizational membership have also been observed: the number of organizations a person belongs to, like the number of words he knows, tends to increase with age until a certain point and then drop off. This process of successive engagement and then disengagement

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[1]The more well-educated a person is the more likely he or she is to belong to organizations. See Taylor (1975).

(Cumming and Henry, 1961) is assumed to be correlated with other measures of social integration. To test this, we will examine the extent to which the available measures of social integration explain the cohort differences observed in organizational membership.

In addition to making tests of common propositions about organizational membership, we also hope to provide methodological answers to some problems that we have encountered in this area. These problems are of two sorts:

1) Wright and Hyman made much of the low percentage in their sample that belonged to any organization at all, concluding that America is apparently not a nation of joiners. A problem with assertions of this nature is that the total percent who say they belong to an organization is to a considerable degree dependent on the number of examples of organizations given in the question (Taylor, 1975). Wright and Hyman didn't have many examples of organizations in their questionnaires, and so did not observe a high rate of joining. In contrast, the 1974 General Social Survey, which has 15 examples (a large number relative to other forms of this question) reports that almost 80 per cent of the population did, in fact, "join" at one time or another. Some way to control for the effect of question wording on the response is needed if we are to examine the results from different surveys or make statements about changes over time.

2) The second problem has to do with the methodological apparatus used to study cohort changes over time. It is difficult to "plug" the cohort variable into the standard methods for time series analysis of qualitative variables (e.g., Taylor, 1975) because not all of the cohorts are in the sample all of the time. For example, a birth cohort that was 21 to 35 years of age in 1974 was too young to be represented in any sample drawn before 1961. The methods of log linear and hierarchical modeling (Goodman, the RAFisher lecture paper) can readily be adapted to cope with these problems; we will incorporate this method in our discussion of the results below.

What follows is in five parts. First, we will present the findings that constitute the central issues of the discussion: the stable correlations (once question wording is controlled) between education, cohort, and organizational membership.

Next, we will discuss the "socioeconomic determinant" school, considering the effects of family background, occupational status, subjective social class, income, and size of place of residence on organizational affiliation. Specifically, we will consider the extent to which these differences are independent of educational differences.

In the third section, we will explore the social-psychological factors more fully. We will consider various measures of social integration or social participation as determinants of "joining." These measures are: intensity of religious belief, frequency of church attendance, electoral participation, health status (perceived), and happiness. Again, we will control for educational differences. In addition, we will consider the extent to which the socioeconomic and social-psychological factors account for cohort differences in organizational membership.

In the fourth section, we will present a brief discussion of the factors generally assumed to be determinants of membership among the oldest members of society: marital status and labor force participation.

Finally, for those measures that continue to be of interest, we will include both cohort and educational effects in the model and attempt to arrive at some conclusion about changes in the level of organizational membership as the demographic processes of cohort succession and changing educational levels continue in this country.

Central Issues and Methods

When we consider whether the correlation between education and organizational membership changes over time, we are really talking about three variables: education, membership, and time. To say that the relation between education and membership is the same at all points in time is to say that the correlation between education and membership does not interact with time. In this case, the relations between these three variables could be expressed as a linear flow graph (Stinchcombe, 1968; Davis, 1976), as in Figure 1.

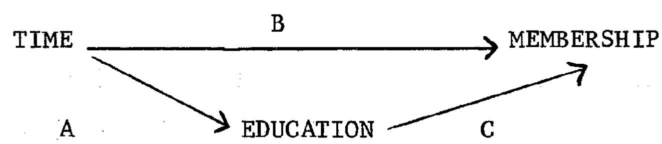


Fig.1--Hypothetical Flowgraph for
Relationship Between Time, Education, and Membership

Figure 1 is equivalent to the following statements about the relations between the variables: (1) At any time, the correlation between education and membership is about the same and equals "C." (2) The overall level of education may or may not be changing over time; if it is changing, then "A" does not equal zero. (3) The level of membership in organizations may be different at different times net of differences that would be caused by changes in the levels of education; in this case "B" does not equal zero. (4) There is no interaction between time, education, and membership. In terms of hierarchical models (Goodman, 1970), this graph would dictate that the following sets of marginal tables be fitted in order to describe the data:

(TIME,MEMBER) (TIME,EDUCATION) (EDUCATION,MEMBER)

As noted above, one limitation of the data available to us is that the same question wording does not appear twice in the series of surveys under examination. For this reason, Figure 1 ought to be corrected (see Figure 2). However, if the path "B" is not zero--that is, if there is a change in the level of membership after controlling for education--we cannot know whether this is some sort of "social" change or merely a result of changes in the wording of the question. Therefore, rather than analyze the correlation between time and membership, we will take it as given. We will consider the (TIME,MEMBER) effect as fixed in the design of the study and include it in every model that is tested, though it will receive little comment. Similarly, since this is a study of changes in determinants of organizational membership and not changes in the levels of education since 1948, we will also consider the (TIME,EDUCATION) effect as fixed in the design of the study. We will assume that this effect is in the data and not make an effort to affirm its significance.

We are left, then, with three possible hypotheses about the relation between education and membership:

1) The relationship was zero at all times.

2) The relationship is constant in each survey.

3) The relationship is different, depending on either time or question wording, and we are not sure which.

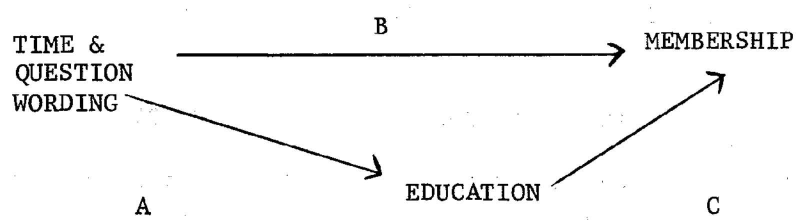


Fig. 2.--Corrected Flowgraph, given the Constraints of the Data Set

These three hypotheses are hierarchical in the sense that each hypothesis is more complicated than the one before it and each is included in those after it. In fact, since we have assumed several effects to be fixed in the research design, the three hypotheses correspond to the hypotheses that can be made about the effect of education on the <u>logits</u> of the dependent variable, MEMBERSHIP (Goodman, 1972). The three hypotheses are interpretable in terms of the results of fitting two models:

a) (TIME,MEMBER) (TIME,EDUCATION)

b) (TIME,MEMBER) (TIME,EDUCATION) (EDUCATION,MEMBER)

Hypothesis 1 says that Model (a) fits. Hypothesis 2 says that Model (a) does not fit and Model (b) does fit. Hypothesis 3 says that Model (a) does not fit and Model (b) does not fit.

We can never completely unravel the effects of question wording differences, but knowing which of the three hypotheses described the data would certainly tell us something about the level of complexity needed to describe the changes in the determinants of organizational membership.

> If Hypothesis 1 fits, we are safe in suspecting that: there is no relation between education and membership; and this is not affected by question wording.
>
> If Hypothesis 2 fits, it is <u>plausible</u>, though not necessarily the case, that: the relationship is stable and wording probably does not matter; and that the main effect of differences in wording would be a change in the marginals of the dependent variable (MEMBERSHIP) and this would be reflected in the (TIME, MEMBER) path "B."
>
> If Hypothesis 3 fits (or, equivalently, if 1 and 2 don't fit) then we must prepare ourselves for the most complex statements possible about the changes over time in the effects of different question wordings on the correlation between education and membership.

The advantage of testing these hypotheses sequentially, starting with the simplest, is that we avoid having to accept the most complicated, least parsimonious, and least interpretable hypothesis about the (EDUCATION,MEMBERSHIP) effect.

When we actually fit models (a) and (b) to the data, we obtain the results presented in Table 1. We accept the second hypothesis: the relation between education and membership is invariant over time and question wording. Our interpretation of this result is that once statistical adjustments for differences in question wording are made (the TIME,MEMBER effect) there is a zero-order relationship between education and organizational membership that is consistent across all surveys.

Now, of course, there is the problem of representing the magnitude of the relationship. The Goodman method is to take the tables of expected values from fitting the three two-way marginal tables (Model (b)), and from this table to calculate the log linear effect parameters that are interpretable as the effect of one variable on the natural logarithm of some root of a conditional odds for the dependent variable. In this paper, we will follow Goodman halfway. We concur in his statistical argument that the modeled data are the most accurate reflection of the true differences in the population. From the modeled data generated under hierarchical Model (b) we will calculate partial percentage difference path coefficients (Davis, 1976), which have a more intuitive justification and which are more susceptible to flow graph manipulations. The two methods for assessing the magnitude of the effects of education yield the results presented in Table 2.

Our interpretation of the Davis coefficients is that once the data have been smoothed to remove certain effects of question wording and random fluctuation, there is a consistent zero-order correlation between education and organizational membership. Persons who have finished high school are about 13 per cent more likely to say they belong to one or more organizations than those who did not complete their high school education. Persons who have had any college at all are even more apt to "join": they are over 25 per cent more likely than those who did not finish high school to say they belong to one or more organizations. Figure 3 illustrates. We will consider this result basic to our later discussion of the effect of socioeconomic and psychological factors in attenuating these zero-order relationships.

TABLE 1

PARTIAL DECOMPOSITION OF CHI SQUARE FOR THE THREE-VARIABLE SYSTEM:
TIME BY EDUCATION BY MEMBERSHIP

		Data			
Model	Marginals Fitted	X^2	d.f.	p	Decision
(a)	(TIME,MEMBER)(TIME,EDUCATION)	327.5	8	$<.05$	reject
(b)	(TIME,MEMBER)(TIME,EDUCATION) (EDUC,MEMBER)	4.8	6	$>.05$	accept

TABLE 2

COEFFICIENTS

	GOODMAN		DAVIS[a]	
Category	Lambda(log) effect	Std. Value	D	Std. Error
0-11	-.302	-13.183	(base category)	
HSG	-.025	- .955	.131	(.014)
Coll	.327	10.087	.266	(.014)

[a] Note that when we apply the Davis method in this case there are no questions of significance testing or interference. We have already concluded the effect is significant. The statistics are for descriptive purposes only.

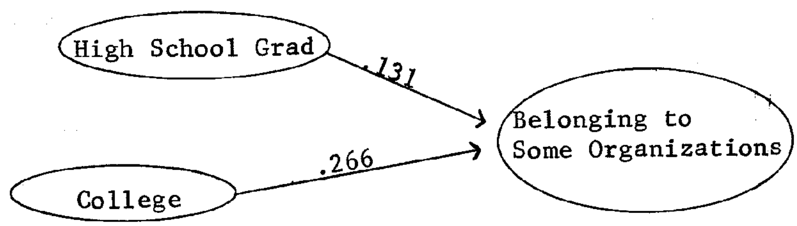


Fig. 3.--The effect of Education on Group Membership, 1952-1974

A second set of findings basic to the development of the argument are the cohort differences. To handle cohort differences in the hierarchical modeling framework we need to make some adjustments. In the discussion of the hierarchical models appropriate for Figure 1 or Figure 2, we replace the variable "EDUCATION" with the variable "COHORT". That is, we still assume the (TIME,MEMBERSHIP) effect is given and we will not analyze the dynamics of cohort succession reflected in the (TIME,COHORT) effect; therefore, the latter effect is also "given." This still leads to three nested hypotheses and two hierarchical models appropriate to test with the data. Briefly, the hypotheses about cohort differences are:

1) At no time are there significant cohort differences.

2) Cohort differences are constant in all surveys.

3) The magnitude of cohort differences depends on when the question was asked (or possibly on <u>which</u> question was asked, and, once again we cannot tell the difference).

Before testing these hypotheses, we need to make one additional adjustment in the estimation procedure to accomodate the fact that the newest cohort (age 18 to 34 in 1974) was too young to be in the samples drawn before 1961. Therefore, we have two surveys which were done at times when the New cohort did not exist (survey-wise). This kind of problem is often encountered in contingency tables where there are <u>structural zeroes</u> (Goodman, 1970b; Fisher, 1968); that is, when there are cells in a table that are logically possible but are, a priori, constrained to be a certain value not of interest to us. Before testing hypotheses on the TIME by COHORT by MEMBERSHIP table, then, we set those cells corresponding to entries for the new cohort before 1961 to be structurally zero and make the corresponding adjustment in the degrees of freedom. When we do this, we obtain the results in Table 3.

We accept Model (b) and Hypothesis 2: cohort differences are significant and consistent across time and question wording. Since log linear effects are not defined for tables that contain structural zeroes, our discussion of the magnitude of the effects will deal only

TABLE 3

MARGINALS

		Data			
Model	Marginals Fitted	X^2	d.f.	p	Decision
(a)	(TIME,MEMBER)(TIME,COHORT)	61.79	8	$\leq .05$	reject
(b)	(TIME,MEMBER)(TIME,COHORT) (COHORT,MEMBER)	9.32	5	$\geq .05$	accept

with the percentage differences. Applying our estimation procedures to the modeled data from (b) in Table 3, we obtain the estimates for the graph coefficients shown in Table 4. Our interpretation of those results is as follows.

After adjustment has been made for differences in question wording and the data are smoothed to remove some randomness, we find that persons in the middle cohort (between 51 and 67 years of age in 1974) are more likely than anyone else to say they belong to one or more organizations, but the differences are small. The newest cohort (under age 35 in 1974) are consistently about 13 per cent less likely to belong to organizations than the middle cohort. Persons a little younger or a little older than the middle cohort are a little over 5 per cent less likely than the middle group to belong to organizations. The data show the inverted "u" shape described above: the middle group is most likely to have joined. We also consider this result basic to what will follow.

Since the time series is weak in providing cases for analysis in the early years,[2] the conclusions in Table 4 could just as well be conclusions about the effects of age in the 1960s. Therefore, it is well to note that the middle cohort is usually assumed to be the most economically and socially integrated, and that integration is assumed to lead to membership in organizations. Therefore, when we control for differences in social and economic integration we might expect that cohort differences will be even smaller than those shown in Table 4.

Of immediate interest in this discussion is what happens to the cohort differences when education is controlled. The older cohorts are less educated and this could account for their lower rate of membership; however, the younger cohorts are better educated than the middle age group and this should make them more disposed toward joining organizations.

[2] In spite of our attempts to do a cohort study, the time series is not sufficiently long to separate age from cohort effects.

TABLE 4

COHORT

Cohort	D	Std.Err.
New	-.130	(.024)
Young	-.064	(.015)
Middle	(base category)	
Old	-.082	(.016)

Their lower rate of membership occurs in spite of their higher educational level and we might therefore expect that the difference between the younger cohorts and the rest of the population will become greater after the adjustment is made for the educational levels in each cohort.

When we fit models to the data we will, once again, assume the (TIME,MEMBERSHIP) relation is a given in the study design since there is very little we can say about it. Likewise, we do not wish to explain the changing patterns of education in each cohort, so we will also take the (TIME,COHORT,EDUCATION) interaction as given. In flow graph notation, Figure 4 shows the relationships taken for granted. Each effect that has not been taken for granted has a substantive interpretation and may be represented by a set of marginal tables that could be included in fitting the hierarchical model. As in our discussion above, we would prefer to not have to interpret models that require assumptions about changes over time since these effects are confounded with changes in question wording. In fitting these models, it is also necessary to arbitrarily set 12 cells to a fitted value of zero. The interpretation of the effects to be analyzed and their representation in hierarchical modeling notation are given in Table 5.

Some of the relevant results from fitting the models presented in Table 5 are presented in Table 6. There are several borderline interactions in the data, but none of them is unambiguously significant. So, although the fit is less than perfect, we opt for the most parsimonious description. Once interactions are allowed between time, cohort, and education (these are not interesting from our point of view), and once some adjustment is made for the effect of question wording on the marginals of organizational membership, then no other three-way interaction terms are necessary and there are significant partial correlations between cohort, education, and the dependent variable--participation in voluntary organizations. In other words, we accept Hypotheses 1 and 2 from Table 5 and reject all of the others.

We are now in a position to study the main substantive question: the extent to which educational differences explain the observed cohort

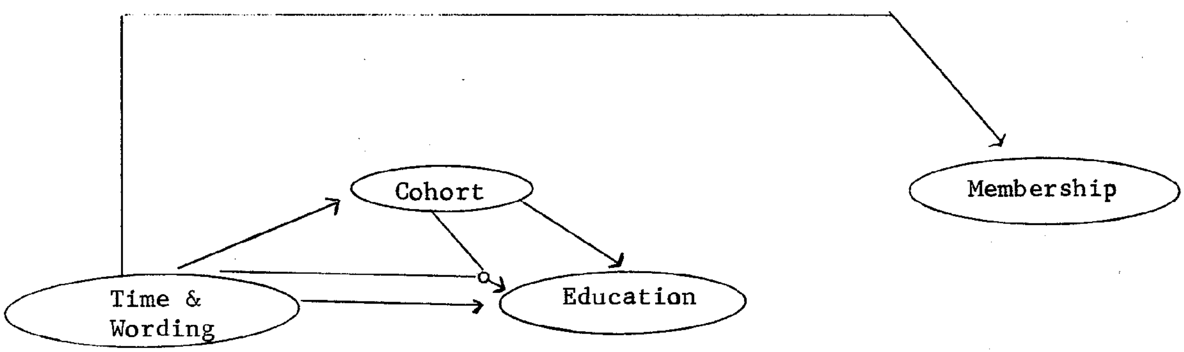


Fig. 4.--Flowgraph which shows the relationships taken as given

TABLE 5

SOME POSSIBLE OUTCOMES FOR THE TIME
BY COHORT BY EDUCATION BY MEMBERSHIP MODEL

EASIER EFFECTS TO INTERPRET...

	DESCRIPTION OF EFFECT	MODELING NOTATION
(1)	The partial correlation between education and membership is the same at all times and in all cohorts.	(EDUCATION,MEMBER)
(2)	The partials between cohort and membership are are constant.	(COHORT,MEMBER)
(3)	The correlation between education and membership is different in each cohort but the same at all times	(COHORT,MEMBER,EDUCATION)

HARDER EFFECTS TO INTERPRET...

	DESCRIPTION OF EFFECT	MODELING NOTATION
(4)	The correlation between cohort and membership is different for different times (or question wordings)	(TIME,COHORT,MEMBER)
(5)	The correlation between education and member is specified by time.	(TIME,EDUC,MEMBER)
(6)	The correlation between education and cohort is affected by time (or wording) <u>and</u> this effect is different in different cohorts.	(TIME,EDUC, COHORT,MEMBER)

TABLE 6

MARGINALS

Model	Marginals Fitted	X^2	d.f.	p[a]	Decision
(a)	(TIME,COHORT,EDUC) (TIME,MEMBER)	457.8			
(b)	(COHORT,MEMBER)(EDUC,MEMBER)	74.9	31	*	
(c)	All three way marginal tables	32.61	10	*	

[a] An asterisk entered for a p-value means that a chi square was significant before the correction for multistage sampling but not after. The standard correction is to divide a chi square by two before making assessments of significance. For a fuller rationale for this see Taylor (1975b). If a result is significant both before and after the correction, our convention is to report a p less than .05.

differences in organizational membership. To operationalize this question, we will use flow graph notation and partial percentage differences for the path coefficients. The question of the effect of education on the cohort differences can be answered by comparing the zero-order correlations between cohorts and membership with the partial coefficients that emerge once education is controlled. These differences are presented in Table 7.

The results are generally in the predicted direction and tell an interesting story. About half of the deficit in membership in the oldest cohort (persons over age 68 in 1974) can be explained by their lower educational levels, which leaves about half (a small 4 per cent) to be explained by other hypotheses about economic position or social disengagement. The educational differences between the young cohort (persons between 35 and 50 years of age in 1974) and the middle cohort (between 51 and 67 in 1974) are not great and the differential rates of joining in these two groups (almost 10 per cent) are therefore attributable either to cohort effects, age effects (given our data set these are hard to distinguish), or other economic or socialization factors. The difference between the newest cohort (under age 35 in 1974) and the middle became half again as large once education was controlled. These groups were then almost 20 per cent apart in the proportion saying they belong to any voluntary organizations. To what extent are these differences caused by general "starting up" problems in the youngest age group, and to what extent do they reflect lasting cohort differences in participation in social institutions? We will attempt to shed some light on the question in the sections of this report that follow.

<u>Educational Differences Net of Economic or Psychological Factors</u>

The main thrust of this section is to reexamine the effects of education on organizational membership after controlling for a series of variables that are thought to explain the relationship. We are able to test three kinds of hypotheses.

TABLE 7

DECOMPOSITION OF EFFECTS: COHORTS BY EDUCATION BY MEMBERSHIP

Cohort	Direct Effect	Std. ERR.	Indirect Via Education	Total (Zero Order)
New	-.172	(.02)	.056	-.12
Young	-.087	(.01)	.024	-.06
Middle	(base category)			
Old	-.043	(.02)	-.045	-.09

Education Category	Direct Effect	Std. ERR.	Spurious from Cohort	Total (Zero Order)
0-11	(base category)			
High School Grad.	.149	(.01)	-.018	.13
College	.270	(.01)	-.004	.27

1) We can examine the partial correlation between education and organizational membership, controlling for the variable of interest, and see how much of the original zero-order effect is attributable to the spurious or intervening effects of this third variable.

2) Likewise, we can observe to what degree the effects of the third variable are attributable to educational differences.

3) If the third variable appears on more than one other survey, we are able to draw some tentative conclusions about the stability of the zero-order and partial correlations between the predictor variables and organizational membership over time.

We chose control variables that are commonly thought to be correlated with membership and, in addition, some variables for which we had not seen previous documentation but which we believed would be associated with affiliation. In all cases, our search was informed by: (1) theoretical justification; (2) the desire to test a wide range of variables; and (3) the availability of variables, for the secondary analysis of surveys, that were not designed to examine organizational membership per se. In this report we will also break one of the informal practices of this sort of research: we will report the results for every variable examined, not just for those that were "significant."

A review of the literature suggested that there were four main kinds of arguments that were often used to explain the effects of education on organizational membership. We will call these four areas: human ecology, socioeconomic status, social competence or social participation, and pyschological integration. We have operationalized each of these arguments and the propositions that are usually made about each variable as summarized in Table 8.

Some observations are in order about the list presented in Table 8. It should be noted that each proposition is assumed to be true <u>net</u> of educational differences. In addition, the propositions are, in a sense, gross statements about general patterns of membership. The chief difficulty is that most statements about organizational

TABLE 8

OPERATIONAL DEFINITIONS AND PROPOSITIONS ABOUT VARIABLES AFFECTING EDUCATIONAL DIFFERENCES IN ORGANIZATIONAL MEMBERSHIP

Domain	Variables (Categories)	Propositions
A. Ecology	Residence at age 16 (Farm, Small Town, City)	People from farms, rural areas, and small towns should be less likely to join.
	City Size (Rural, 0-50K, 50K+)	People from bigger cities ought to be more likely to join.
B. SES	Father's Occupation (White Collar, Blue Collar, Farm)	People from white collar origins should join a bit more often than blue collar origins, and a lot more often than farmer's children.
	Occupation (White, Blue, Farm)	High, medium and low rates of membership for White, Blue and Farm workers respectively.
	Income (Above Median, Below)	People who make more than the median income in any year should be more likely to join.
	Subjective Social Class (Low and Working, Middle and Upper)	The higher the subjective status the more likely a person will join.
C. Participation and/or Competence	Church Attendance (Weekly, Monthly, Yearly and Less)	People that go to church more often will be more likely to join organizations.
	Voting in Last Election (Yes, No)	People who vote are also more likely to join.
	Vocabulary (Large, Small)	People with better verbal or conceptual skills (number right on a vocabulary test) are more likely to join.
D. Psychological Integration	Intensity of Religious Belief (High, Low)	People with strong religious beliefs are more likely to join.
	Happiness (Very Happy, Less)	People who are happier are more likely to be members of organizations.
	Health (Excellent, Less)	The more healthy a person is the more likely he/she is to join an organization.

membership do not discriminate among the types of organizations that people may join. (For instance, persons who are politically active ought to be more likely to join political organizations than they are other types of organizations.) Our procedure for testing the propositions in Table 8 will be to introduce each test variable into the TIME by EDUCATION by MEMBERSHIP model described above. Each variable will be introduced either as a prior control variable or as an intervening variable as shown in Figure 5. We will employ the hierarchical modeling procedure described in the first part of this paper to answer the following questions:

1) What is the effect of education once the test variable is controlled?

2) What is the effect of the test variable once education is controlled?

3) The paths that are drawn in as solid lines will be taken for granted and not analyzed, but for the paths that are problematic (the dotted lines) we seek to know if the partial correlations are stable over time and/or if there are any other interactions.

Questions 1 and 2 involve testing the significance of the partial correlations; that is, if, in the four-variable model, it is necessary to fit the following marginal tables:

Question Number	Relevant Marginal Tables
1	(EDUCATION,MEMBERSHIP)
2	(TEST VARIABLE,MEMBERSHIP)
3	We always fit (TIME,MEMBERSHIP)[3] and (TIME,TEST VAR, EDUCATION). Is it necessary to include any other three-way or higher interactions?

As a first substantive result, we note that in analyzing the series of models implied by Table 8 we did not find a single case where it was necessary to include interaction terms in the models. This

[3]This allows us to stay within the logit analysis framework described above, and also has some intuitive appeal since we are not interested in analyzing determinants of education.

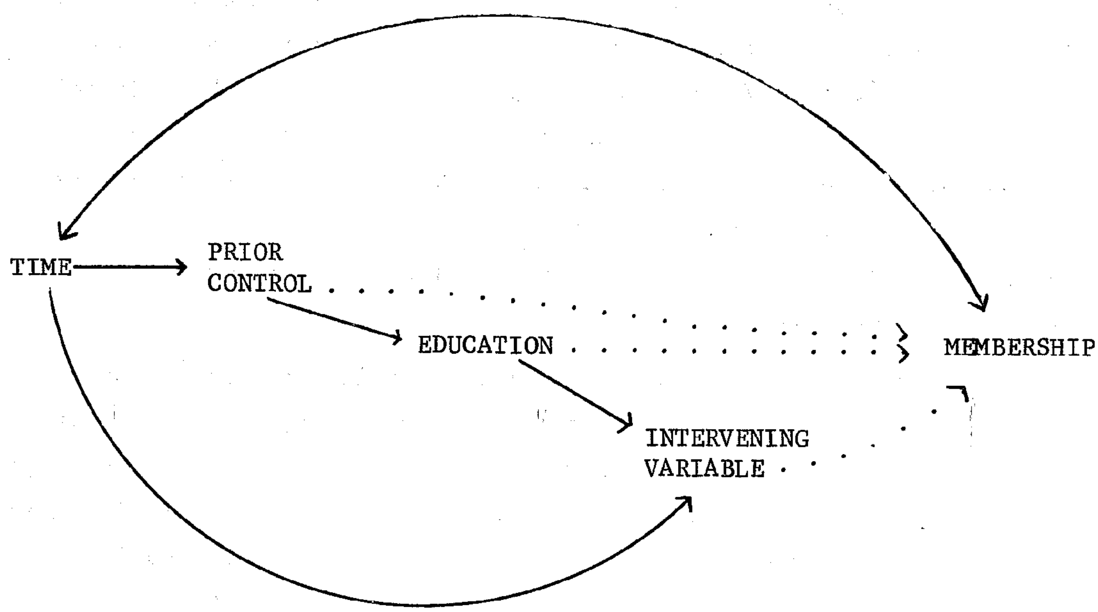


Fig. 5.--Figure illustrating the logic of the analysis of this paper and the coefficients which will be taken for granted (solid arrows)

means that correlates of organizational membership did not interact with time or question wording, and that in all cases, an additive linear model obtained between the effects of education and the test variables on organizational membership. With these kinds of results it is possible to classify each test variable according to whether it (1) had no effect whatsoever on organizational membership; (2) had a zero-order effect on membership that was totally explained by education; (3) had a zero-order effect on membership that was partly explained by education; or (4) had a zero-order effect that was not changed much by controlling for education (the variable was not correlated with education).

Table 9 presents an overview of the results in this section. Each test variable is classified according to its ability to tell us something about why persons with more education are more likely to join organizations. All in all, for half of the variables in Table 8 we have found basically negative results. Perhaps the most theoretically interesting way to interpret the findings would be to look at the results within each of the four broad domains of variables distinguished in Table 8.

Ecology

Neither of the "ecological" variables shows any significant relationship to organizational membership once education is controlled. The analysis of the modeled data for the effect of city size on joining produced Figure 6. We conclude from this graph that: (1) city size does not explain any of the relation between education and membership; and (2) persons who live on farms or in rural areas are slightly less likely to join organizations, but this difference is almost entirely attributable to educational differences.

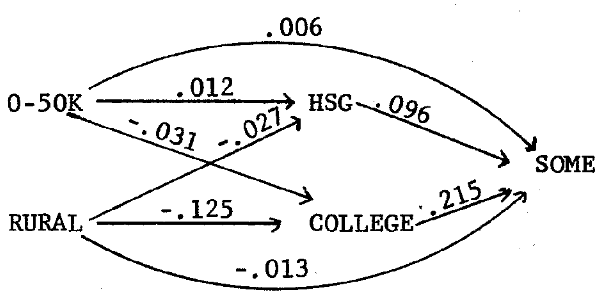
The second ecological variable shows a similar result. Persons who grew up on farms are less likely to join organizations when they are adults, but this difference too is attributable to the fact that they are not as well-educated as other adults. Figure 7 presents the flow graph of the modeled data. From this graph we observe that

TABLE 9

OUTCOMES OF TESTING THE PROPOSITIONS IN TABLE 8

Type of Outcome	Variables
1. No effect whatsoever (partial = zero)	City Size Intensity of Religious Belief Form A[a]
2. Effects are explained by education (partial = zero)	Residence at Age 16 Father's Occupation Occupation Subjective Health Status
3. Somewhat, but not entirely explained by education (partial is significant)	Income Subjective Social Class Voting Vocabulary Subjective Happiness
4. Effects are significant and not changed by controlling education (partial is significant)	Church Attendance Intensity of Religious Belief Form B[a]

[a]Two different versions of the question "Intensity of Religious Belief" were used and each produced a different interpretation of the effect of this variable. The Glock and Stark Anti-Semitism Study (SRS760, October 1964) asked, "All in all, how important would you say that religion is to you?" Persons who said religion was extremely important did not differ from the rest of the population on organizational membership. The 1974 General Social Survey (March 1974) asked respondents how strongly they felt their religious identification. People who had strong commitments to their faith were more likely to join organizations, but this variable was not correlated with education.



CATEGORY	EFFECTS Direct	Indirect
HSG	.096	
COLL	.215	
0-50K	.006	-.005
RURAL	-.014	-.029

Fig. 6--Education controlling for City Size

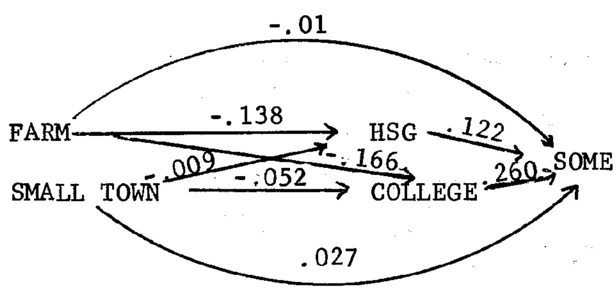
NOTE: Some comments on reading the percentage difference flow graphs in this report:

1) The graphs are D-system flowgraphs (Davis, 1975) estimated from the modeled data which includes all of the effects which are found to be significant using Goodman's procedures of hierarchical modeling.

2) The direct effects are the partial percentage differences between the categories in the graph and the dependent variable: the percent reporting that they belonged to at least one organization.

3) The indirect effects are the sum of the path products for all of the intervening paths between a category and the dependent category--e.g., the RURAL indirect effect = (-.027*.096)+(-.125*.215) = .029.

4) The data were tested to see whether or not the coefficients changed over time. In every single case in this report we concluded that the coefficients are stable over time. Therefore, an interpretation of the graphs presented here is that they represent the relations between these variables which have been obtained between 1952 (the first data point) and 1974.



CATEGORY	EFFECTS Direct	Indirect
HSG	.122	
COLL	.260	
FARM	-.010	-.060
SMLTWN	.027	-.015

Fig. 7--Education controlling for Residence at age 16

persons who were raised on farms are 7 per cent less likely to join organizations. This is one of the more thoroughly documented findings in the field. Inspection of the indirect path tells us that -.06/-.07, or 86 per cent of this difference is attributable to the effects of lower education among persons raised on farms.

Socioeconomic Status

Among the measures of socioeconomic status (SES) that we analyzed, we find the following results:

1) The effect of father's occupational status on respondent's organizational membership is almost wholly transmitted through education.

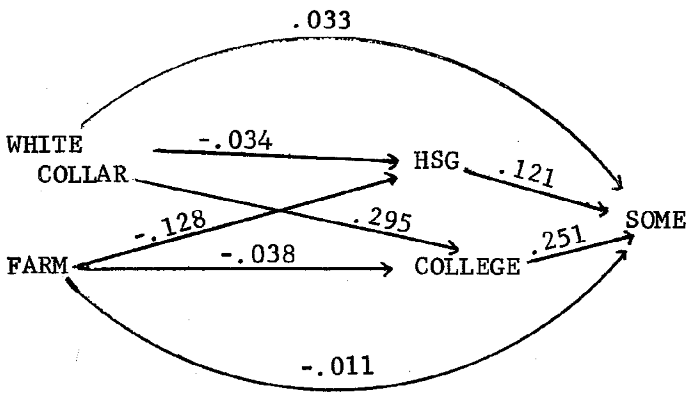
2) The well-known correlation between our measures of occupational status and organizational participation is attributable, in our data, to the fact that both are strongly correlated with education.

3) Persons who consider themselves middle or upper class are a little more likely (6 per cent) to join organizations, but this explains little more than 10 per cent of the correlation between education and membership.

4) Over the entire range of variables in Table 8, income is one of the best predictors of membership. In any educational level, persons who earn more than the median income are 14 per cent more likely to join organizations. This explains between 25 and 50 per cent of the correlation between education and joining.

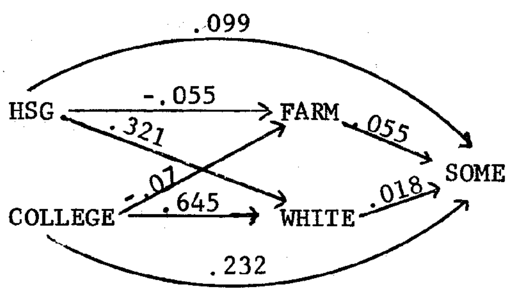
The SES variables important in understanding organizational membership are: education (very important), income (very important) and subjective social class (less important). If we understand these relationships, it is not necessary to consider the effects of occupational status or father's occupation separately in predicting organizational membership. The details for these conclusions are presented in Figures 8 through 11.

Beginning with the effects of father's occupation, we find that it does make a difference. Persons from white collar families are 10.3 per cent more likely to join organizations, but .07/.103 or 68 per cent, of this



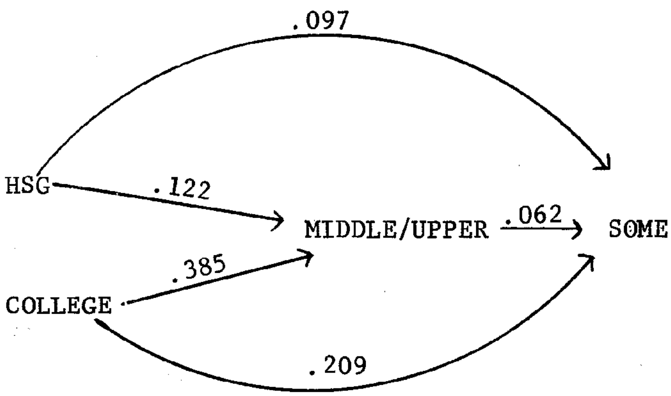
CATEGORY	EFFECTS Direct	Indirect
HSG	.121	
COLL	.251	
WHITE	.033	.070
FARM	-.011	-.025

Fig. 8--Education controlling for Father's Occupation



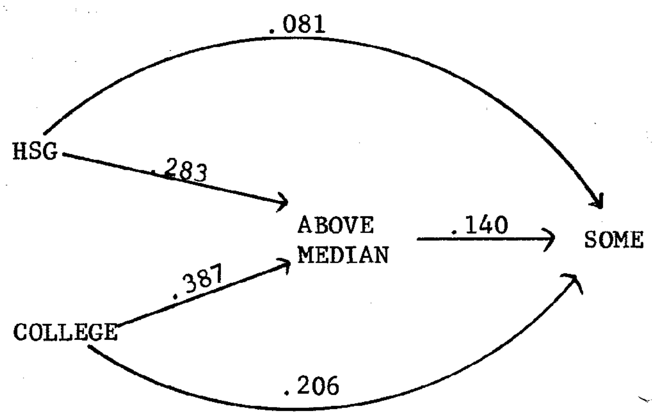
CATEGORY	EFFECTS Direct	Indirect
HSG	.099	.006
COLLEGE	.232	.012
WHITE	.018	
FARM	.055	

Fig. 9--Education controlling for Occupation



CATEGORY	EFFECTS Direct	Indirect
HSG	.097	.008
COLLEGE	.209	.024
MIDUP	.062	

Fig. 10--Education controlling for Subjective Social Class



CATEGORY	EFFECTS Direct	Indirect
HSG	.081	.040
COLLEGE	.206	.054
ABOVE	.140	

Fig. 11--Education controlling for Income

difference is caused by the fact that children from white collar families are a lot more likely to go to college and persons who have been to college are a lot more likely to join organizations. A similar kind of reasoning should be applied to understanding why persons with white collar jobs are more likely to belong to organizations (see Figure 9): those in white collar jobs are more likely to have been to college and this accounts for almost all of the occupational difference.

The results from our data indicate that, controlling for education, it is the subjective estimate of social status (not objective white collar vs. blue collar distinctions) that predicts whether a person will join an organization. This is shown in Figure 10. While we conclude that subjective social class has some independent bearing on whether or not a person will join an organization, this does not explain much of the reason why persons who have finished high school or gone to college are more likely to join organizations. About 8 per cent of the original high school difference and about 10 per cent of the original college difference is explained by the fact that persons with more education are more likely to think of themselves as members of the middle or upper class.

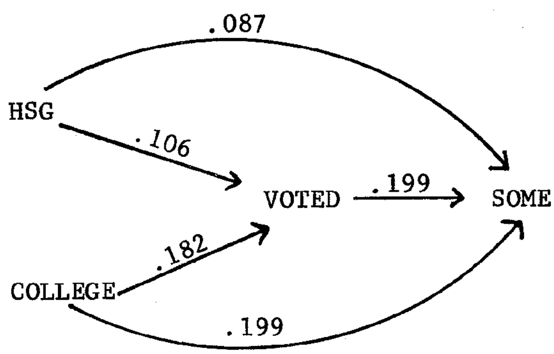
The explanation for the class-membership correlation is usually explained in one of two ways: either that persons who consider themselves middle class are more likely to allocate time and energy to organizational membership, possibly because they are in work or community roles where community participation is expected; or, that middle class people can afford to join. We cannot really decide this question, but it is worth noting that of the four socioeconomic determinants of membership considered here, income is the strongest and goes the furthest in explaining the education-membership correlation (see Figure 11). Controlling for education, persons who are above the median in income (in any year) are 14 per cent more likely to report that they belong to organizations; those with more education are more likely to be in the upper end of the income distribution. This line of reasoning accounts for 33 per cent of the original high school difference and 21 per cent of the original college difference in membership.

Social and Intellectual Competence

The phrase "social competence" comes from Almond and Verba (1965), who reported that persons who had greater feelings of political efficacy or social competence were more likely to vote. They were also more likely to join organizations, but it wasn't clear whether joining an organization made people more competent or more competent people tended to join organizations. Almond and Verba chose the former interpretation (and direction for the arrow), and we will choose the latter, since this report is an attempt to see how far sociological concepts will take us in understanding organizational membership as a dependent variable. The phrase "intellectual competence" comes from our using the results of a vocabulary test on the 1974 General Social Survey as a predictor of membership. We hypothesize that persons with greater verbal or conceptual skills will more often be found in leadership positions in the community and therefore more often among the dues-paying members of voluntary organizations.

All three of our measures of participation and competence show independent effects on organizational membership once education is controlled. It is well known that persons with more education are more likely to vote (social competence) and also to know more words (intellectual competence). Controlling for education, we find that, among the variables we consider here, voting is the single best predictor of organizational membership (the largest partial correlation) and the score on the vocabulary test does just as well as income in explaining the education-membership correlation (the largest reductions in the zero-order correlations). An alternative measure of social participation, church attendance, is only weakly related to education. However, this variable also exerts a non-trivial and independent effect on organization membership.

We begin with the American voters (see Figure 12). The independent effect of voting on membership is as large as the independent



CATEGORY	EFFECTS Direct	Indirect
HSG	.087	.021
COLLEGE	.199	.036
VOTING	.199	

Fig. 12--Education controlling for Voting

effect of having gone to college. Furthermore, electoral participation explains 19 per cent of the original high school difference and 15 per cent of the original college difference in membership.

The number of words a person knows is also related to whether or not that person joins an organization, and this is not just a result of the large educational effects on both variables (see Figure 13). The line of reasoning that predicts that more verbal people would be members of voluntary organizations explains 35 per cent of the original high school difference in membership and 22 per cent of the college difference.

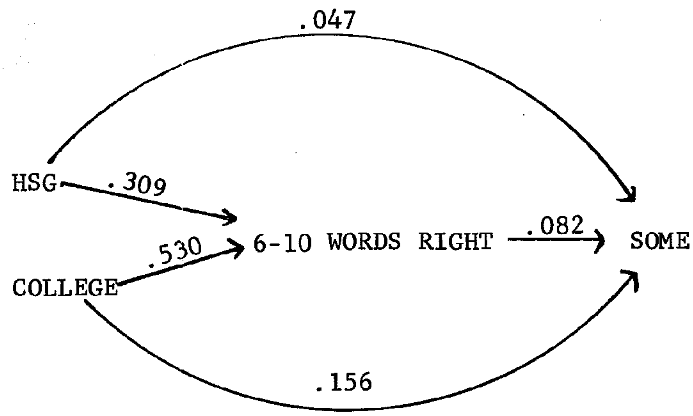
Next, we examine an alternative measure of social participation: frequency of church attendance. Figure 14 indicates that the more education a person has, the more likely he or she is (by a small margin) to go to church frequently. In addition, no matter the level of education, persons who go to church frequently are more likely to join organizations. This combination of factors, however, does not explain much of the observed educational difference in membership. It is perhaps better to think of two types of social involvement--political and religious; both are related to organizational membership, but only the former is related to education.

So far, then, the best predictors of organizational membership are education, subjective social class, income, and the social participation/social competency variables (voting, church attendance, and vocabulary). Next, we consider some social-psychological variables that are sometimes assumed to be formal measures of anomie or disengagement.

Psychological Integration

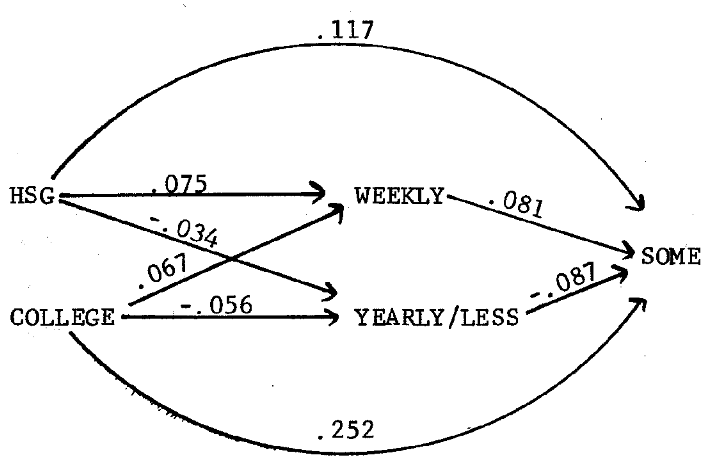
In this section the numbers are smaller: measures of integration do not correlate as highly with education or organizational membership as some of the other measures that we have considered. But these measures cannot be dismissed. Our evidence indicates that:

1) One of the measures of intensity of religious belief shows an independent effect on organization membership. (The other shows none at all.)



CATEGORY	EFFECTS	
	Direct	Indirect
HSG	.047	.025
COLLEGE	.156	.043
VERBAL	.082	

Fig. 13--Education controlling for Vocabulary Skill



CATEGORY	EFFECTS Direct	Indirect
HSG	.117	.009
COLLEGE	.252	.010
WEEKLY	.081	
RARELY	-.087	

Fig. 14--Education controlling for Religious Participation

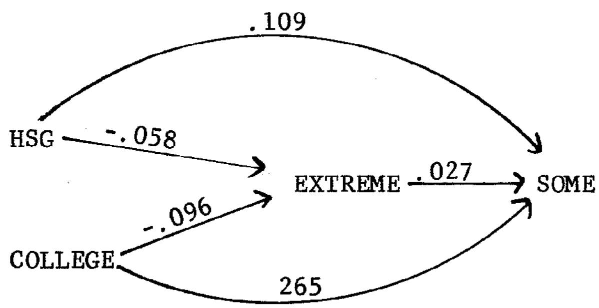
2) Persons who are happier join organizations more often, although this does not explain much of the educational difference.

3) Once we control for education, a person's perceived health status does not predict whether he or she will join an organization.

For the Glock and Stark (1966) measure, we find that persons with more education are less likely to say that their religion was extremely important to them and that the importance of one's religion has nothing to do with organizational membership once education is controlled. (See Figure 15.) The General Social Survey version, however, which asks respondents their religious preference and then whether or not they would call themselves a strong (name of denomination), finds that intensity of religious involvement is associated with membership but not with education. (See Figure 16.) We will deal with this result by calling for further research on the topic, noting, however, that the differences associated with intensity of religious involvement are likely to be small (although they are not likely to be attributable to education.)

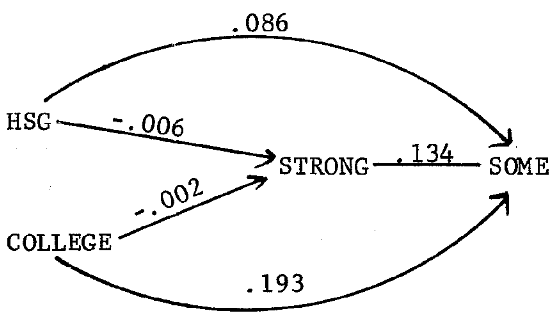
In their Reports on Happiness (1965), Bradburn and Caplovitz suggest that one of the factors contributing to positive mental health is social participation, which they at one point operationalize as organizational membership. In our replication of this finding we have taken data from a national population and reversed the direction of the arrow. Our finding (illustrated in Figure 17) is that no matter the educational level, happier people join (a little bit) more often. The differences are too small, however, to go so far as to say that better educated people belong to organizations because they are happier.

If persons in better psychological health are more likely to join, then it might be hypothesized that persons in better physical health might also join a little more often. In our judgment, the data do not support this contention (once education is controlled). The findings in Figure 18 indicate that the association between health and membership is largely a result of the effects of education. (That is, knowing that a person is in excellent health does not help in predicting



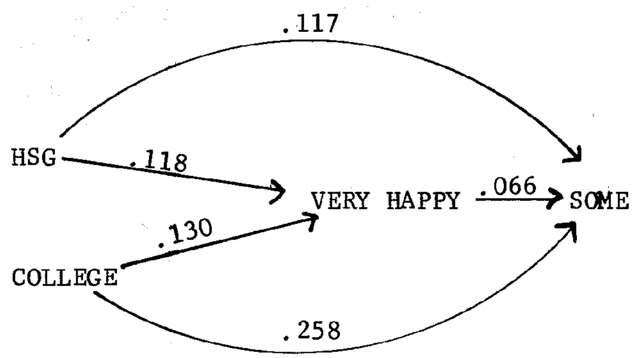
CATEGORY	EFFECTS Direct	Indirect
HSG	.109	-.002
COLLEGE	.265	-.003
EXTREME	.027	

Fig. 15--Education controlling for Importance of Religion



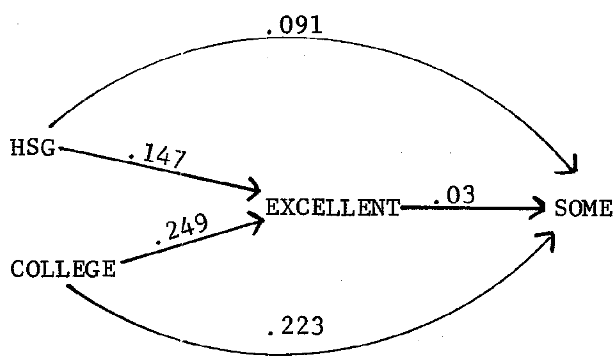
CATEGORY	EFFECTS Direct	Indirect
HSG	.086	-.001
COLLEGE	.193	.000
STRONG	.134	

Fig. 16--Education controlling for Intensity of Religious Belief



CATEGORY	EFFECTS Direct	Indirect
HSG	.117	.008
COLLEGE	.258	.009
VERY HAPPY	.066	

Fig. 17--Education controlling for Happiness



CATEGORY	EFFECTS Direct	Indirect
HSG	.091	.004
COLLEGE	.223	.007
EXCELLENT	.030	

Fig. 18--Education controlling for Health

whether he is a member of an organization if you already know how far he got in school.)

We have found, in this section, that the effects of psychological integration are small; they do not help at all in explaining the correlation between education and organizational membership, but they constitute an independent (although only marginally important) dimension in predicting whether or not a person will join a voluntary organization. The finding that mental health, though not physical health, correlates with membership gives us some understanding of the meaning of this dimension. It might be thought of as a weaker version of the psychological competence construct from the previous section.

Summary

The correlation between education and organizational membership has remarkable staying power--we have yet to come anywhere near explaining the full relationship. What we have learned is that there are a few dimensions of organizational involvement, some of them correlated with education and some not. It turns out that if a variable predicts organizational membership well, chances are that it is correlated with education. The results reported here suggest that the main dimensions of organizational involvement, in order of importance, are:

Dimension	Operational Measure
1. Education	Education
2. Money and Class Consciousness	Income, Subjective Social Class
3. Social and Psychological Competence	Voting, Vocabulary
4. Religious Commitment	Attendance, Intensity of Belief
5. Social Adjustment	Happiness

An obvious hypothesis would be that for Dimensions 2 through 4 each dimension of organizational involvement is correlated with both a certain type of participation (leadership, passive, status seeking, expressive), and participation in a certain type of organization (political, social, fraternal). An adequate test of the first hypothesis awaits the collection of more adequate data on the level and quality of activity in the organizations joined. The test of the second hypothesis awaits an empirically founded, operationally defined classification of the types of organizations in the society. The explanation of the persistent correlation between education and membership awaits a fuller multivariate understanding and treatment of the effects of education on social participation.

Cohort Differences Net of Economic or Psychological Factors

We could not find a single study on cohort differences in organizational membership. Most of the literature attempts to explain the correlation between age and membership, which, we have noted, appears to be small but stable. Wilensky (1961) hypothesizes that the pattern of age differences in membership is caused by the pattern of strains and obligations that an individual undergoes during various phases of the life cycle. If this is true, each cohort should follow a similar pattern of membership in organizations over time (assuming that the opportunities for joining organizations are relatively constant across time.) A second hypothesis asserts that age is correlated with psychological integration and that integration is correlated with membership (which we verified in the last section). What are the implications of this hypothesis for cohort analysis? If integration was correlated with age but not with cohort, then we would expect to see each cohort showing a similar pattern in the level of membership as it aged and went through the successive processes of engagement and disengagement. Or, and this would not negate the first possibility, if one cohort was intrinsically more integrated than another, we would expect that the more integrated cohort would participate more often than the less integrated cohort at any time and at any point in the life cycle. If this were the case, a graph of cohort differences in organizational membership over time would show parallel lines.

The data in this report are not really sufficient to test any of the above hypotheses. We have only four surveys, there were not many cases in the first, and the newest cohort does not appear until the last two surveys. A separate analysis of these data reported elsewhere (Taylor, 1975a) used methodological tools that were especially sensitive to the above hypotheses about cohort differences and found that the life cycle hypothesis appears to apply to the young cohort (age 35 to 50 in 1974). As the people who constituted the youngest segment of the population after World War II aged, they became more and more like the older cohorts in organizational membership. The data suggest, however, that this same pattern of engagement has not yet begun to occur in the newest cohort (under age 35 in 1974): these people have been consistently less likely to belong to organizations than the middle cohorts. This latter difference is attributable either to a life cycle interpretation (they have not quite reached the age when organizational membership becomes much more likely) or the hypothesis of a correlation between being a member of the youngest cohort and not joining organizations as often (permanent non-engagement).

The methods used in the first part of this report are less sensitive to these specific hypotheses and the result is less illuminating. In Table 4 constant differences among the cohorts are shown. The middle cohort (age 51 to 67 in 1974) has always been more likely to join organizations. It has been suggested that persons in this age group, who were socialized mainly during the Depression era, were exposed to social circumstances which would make them more likely to join organizations. Table 4 reports that the middle cohort is between 5 and 10 per cent more likely than the next oldest and the next youngest cohorts to join organizations. And each of these three cohorts is more likely than the youngest cohort (under age 35 in 1974) to join. The difference between the youngest and the middle cohort is 13 per cent.

The task of this section is an attempt to understand and explain statistically these cohort differences. In selecting variables for analysis we are faced with two problems: (1) Although there is a large literature on the variables that explain the correlation between age and membership, there are few empirical or substantive leads to suggest what would account for cohort differences on our dependent variable. (2) We have already noted that our data do not readily allow discriminations between cohort and age effects because of the nature of the time series. Since there is an absence of substantive literature on the kinds of variables that should explain cohort effects, we will use the same set of general categories as used earlier in this paper (Ecology, SES, Competence, and Integration) and assess the relative merits of each category in explaining cohort differences in affiliation. Since the data are limited, we will be cautious about passing off age effects as cohort effects.

In Table 10 we have the outcome of testing each model. Each control variable (the cell entries) is evaluated in terms of its ability to explain cohort differences. Since it is possible that a variable would explain a difference for one cohort but not for another, we evaluate each variable separately for the oldest (Column 1) and the two youngest (Column 2) cohorts.

There is no neat pattern to the results in Table 10. It appears that the factors that account for the participation rates in the older cohort are the same factors that account for the rate among the less educated: money and competence. We see that some of the lower participation rate in the younger cohorts is obscured by the fact that they are healthier and better educated. Controlling for these factors, we see an even lower rate for these people. However, less money and less political competence (voting) among the young accounts for some of their lower participation. (We did not include subjective social class and religious attendance in our analyses here since much published and non-published research indicates that these variables are not associated with cohort.)

In the rest of this part of the report we will present a more detailed analysis of the results reported in Table 10. We will break the control variables into the same four content areas as in the last section of this report.

TABLE 10

OUTCOMES FROM ATTEMPTS TO EXPLAIN COHORT DIFFERENCES

Type of Outcome	Old Cohort	New Cohorts
1. No effect whatsoever (partial =0)	Religious Intensity Form A	Religious Intensity Form A
2. Effects are explained by cohort (partial =0)	Father's Occupation	
3. Somewhat, but not entirely explained by cohort (partial is significant)	Marital Status Subjective Health Income Retirement Voting Education Vocabulary	Marital Status Income Voting Religious Intensity Form B
4. Suppression of cohort effect	Religious Intensity Form B	Subjective Health Education
5. Significant EFFECTS, not changed by controlling cohort	City Size Occupation Residence at age 16 Subjective Happiness	City Size Father's Occupation Occupation Residence at age 16 Subjective Happiness Vocabulary

Ecology

The findings from considering the ecological variables are that:

1) City size is so weakly correlated with cohort that it does not affect the zero-order relationship very much. There is a slight tendency for rural people not to join, which we observed in the last section to be attributable to educational differences.

2) Some of the lower rate of participation of persons raised on farms is masked by the fact that these people are concentrated in age groups where membership is more widespread. Controlling this factor makes the farm/urban difference larger, although it is still comparatively small. Again, we note that much of this difference is explained by educational levels. The data for these results are in Figures 19 and 20.

Socioeconomic Status

In controlling for three different measures of socioeconomic status we find:

1) Occupation is too weakly correlated with cohort to explain much of the difference. There is an independent effect of occupation (which, we note, is explained by education).

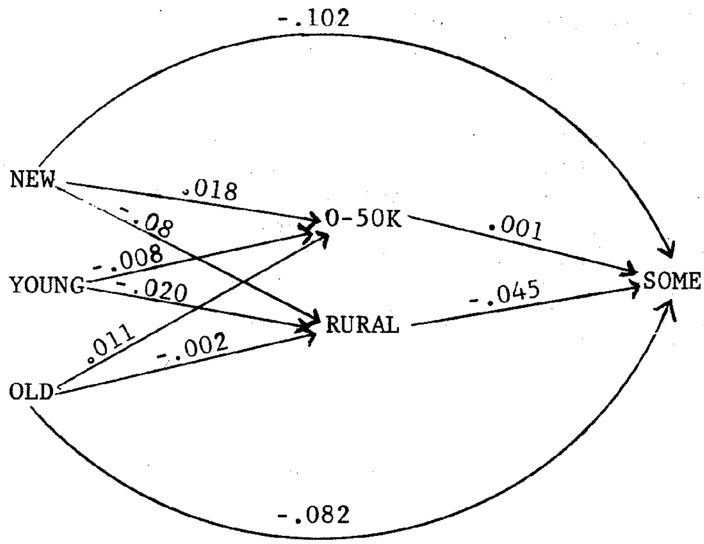
2) The correlations between cohort and father's occupation are also too weak to make much difference. Controlling for cohort produces a stronger deficit in joining among farmers' children (which is probably explained by education as well).

3) Low income explains some (15 per cent) of the reason younger people don't join and a lot (64 per cent) of the reason older people don't join. This variable is worth future consideration since it explains some (but not all) of the education difference and some (but not all) of the cohort difference.

Figures 21 through 23 present the data that support these conclusions.

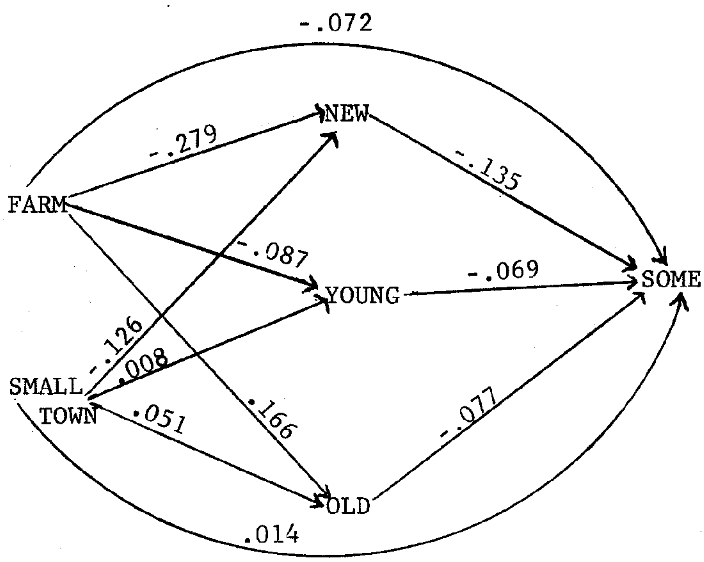
Participation and Competence

We find, once again, that (not counting income) this is the most fruitful category for understanding the relationship between our independent variable (this time cohort) and organizational membership.



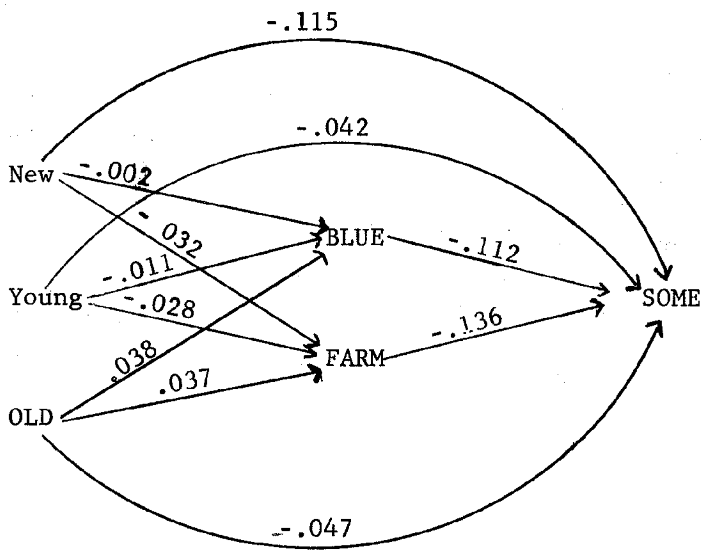
CATEGORY	EFFECTS	
	Direct	Indirect
NEW	-.102	.004
YOUNG	-.050	.001
OLD	-.082	.000
0-50K	.001	
RURAL	-.045	

Fig. 19--Cohort controlling for Size of Place



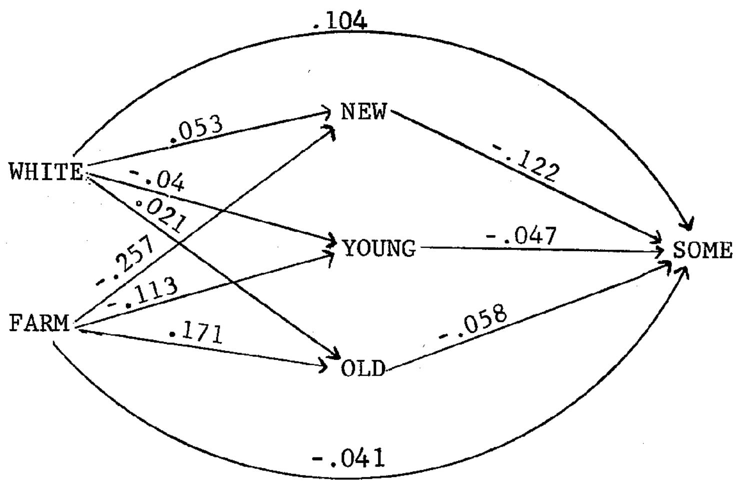
CATEGORY	EFFECTS Direct	Indirect
NEW	-.135	
YOUNG	-.069	
OLD	-.077	
FARM	-.072	.031
SMLTWN	.014	.013

Fig. 20--Cohort controlling for Residence at age 16



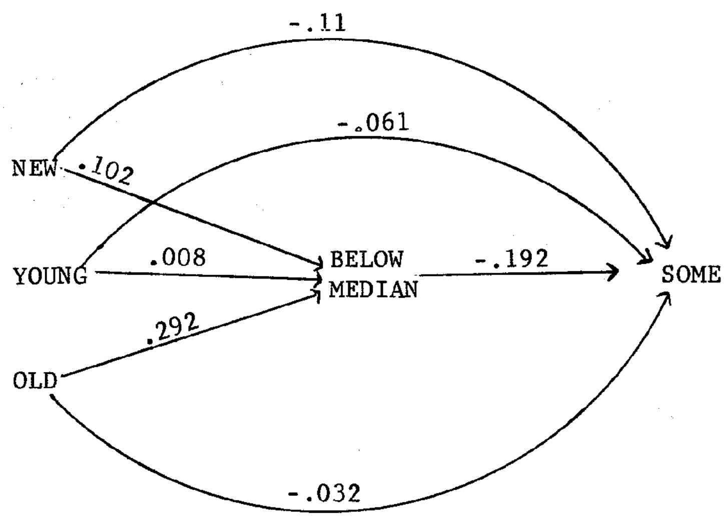
CATEGORY	EFFECTS Direct	Indirect
NEW	-.115	.004
YOUNG	-.042	.005
OLD	-.047	-.009
BLUE	-.112	
FARM	-.136	

Fig. 21--Cohort controlling for Occupation



CATEGORY	EFFECTS Direct	Indirect
NEW	-.122	
YOUNG	-.047	
OLD	-.058	
WHITE	.104	-.006
FARM	-.041	-.036

Fig. 22--Cohort controlling for Father's Occupation



CATEGORY	EFFECTS Direct	Indirect
NEW	-.110	-.20
YOUNG	-.061	-.002
OLD	-.032	-.056
BELOW	-.192	

Fig. 23--Cohort controlling for Income

NOTE: The absence of interaction in Figure 23 means that the effect of low income on organization membership is the same in the older as in the younger cohorts.

We find that:

1) About 50 per cent of the lower participation rate in the oldest cohort (in 1974) can be attributed to its lower score on conceptual or mental abilities (vocabulary test). Since we only have data at one time point, we have actually documented an age effect. This supports the hypothesis that the lower rate of participation in the older cohort is associated with declining (or possibly lower) verbal capacities.

2) About 50 per cent of the lower participation rate in the younger age groups can be attributed to the fact that they don't participate politically (vote) as often as older people.

The data that support these results are displayed in Figures 24 and 25.

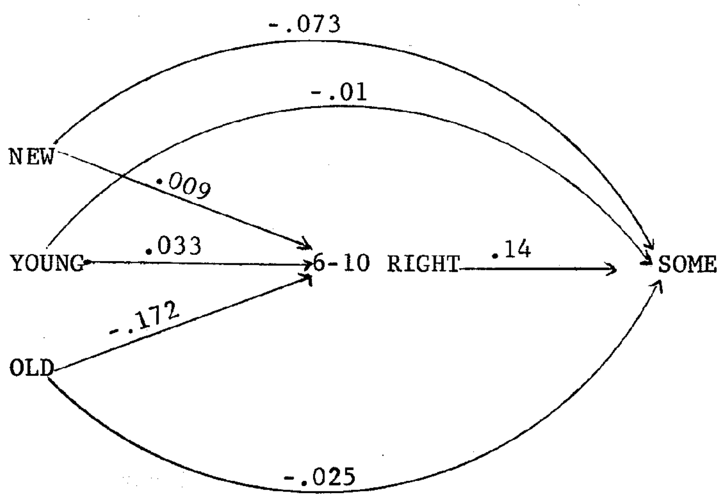
Psychological Integration

The measures of psychological integration that we tested for this section do not explain much of the observed difference among cohorts. An overview of the results displayed in Figures 26 through 28 shows that:

1) In all cohorts, those who are less physically healthy are about 8 per cent less likely to join organizations.

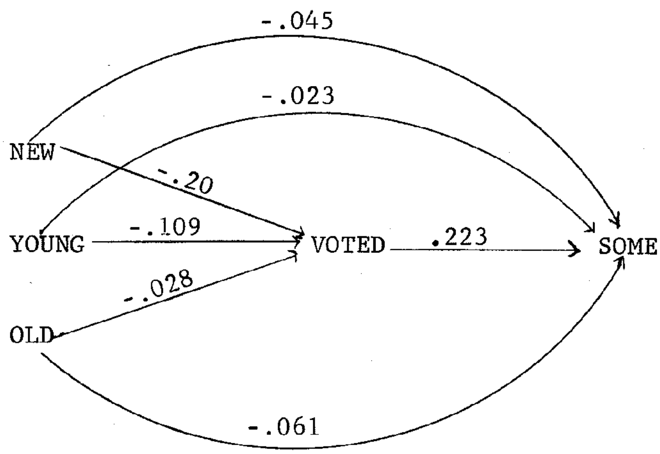
2) Similarly, persons who are happier are more likely to join, by about 9 per cent. This correlation is still robust and represents a predictor of membership that is relatively independent of the factors that cause differential participation in different cohorts and educational groups.

3) Intensity of religious belief is not an important variable in explaining cohort differences, although we again find some different results for the two different question wordings. The Glock and Stark version of the question ("How important is your religion?") tells us absolutely nothing about cohorts or joiners. The General Social Survey version of the question ("Do you consider yourself a strong (name of denomination)?") shows that about 20 per cent of the reason the younger cohort joins less is that they are less likely to have intense religious beliefs. In the older



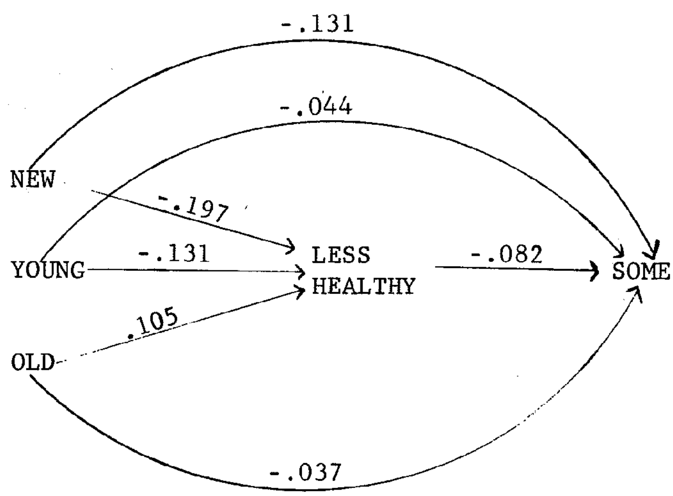
CATEGORY	EFFECTS	
	Direct	Indirect
NEW	-.073	.001
YOUNG	-.010	.005
OLD	-.025	-.024
VERBAL	.140	

Fig. 24--Cohort controlling for Vocabulary Test Score



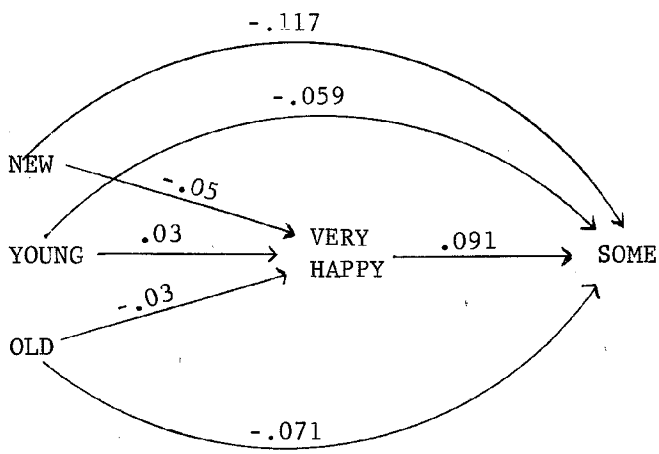
CATEGORY	EFFECTS Direct	Indirect
NEW	-.045	-.045
YOUNG	-.023	-.024
OLD	-.061	-.006
VOTING	.223	

Fig. 25--Cohort controlling for Voting



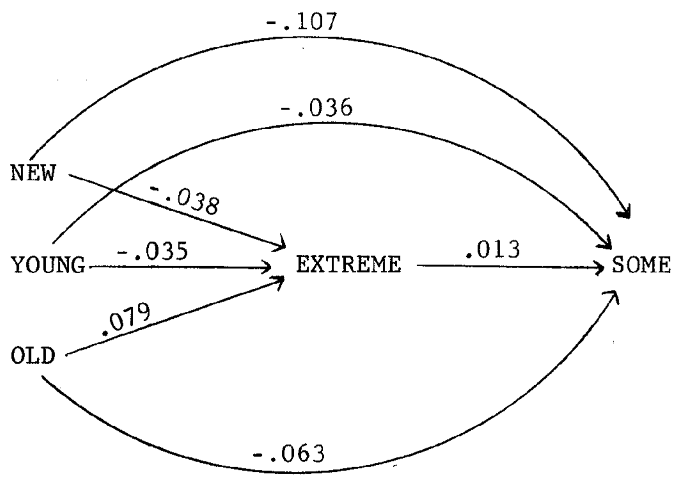
CATEGORY	EFFECTS Direct	Indirect
NEW	-.131	.016
YOUNG	-.044	.011
OLD	-.037	-.009
LESS	-.082	

Fig. 26--Cohort controlling for Physical Health



CATEGORY	EFFECTS Direct	Indirect
NEW	-.117	-.005
YOUNG	-.059	.003
OLD	-.071	-.003
HAPPY	.091	

Fig. 27--Cohort controlling for Happiness



CATEGORY	EFFECTS Direct	Indirect
NEW	-.107	.000
YOUNG	-.036	.000
OLD	-.063	.001
EXTREME	.068	

Fig. 28--Cohort controlling for Importance of Religion

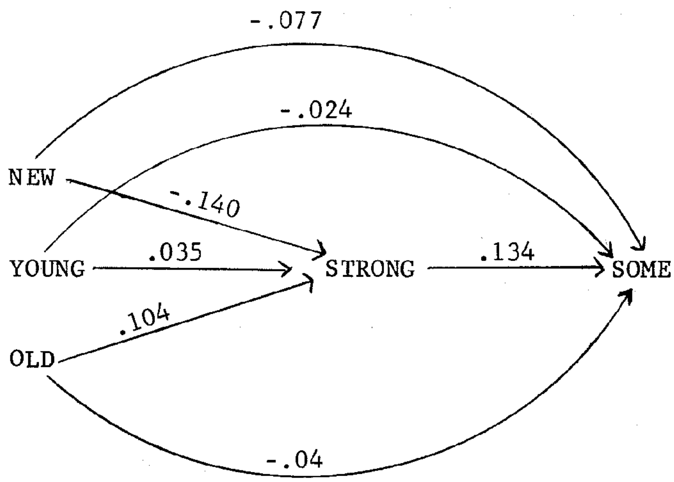
cohort, the relatively greater strength of religious beliefs operates to offset some of the other reasons that predispose these people not to join organizations. In both cases, then, the integration hypothesis is at work. The relative importance of this hypothesis compared to other variables in our study is quite small. These data are displayed in Figures 26 through 29.

Factors Thought to Influence Participation, Particularly Among the Aged

In this section we will interpret our data in a different way and look at the extent to which cohort differences are explained by variables that are commonly thought to have a greater impact among the aged. These variables are labor force participation (the retirement of old people is thought to reduce their social participation in general) and marital status (old people who are single are thought to be less likely to participate; single people, and especially single men, are thought to be less socially and psychologically integrated). In this section we find that:

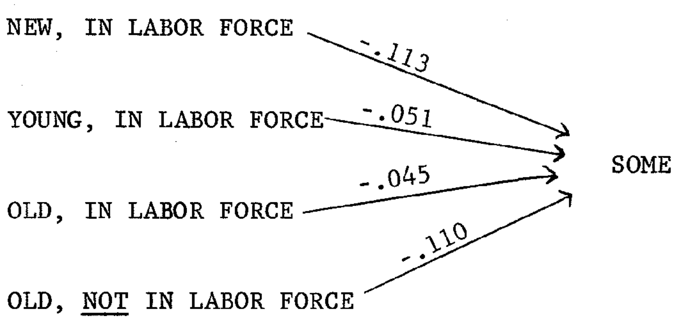
1) Old people who are retired are less likely than old people who have not retired to belong to organizations. The participation rate among members of the old cohort who are not in the labor force is about equal to the rate among the members of the younger cohort who are in the labor force. But, retirement does not explain entirely the difference among the aged. Old people who are working are still less likely to be in organizations than people in the middle cohort who are working. (See Figure 30.)

2) Being single affects each cohort in about the same way. In fact, inspection of the percentage tables in the supplement to this report indicates that, if anything, the difference in marital status is less important among the aged than among the younger cohorts. Figure 31 indicates that members of the oldest cohort and members of the youngest cohort are more likely than the rest of the population to be single. The difference in the oldest cohort is generally attributed to mortality. The difference in the youngest cohort, if it persists, will be a true "cohort" effect and should, as Figure 31 suggests, have some consequences for the social life of the generation that was socialized in the 1950s and 1960s. These results are presented in Figures 30 and 31.



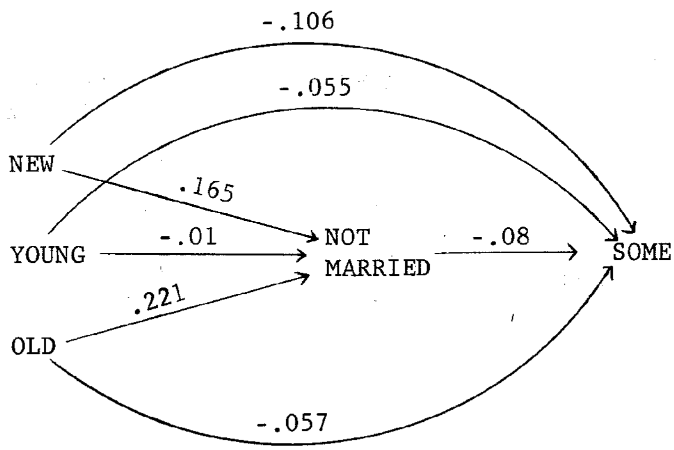
CATEGORY	EFFECTS Direct	Indirect
NEW	-.077	-.019
YOUNG	-.024	-.005
OLD	-.041	.014
STRONG	.134	

Fig. 29--Cohort controlling for Intensity of Religious Belief



CATEGORY	EFFECTS Direct	Indirect
NEW, IN	-.113	
YOUNG, IN	-.023	
OLD, IN	-.045	
OLD, OUT	-.110	

Fig. 30--Cohort controlling for Labor Force Participation



CATEGORY	EFFECTS Direct	Indirect
NEW	-.106	-.013
YOUNG	-.055	.001
OLD	-.057	-.018
ALONE	-.080	

Fig. 31--Cohort controlling for Marital Status

Summary

We have learned that the factors that explain the cohort differences in participation are approximately the same factors that explain the educational differences. If we were to rank the dimensions of participation in terms of their ability to explain the cohort effects in our data, we would arrive at the following list:

Dimension	Operational Measure
1. Education	Education
2. Income	Income
3. Competence	Voting, Vocabulary
4. Density of Social Relations	Marital Status, Labor Force Participation

To pull together our discussion of this section and the previous section on educational differences, we will crossclassify each variable according to its ability to tell us about the cohort differences and the educational differences in participation. This crossclassification is presented in Table 11.

In addition to this classification we should note that there is a dimension of psychological adjustment (Happiness, Intensity of Religious Belief, Form B) which has a non-trivial effect on organizational membership and which operates fairly independently from cohort or educational differences.

Conclusion

In this paper we have attempted to sift methodically through much of the available data on organizational membership with the aim of locating the few variables or dimensions crucial to an understanding of the variations in organizational membership.

There are a few broader points to be made now that we have seen all the data.

1) Although there were four different wordings of the question on organizational membership, we found that there was little reason to suspect that this caused any variation in our evaluation of which variables correlated with membership and which didn't.

TABLE 11

VARIABLES CLASSIFIED ACCORDING TO ABILITY TO EXPLAIN EDUCATIONAL DIFFERENCES AND ABILITY TO EXPLAIN COHORT DIFFERENCES

		Educational Differences: Helps	Educational Differences: Doesn't Help
Cohort Differences	Helps	Income Voting Vocabulary	Marital Status Retirement
	Doesn't Help	Subjective social class Church attendance	Residence at age 16 City size Father's occupation Occupation Intensity of religious belief (Form A) Subjective health status

2) There were, however, two different measures of the intensity of religious belief and our conclusion is that they are quite different in their relationships with the other variables in the analysis. (Although it could also be true that the correlation between intensity of belief and participation changed between the time the first and the second forms of the question were asked.)

3) Our answer to the question of whether or not the level of organizational membership will go up in the next decades depends on how we interpret the cohort differences that we have observed. If the lower rates of participation in the younger cohorts are a result of the fact that these people are not yet thoroughly socialized, then we would expect that they will soon get into the swing of things, and membership will rise because real income and education are going up and these are correlated with participation. If, however, the younger cohorts are not joining because they have chosen not to and don't intend to, then the influx of less participatory cohorts will offset the increasing educational levels, producing minor changes in the aggregate levels of membership, perhaps on the order of those observed by Hyman and Wright (1971); they don't get much change on exact replications of the question between the fifties and the mid-sixties.

4) A very fruitful approach for continued research would be to start with the dimensions of organizational involvement that have been identified here (and in other works to be sure) and determine if there are types of organizations to meet these specific demands and trends in these particular dimensions of involvement.