OCCUPATIONAL VALUES AND POST-COLLEGE CAREER CHANGE

By

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CHAPTER I

INTRODUCTION

Empirical studies of career choice among college students have repeatedly found a strong relationship between the occupational values a person holds and the career he chooses. Occupational values may be conceived as the rewards and satisfactions tangible and intangible which a person hopes to derive from his work. He may, for example, want money, or an opportunity to be helpful to others, or the chance to exercise his creativity, or he may want all of these things.

Although the existence of the relationship between values and occupations is well known, the nature of this relationship is not sufficiently clarified. It has been generally assumed by theorists of occupational choice that values or interests are given and that a person then makes the choice of occupation in terms of those values and interests. The evidence supporting this assumption is not easy to find. The reasons for the widespread acceptance of this view probably have more to do with the fact that it makes good common sense than they have to do with empirical evidence.

Robert K. Merton's[1] writings on anticipatory socialization suggest one way that a reverse process could take place. Merton suggests that a person

[1] Robert K. Merton, Social Theory and Social Structure (rev. ed.; Glencoe, Ill.: The Free Press, 1957).

will begin to adopt the attitudes and values appropriate to a new position in life before he actually enters that position. If this theory is correct we will find that, given an occupational choice, a person whose values were not originally appropriate to that occupation will tend to modify them in the direction of greater consistency with the occupational plans. It is thus not unreasonable to believe that either or both of two processes may occur. People may choose, or change, their occupations, bringing them into line with value dispositions, or they may change their values bringing them into line with career intentions.

The use of attitude measures as a predictor of career choice is not a new endeavor. "Vocational interest inventories" have long been used by psychologists in advising students about which careers are consistent with their interests and values. Although there is a large body of literature by many researchers on this subject,[1] the work of Edward K. Strong[2] is the most notable. In his 1943 work he showed that the average profile of answers to a large number of attitudinal items differed substantially for groups of people engaged in different occupations. Moreover, in his 1955 book Strong reports sizable correlations between the vocational interest profile scores of students in college and the occupations in which they were actually engaged eighteen years later.

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[1] See Lee J. Cronbach, Essentials of Psychological Testing (2nd ed.; New York: Harper and Row, 1960), pp. 405-39; and Anne Roe, The Psychology of Occupations (New York: Wiley, 1956), for detailed discussion of this subject.

[2] Edward K. Strong, Vocational Interests of Men and Women (Stanford, University Press, 1943), and Vocational Interests 18 Years After College (Minneapolis: University of Minnesota Press, 1955).

Among sociologists, Morris Rosenberg[1] demonstrated conclusively the strong relationship between values and career choice and provided the stimulus for subsequent NORC investigations in this area, including the present investigation. Rosenberg made use of the following values in his analysis: (1) provide an opportunity to use my special abilities or aptitudes; (2) provide me with a chance to earn a good deal of money; (3) permit me to be creative and original; (4) give me social status and prestige; (5) give me an opportunity to work with people rather than things; (6) enable me to look forward to a stable, secure future; (7) leave me relatively free of supervision by others; (8) give me a chance to exercise leadership; (9) provide me with adventure; (10) give me an opportunity to be helpful to others.

Through cluster analysis of intercorrelations of these ten values he identified three relatively independent dimensions of value orientation: (1) the people-oriented value complex (values 5 and 10); (2) the extrinsic-reward-oriented value complex (values 2 and 4); (3) the self-expression-oriented value complex (values 1 and 3). These value complexes were shown to be strongly related to the choice of particular careers. For example, social work, medicine, and teaching were especially likely to be high on "people orientation" while engineering and natural science were quite low. Business careers and law were disproportionately likely to be high on "extrinsic-reward orientation" while teaching and social work were low. Architecture, journalism-drama, art, and natural science were high on "self-expression" whereas business careers were at the bottom.

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[1] Morris Rosenberg, Occupations and Values (Glencoe, Ill.: The Free Press, 1957).

Panel data on 712 Cornell graduates suggested that for the people-oriented value complex and a group of people-oriented occupations, students changed their occupational choices to coincide with their values to a somewhat greater degree than they changed values to coincide with occupational choices. Since Rosenberg used only the people-oriented value complex for this purpose and did not control for sex, which is related to both values and occupational choices, his findings must be considered suggestive rather than conclusive.

Our approach in this is somewhat different from Rosenberg's. The basic finding that there are strong correlations between career choices and values implies: (1) There are variations across careers in the proportions endorsing various values. (2) When combinations or configurations of values are specified, there are variations across value configurations in the proportions entering various careers. Since there is not a one-to-one relationship between a particular career and a particular pattern of values, two different analytic strategies are possible, corresponding to the above two propositions.

Rosenberg's strategy was to define an aggregation of different careers as "consistent" with a particular value. Thus he speaks, for example, of "people-oriented occupations." Our strategy is to define an aggregation of value patterns as "consistent" with a particular career. This enables us to speak of "business values" or "education values."

In sum, our approach permits examination of variations across careers in the nature of the relationship between occupations and values, whereas Rosenberg's approach permits examination of variations across values in this relationship.

Joe L. Spaeth[1] investigated the relationship of occupational values to the choice of academic careers among arts and science graduate students. Using a two-stage probability sample of 2,842 graduate students from twenty-five universities and a list of values slightly modified from Rosenberg, he found that the choice of academic careers was related to "altruistic" values and to "self-expressive" values. The relationship became even stronger when altruism and self-expression were used in combination.

The National Opinion Research Center, in its present series of studies on 1961 college graduates, again made use of a list of values slightly modified from Rosenberg with a more representative and much larger sample of students.

James A. Davis,[2] in the primary analysis of these data, again found strong correlations between values and occupational choices. In addition, using the three largely independent values of "work with people," "original and creative," and "money," Davis was able to cross-tabulate all three values simultaneously against particular occupations and thus to establish value patterns or configurations appropriate to each of ten occupational groupings.

In sum we may say of these studies that it has been empirically established that there is a strong correlation between occupational values and career choice among college students. However, it is not known whether values determine career choice, or career choice determines values or both.

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[1] Joe L. Spaeth, "Value Orientations and Academic Career Plans" (unpublished Ph.D. dissertation, Department of Sociology, University of Chicago, 1961).

[2] James A. Davis, Undergraduate Career Decisions (Chicago: Aldine Publishing Co., 1965).

While it is easy to conceive of a person changing his career because it does not suit his value dispositions the converse is perhaps not so obvious. However, one can imagine a prospective physician who, upon failing to gain admittance to medical school, decides upon a business career. What thoughts might accompany that decision? Our new businessman might argue to himself that he was not really so fond of science after all and the prospect of a good income in the near, rather than far distant, future is actually very attractive. We should not be surprised if such rationalizations occur often.

To the extent that students change their values to correspond to occupational plans, the utility of predicting future occupational behavior from present measures of value is reduced. Might we not do as well or perhaps even better, if we predicted future occupation from present occupational plans alone?

In this report we shall employ the tools of longitudinal analysis in an effort to clarify these matters.

The Data

Our data are taken from an ongoing NORC survey of the career and post-graduate training plans of June, 1961, American college graduates. The sampling and design of this study are described in detail in reports by James A. Davis[1] and by Norman Miller.[2]

In brief the study may be described as follows. In June, 1961, self-administered questionnaires were collected from 33,782 college seniors in 135

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[1] James A. Davis, Great Aspirations (Chicago: Aldine, 1964), esp. pp. 278-294, and Undergraduate Career Decisions.

[2] Norman Miller, "One Year After Commencement" (NORC Report No. 93; Chicago: National Opinion Research Center, 1963), esp. pp. 134-135. (Multilithed.)

colleges and universities. These seniors constituted 83 per cent of the names in a national probability sample of June, 1961, bachelor's degree recipients. The entire sample received a second-wave questionnaire in the spring of 1962 with 85 per cent of the first wave respondents also responding to the second wave. Taken together 70 per cent of the original sample (28,713 cases) participated in both waves.

In February, 1963, a much abbreviated third wave questionnaire was sent to the entire sample. The return was 29,999 cases and 62 per cent of the original sample (25,257 cases) were included in all three waves.

Although this is a respectable response rate as panel studies go it may be asked whether the 62 per cent who have responded to all three waves differ from the total sample in ways which might affect our findings. A partial answer to this question is provided by Davis in an unpublished memorandum on response bias in this study. Davis asks, among those who responded to the first wave, what characteristics are associated with responding or failing to respond to subsequent waves of the study. He analyzed 522 separate items (IBM punches) on the first wave questionnaire and found very few that had any relation to response on subsequent waves. Fifty-five per cent of the items showed deviations from the total sample response rate to the second wave of less than 2 per cent. Only 6.5 per cent of the items showed response rate deviations of as much as 5 per cent and only 0.3 per cent of the items showed response deviations of as much as 10 per cent. Davis interprets most of these deviations as random error. He was only able to identify seven items for which the response deviations were in the same direction on both the second and third waves of the study, an example of such an item is Negro race. Negroes had response rates slightly below the total sample on both the second and third waves. No value or career choice items are included among these seven items. Thus non-response appears to be unrelated to the findings we shall report here, and it appears extremely unlikely that response bias, in general, could affect our findings.

Information on career choice is available from all three waves of the study. Information on values is available from waves one and two. Since the process and meaning of career choice are different for men and women, the present investigation is limited to males. The number of males who responded to all three waves of this study is 15,850. The sample, however, is not a simple random sample. It is a stratified probability sample with an over-representation of students from larger, better quality colleges. A student from such a college simply receives a weight of one in the analysis. Students from smaller, low quality colleges on the other hand were undersampled. These students were assigned weights of two, three, or six in the analysis in order to make the sample representive of the total population of June, 1961, graduates. The weighting procedure was actually carried out by duplicating the IBM cards of those who received weights greater than one. This resulted in a weighted N for the analysis of 23,956 males. The acutal unweighted number of male cases again is 15,850.

Most of our tables are based upon the weighted N. In some cases, however, we shall report tables based upon an N of 1,712. This is a random subsample of the total number of males responding to the first two waves. It is also a representative sample of males who graduated in June, 1961. Moreover this sample is drawn in such a way that it contains no duplicate cards.

It is therefore a random, representative, and unweighted subsample of the total group. If the reader wishes to pursue these sampling procedures in more detail, a complete discussion can be found in Davis.[1]

Organization of the Report

Chapter I: The introduction contains a statement of the problem, a brief and highly selective review of relevant literature, a description of the data and the study from which it comes, and a resume of what is to be found in the various chapters.

Chapter II: The second chapter is entitled, "Distinguishing Cause and Effect in Longitudinal Data," and is entirely methodological.

There are a number of different causal situations in everyday life which could conceivably produce a statistical correlation between occupational value and career choice measures. For one thing, both values and career choices could be caused by some unidentified third factor. If this is the case, there is no direct causal link between them and we would say that the correlation is "spurious." Longitudinal data provides no more protection against the problem of spurious correlation than does cross-sectional data.

If the correlation between values and career choice is not spurious--and we shall have to assume that it is not--it then becomes meaningful to ask whether values are the cause of career choices or career choices are the cause of values. When data is cross-sectional the researcher is at a loss to provide an empirical answer to such a question. He must instead assume that one variable is prior in time to the other variable. Or, more precisely, that changes in one variable are prior in time to changes in the other.

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[1] Davis, Great Aspirations.

The validity and reasonableness of this kind of assumption varies considerably. For example, we know that sex and career choice are correlated. In this case it is clear that the determination of sex is prior in time to the determination of career choice and the assumption that sex is prior is the only reasonable one to make. As between values and career choices, however, temporal priority is not obvious. If one or the other is assumed to be first the risk of being wrong is high.

Longitudinal data, by introducing the time dimension empirically rather than by assumption, allows a more realistic approach to such questions than does cross-sectional data. But how does one proceed with the analysis? In Chapter II we review a number of approaches which have been used by various researchers in the past and note that all methods will not always lead to the same conclusions. We then suggest a general type of approach employing formal causal models and based on the work of Simon[1] and Blalock.[2] Perhaps the most important virtue of this approach lies in making explicit the assumptions involved in the analysis. In addition it enables us to specify most of the circumstances under which the various methods used by researchers in the past will, or will not, lead to similar conclusions.

Employing the formal models, we examine the assumptions involved in various approaches and decide that "cross-lagged partial correlations" are a sound approach to the problem of causal priority in longitudinal data, although

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[1]Herbert A. Simon, Models of Man (New York: John Wiley and Sons, 1957), pp. 4-61.

[2]Hubert M. Blalock, Jr., Causal Inferences in Nonexperimental Research (Chapel Hill: University of North Carolina Press, 1964).

there are a number of related approaches which, starting from the same assumptions, will lead to the same inferences.

Chapter III: While Chapter II provides a methodological rationale for dealing with the main question, the third chapter, "Occupational Values and Career Choices at College Graduation," is a substantive prelude. In it we identify patterns of values which are consistent with choice of various careers among college seniors. Prospective businessmen, for example, are found to be high in "enterprise"--largely an orientation to extrinsic rewards. Future scientists, as another example, are characterized by high "intellectualism." For still another example, prospective engineers quite logically, are disproportionately high in both "enterprise" and "intellectualism." If we conceive of each career as having a location in a "value space," the location of engineering is thus about halfway between the physical sciences and business.

The chapter begins by describing in detail the measurement of career choices and values. Then, using cluster analysis of value items and certain self-descriptive adjectives, three largely independent dimensions of value orientation are established.

These in turn are cross-tabulated by particular career choice categories in order to establish a value pattern appropriate to each of twenty careers. The concept of a "value space" is introduced in describing the consistency between career choices and values. Careers can then be described in terms of their location in the value space.

Finally we ask whether those value patterns which are consistent with a particular career at college graduation remain consistent one year later.

Chapter IV: The fourth chapter, "The Relative Effects of Careers and Values," discusses the main problem of the investigation. Does career choice determine values, or values determine career choice, or both? For each of twenty careers two "cross-lagged partial associations" are compared. The association of initial career with subsequent values controlling for initial values, measures career effects while the association of initial values with subsequent career, controlling for initial career, measures value effects. This is equivalent to comparing the association of initial career with "deviational changes" (residuals from the regression of values 2 on values 1) in values, and the association of initial values with deviational changes in career. These comparisons are summarized first in terms of a typology of career and value effects, then in terms of the degree of career predominance over values for each career.

A number of possible methodological objections to the results are considered. These include the question of statistical significance, first order interactions in the cross-lagged partials, measurement unreliability in value measures, inadequate "sampling" of careers, and inadequate "sampling" of time. An attempt is made to elicit empirical evidence on each of these problems.

Chapter V: In order to explain such variation as occurs by career in the relative effect of career choice upon values and values upon career choice, we examine the phenomenon of career change in some detail in the fifth chapter, "Variations in Career Predominance."

Patterns of movement and stability among careers are examined. We note that careers can be grouped into clusters such that within a cluster, movements from one career to another are relatively frequent while movements to careers outside the cluster are relatively infrequent. The relation of these groupings to the degree of career predominance is then considered.

Findings on the relative strength of career and value effects are subjected to controls for academic performance and for attendance or nonattendance at graduate school and some implications of the results are considered.

Finally, we consider what the most important findings actually show and what some of the implications are for the practical problem of predicting career choice and for various theoretical notions about the process of career choice.

CHAPTER II

DISTINGUISHING CAUSE AND EFFECT IN LONGITUDINAL DATA

In this chapter we shall consider methods for inferring causal priority between two correlated variables which have each been measured at two points in time. In other words, we shall consider the problem of direction of causation. Longitudinal data, by introducing the time dimension facilitates a more realistic approach to the problem than does cross-sectional data, although some methods of analysis can lead to incorrect inferences.

A correlation between two variables can reflect a number of quite different causal situations in the real world. If a correlation between X and Y is observed, it may reflect the influence of some other factor which is the cause of both X and Y. In this case there is no causal link between X and their correlation is "spurious."[1] The researcher will sometimes find a correlation which will not disappear under controls for all factors which are thought to be causally prior, but is still spurious. A particularly subtle form of this situation can arise when attitudinal items are correlated with one another.

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[1]For a full discussion of this subject see, Herbert Hyman, Survey Design and Analysis (Glencoe, Ill.: The Free Press, 1955), pp. 242-274; or Blalock, op. cit.

Suppose, for example, we find a substantial correlation between measures of "happiness" and measures of "work satisfaction."[1] We might find that the correlation did not disappear under any of our controls for demographic factors and the like. However, happiness and work satisfaction may still be "spuriously" related, both being "caused" by an underlying common factor such as general adjustment which cannot be measured by any single item. This may or may not, in fact, be the case for these particular variables, but the type of problem is one which the researcher should be attuned to. Longitudinal data provides no more protection against the problem of spurious correlation than does cross-sectional data.

If the correlation between X and Y is not spurious it becomes meaningful to ask whether X causes Y or Y causes X. If X precedes Y in time we commonly infer that X is the cause of Y. What criteria shall we apply to longitudinal data in order to determine whether X precedes Y or Y precedes X?

Review of Various Approaches

A number of different approaches to this problem emerge from the literature. Sociologists are perhaps most familiar with Paul F. Lazarsfeld's method (or methods) for analyzing the "16-fold table."[2] A 16-fold table results when

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[1]This correlation is reported in, Norman Bradburn and David Caplovitz, Reports on Happiness (Chicago: Aldine Publishing Co., 1965), p. 37.

[2]The term was coined in Paul F. Lazarsfeld and Robert K. Merton, "Friendship as a Social Process: A Substantive and Methodological Analysis," in Monroe Berger, Theodore Able, and Charles H. Page (eds.), Freedom and Control in Modern Society (New York: D. Van Nostrand Co., 1954), pp. 21-54.

two dichotomous attributes, each measured at two points in time are cross-tabulated. The number of logical combinations is, 2 x 2 x 2 x 2 = 16, giving a table with 16 cells.

Table 1 is an example of such a table. It cross-tabulates viewing a television program and buying of the sponsor's product at two times, February and May, 1953, and is taken from Hans Zeisel.[1] According to Lazarsfeld's rationale[2] we would analyze it as follows. Consider only those whose original (T_1) viewing and buying habits were not "in harmony." These are people who viewed but did not buy or bought but did not view at Time 1. They are to be found in the lower left four cells and upper right four cells of Table 1, which correspond to the lower left and upper right cells of the Time 1 four-fold table for viewing and buying.

If any of these people are to "harmonize" their viewing and buying habits, they must change either viewing or buying but not both. If they are more likely to change buying than they are to change viewing then we should infer, according to this rationale, that viewing causes buying rather than the reverse.

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[1] Hans Zeisel, Say It with Figures (New York: Harper and Brothers Publishers, 1957), p. 232.

[2] Seymour M. Lipset, Paul F. Lazarsfeld, Allen H. Barton, and Juan Linz, "The Psychology of Voting: An Analysis of Political Behavior," in Gardner Lindzey (ed.), Handbook of Social Psychology, II (Reading, Mass.: Addison-Wesley Publishing Co., 1954), 1124-1176; see also Allen H. Barton and Paul F. Lazarsfeld, "Methodology of Quantitative Social Research," in Baidya N. Varma, A New Survey of the Social Sciences (New York: Taplinger Publishing Co.), p. 163.

TABLE 1

VIEWING OF TELEVISION PROGRAM AND BUYING OF SPONSOR'S PRODUCT

(February and May, 1953)*

			Buying				
		T_1	Yes	Yes	No	No	
T_1	T_2	T_2	Yes	No	Yes	No	Total
Viewing							
Yes	Yes		82	53	57	491	682
Yes	No		31	28	24	231	314
No	Yes		27	20	24	219	290
No	No		104	80	81	891	1,156
Total			243	181	186	1,831	2,442**

*Source: Hans Zeisel, Say It with Figures (New York: Harper Bros., 1957), p. 232.

**Zeisel reports that this table is not for one program and corresponding product, but the average for fifty-five programs and products.

The four cells which are circled in Table 1 provide the basis for Lazarsfeld's inference. He arranges them as in Table 2. The major diagonal cells (27 and 231 cases) change viewing to correspond to buying while the minor diagonal cells (80 and 57 cases) changed buying to correspond to viewing. Whether we compute a measure of association or simply note that there are more cases on the main diagonal is in this case irrelevant. Lazarsfeld's method leads to the somewhat surprising inference that buying is the cause of viewing.

Rosenberg[1] uses a different method which he attributes also to Lazarsfeld. His method requires that we exclude all cases who changed neither viewing nor buying and all cases who changed both viewing and buying. This leaves those who changed one habit but not the other. Eight of the original sixteen cells are analyzed. These cells can be identified in Table 1 by the

[1]Rosenberg, op. cit., p. 21.

fact that they contain the following numbers of cases: 53, 57, 80, 81, 31, 27, 231, 219. Rosenberg argues that if viewing has an effect on buying, those who view at both times should be more likely to start buying (as opposed to stop buying) than those who view at neither time. That is, $\frac{57}{57 + 53} = 52$ per cent should be greater than $\frac{81}{80 + 81} = 50$ per cent. The percentage difference, 52 - 50 = +2 per cent is attributed to the influence of viewing on buying. If buying has an influence on viewing, those who buy at both times should be more likely to start viewing than those who buy at neither time:

$$\frac{27}{27 + 31} - \frac{219}{219 + 231} = 47\% - 49\% = -02\%$$

TABLE 2

RESPONSE PATTERN OF PEOPLE WHO "HARMONIZE" THEIR HABITS BETWEEN TWO INTERVIEWS

First Interview	Second Interview	
	Buy and View	Don't Buy and Don't View
Buy and don't view	27	80
Don't buy and view	57	231

Although these differences are too small to be of much practical importance they suggest that, if anything, viewing causes buying. This result clearly contradicts the method suggested by Lazarsfeld in the <u>Handbook of Social Psychology</u>.

Hans Zeisel,[1] from whom Table 1 is taken, termed the problem "reversal of cause and effect." He assumed that viewing was the cause of buying and

[1] Zeisel, <u>op. cit</u>., pp. 236-238.

tested for reversal of this sequence, i.e., tested for the possibility that buying also caused viewing. He suggests that two tests are possible, one test among those who were Time 1 viewers and a second test among those who were not Time 1 viewers. Among the Time 1 viewers, those who bought at Time 1 should be more likely to continue viewing than those who did not buy at Time 1. He found that 69.6 per cent of the 194 Time 1 buyers continued viewing, while 68.2 per cent of the 802 Time 1 non-buyers continued viewing. He termed the difference insignificant.

He made a second test among those who were not viewers at Time 1. He found that of 230 Time 1 buyers, 20.0 per cent started to view and of 1,216 Time 1 non-buyers 20.0 per cent started to view. This test showed no difference whatsoever. Zeisel concluded that buying had no influence on viewing and that there was no reversal of cause and effect.

Although Zeisel's argument is an analogy to an experimental situation[1] we can rephrase his procedure in the language of "partial correlation." Zeisel determined that there was no partial correlation between Time 1 buying and Time 2 viewing when Time 1 viewing was controlled.

If Zeisel wished to make his procedure symmetrical by testing for the effect of viewing on buying, he would ask whether there was a partial correlation between Time 1 viewing and Time 2 buying when Time 1 buying was controlled. Computing partial Q's by taking a weighted average of the Q's for the separate categories of the control variable gives the following results for the data of Table 1:

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[1]Note that the analogy is imperfect since subjects were not assigned to the "treatment" (Time 1 buying) at random. There is thus no protection against the possibility that Time 1 buyers and non-buyers differ in respects other than their buying and viewing habits. This increases the risk that effects (or lack of effects) may be spurious.

$$Q_{V_1B_2 \cdot B_1} = +.08$$

$$Q_{V_2B_1 \cdot V_1} = +.02$$

where:

V = viewing

B = buying

Subscripts 1 and 2 indicate Time 1 and Time 2 respectively.

The direction of the difference between these partial Q's leads to the inference that viewing is the cause of buying.

A number of authors have used still another approach which is applicable not only to the 16-fold table, or dichotomous attribute case, but also to continuous variables. This approach involves comparing the relative size of "cross-lagged panel correlations."[1]

Campbell argues that if a variable, X, is the cause of a variable Y, then the "effect" should correlate higher with a prior "cause" than with a subsequent "cause," i.e.:

$$r_{X_1Y_2} > r_{X_2Y_1}$$

Pelz and Andrews,[2] in a recent article, also advocate the comparison of cross-lagged panel correlations and attempt to assess some of their limitations.

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[1]Donald T. Campbell, "From Description to Experimentation: Interpreting Trends as Quasi-Experiments," in Chester W. Harris (ed.), Problems in Measuring Change (Madison: University of Wisconsin Press, 1963), pp. 212-242.

[2]Donald C. Pelz and Frank M. Andrews, "Detecting Causal Priorities in Panel Study Data," American Sociological Review, XXIX (December, 1964), 836-848.

Berelson, Lazarsfeld, and McPhee[1] use cross-lagged correlations (correlation measured by percentage difference) to infer causal priority between "salience of class issues" and "image of Truman" during the 1948 presidential campaign.

When we compute cross-lagged associations of the data of Table 1, using Yule's Q as the measure of association, the results are as follows:

$$Q_{V_1B_2} = +.11$$

$$Q_{V_2B_1} = +.07$$

Although the difference between these Q's is very slight, the direction of the difference suggests the inference that viewing is the cause of buying.

It may occur to the reader that this approach is not very different from Zeisel's[2] approach discussed above, and indeed, in the case of our present example we have:

$$Q_{V_1B_2} - Q_{V_2B_1} = (+.11) - (+.07) = +.04$$

and,

$$Q_{V_1B_2.B_1} - Q_{V_2B_1.V_1} = (+.08) - (+.02) = +.06$$

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[1]Bernard R. Berelson, Paul F. Lazarsfeld, and William N. McPhee, <u>Voting</u> (Chicago: University of Chicago Press, 1954), p. 266.

[2]Zeisel, <u>op. cit</u>.

Although the results are not too different for this particular example, we shall attempt to show later that the use of the partials involves less restrictive assumptions.

Still another analytic technique or group of techniques has been suggested for the analysis of 16-fold tables. A generic term for this group of techniques might be "decomposition of degrees of freedom." Leo Goodman[1] has pointed out that the 16-fold table can be viewed as a contingency table with $(r-1)(c-1) = 3 \times 3 = 9$ degrees of freedom. He shows that the total chi-square for the table can be decomposed or partitioned so as to test various hypotheses about the table (e.g., the hypothesis that changes in Y are independent of changes in X). Further partitioning enables one to test even more specific hypotheses such as the hypothesis that Y and X are independent in some particular sub-region of the total table.

Whereas this type of technique facilitates <u>testing</u> of hypotheses, it provides no guidance as to the <u>formulation</u> of hypotheses. It is thus not necessarily different from any of the approaches discussed so far. It might be viewed as complementary to these other approaches providing one means of testing the hypotheses deduced from them.

James A. Davis,[2] advocates a related approach although he does not decompose chi-square. He argues that the 9 degrees of freedom imply that 9 "independent" (independent in the sense that no table can be obtained by subtracting from entries in the other tables) 4-fold tables can be constructed.

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[1]Leo Goodman, "Statistical Methods for Analyzing Processes of Change," <u>American Journal of Sociology</u>, LXVIII (July, 1962), 57-78.

[2]James A. Davis, "Panel Analysis: Techniques and Concepts in the Interpretation of Repeated Measurements "(unpublished manuscript).

In each of these tables the degree of association cannot be determined by the degree of association in the other tables.

As Davis points out, there are many ways in which these tables can be constructed (since there are many ways in which the degrees of freedom can be decomposed).

Both Goodman and Davis make use of 9 degrees of freedom in their analyses. It should be pointed out that there are 9 degrees of freedom after the row and column totals have been fixed. Since there is more than one way to lay out a 16-fold table, the researcher in effect is free to choose two zero-order correlations which will appear in the margins of the table. In Table 1 the zero-order correlation between Time 1 viewing and Time 2 viewing appears in the row totals and the correlation between Time 1 buying and Time 2 buying appears in the column totals. What has been done is to allocate 2 degrees of freedom to the stability of the attributes over time.

Another arrangement frequently used is to allow the zero-order correlation between Time 1 viewing and Time 1 buying to appear in the row totals and the Time 2 correlation between viewing and buying to appear in the column totals. In this case 2 degrees of freedom are allocated by fixing the correlations between the attributes.

The point is that the way in which the table is layed out has considerable effect on "decomposition of degrees of freedom" techniques. Perhaps it is best to consider the decomposition as beginning with 16 degrees of freedom (5 of the 16 are uninteresting) rather than 9. One possible decomposition of these 16 degrees of freedom which might be of interest is given in Table 3.

Here we allocate 1 degree of freedom to the total N, 1 degree of freedom to the number of cases possessing each of the four attributes, 1 degree of freedom to the stability of each attribute over time, 1 degree of freedom to each of the correlations between attributes at the same time, 1 degree of freedom to each of the "cross-lagged" correlations, and 5 degrees of freedom to first and second order interactions. Since the models which we shall discuss for inferring causal priority will not be concerned with interaction effects, and since there are 5 degrees of freedom available for interaction effects, we have, so to speak, just begun to tap the information available in a 16-fold table.

TABLE 3

POSSIBLE DECOMPOSITION OF DEGREES OF FREEDOM IN A SIXTEEN-FOLD TABLE

Allocation	Degrees of Freedom	
N	1	
n_{X_1}, n_{X_2}, n_{Y_1}, n_{Y_2}	4	
$Q_{X_1X_2}$, $Q_{Y_1Y_2}$	2	7
$Q_{X_1Y_1}$, $Q_{X_2Y_2}$	2	
$Q_{X_1Y_2}$, $Q_{X_2Y_1}$	2	
1st order interactions	4	
2nd order interactions	1	9
Total	16	16

We have discussed four methods of distinguishing cause and effect and an additional technique for testing hypotheses about the 16-fold table. Still other methods can readily be devised some of which will be discussed subsequently. In view of this multiplicity of methods, how is one to proceed with a particular analytic problem?

Experienced researchers frequently assert that there is no single best way to analyze longitudinal data or, in particular, to analyze the 16-fold table. They argue that one's method of analysis ought to depend on the specific, highly operationally defined, questions asked of the data. While we agree that there is no single best way to approach the problem, we do not feel that any and all methods are equally appropriate.

For some bodies of data, all the methods discussed above would lead to the same inferences about which variable is cause and which effect. In other circumstances, however, different methods lead to opposite conclusions. Little is generally known about what these circumstances might be.

It appears that the various methods have by and large been devised in an ad hoc fashion in response to particular analytic needs. The reasoning involved in devising these methods is largely based on analogies to experiments or on intuition. The assumptions involved in the use of a particular method are largely unrecognized or, at best, implicit. Thus, although a particular method might have worked well in the situation for which it was, ad hoc, devised, the extent to which it can be applied appropriately to other situations is, in general, not known.

Formal Causal Models

We should like to propose a general type of approach which allows us to evaluate the relative merits of alternative ad hoc procedures and permits the specification of circumstances under which they will or will not lead to similar inferences.

This approach consists in the construction of formal causal models and is based on the work of Simon[1] and Blalock.[2] In order to evaluate a particular method of analysis, e.g., the comparison of zero-order cross-lagged correlations, $r_{X_1Y_2}$ vs $r_{X_2Y_1}$, we attempt to construct formal causal models which contain predictions for the values $r_{X_1Y_2}$ and $r_{X_2Y_1}$. We are then in a position to (1) compare the observed values with the values predicted from the models, (2) empirically test some of the assumptions required by the models, (3) know explicitly what the nontestable assumptions are.

The general assumptions underlying the Simon-Blalock approach are that correlations among variables are linear, causal relationships are recursive (i.e., go in only one direction), and that "error" terms are uncorrelated. "Error" can be viewed as the extent to which variables within the model are caused by variables outside or not included in the model. Thus, an error term corresponds to variance which is unexplained by the variables in the model. Each variable has an error term, and is assumed to be caused by (1) an additive combination of the factors which precede it in the causal model, and (2) the error term.[3]

An example of a simple causal model is given in Figure 1. This model diagrams a causal situation in which T is caused by X and in turn causes Y.

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[1] Simon, op. cit., pp. 4-61.

[2] Although Blalock has written several papers on this subject, a good understanding of his approach can be gained from Blalock, op. cit.

[3] These assumptions are expressed in a set of simultaneous linear regression equations. For the precise form of these equations see ibid., p. 54.

In other words, T is an intervening variable between X and Y. The model assumes that e_X, e_T, and e_Y are uncorrelated and asserts the following:

(1) X is caused by e_X.

(2) T is caused by e_T and X.

(3) Y is caused by e_Y and T but not directly by X.

One prediction can be derived from this model, namely, there is zero correlation between X and Y when T is controlled. If the correlations are measured by r, this can be expressed another way; "the correlation between X and Y is the product of the correlations of X with T and T with Y," i.e.:

$$r_{XY} = r_{XT}r_{TY} \tag{1}$$

or

$$r_{XY.T} = \frac{r_{XY} - r_{XT}r_{TY}}{\sqrt{1-r_{XT}^2}\sqrt{1-r_{TY}^2}} = 0 \tag{2}$$

Inspection of the numerator of the formula for $r_{XY.T}$ shows why expressions (1) and (2) give the same prediction.

In subsequent diagrams the error terms will be omitted. Their presence is to be understood.

Let us first attempt to construct a pair of causal models which will lead to predictions for the values of $r_{X_1Y_2}$ and $r_{X_2Y_1}$. Figures 2 and 3 provide such predictions. In Figure 2, X is assumed to be the cause of Y. Since there is no causal connection, either direct or indirect, between X_2 and Y_1, the value of $r_{X_2Y_1}$ predicted from this model is zero. Figure 3 is

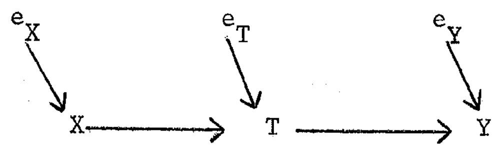
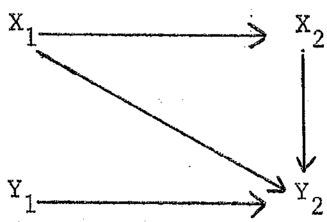
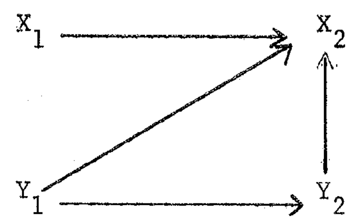


Fig. 1.--Casual Model for an Intervening Variable



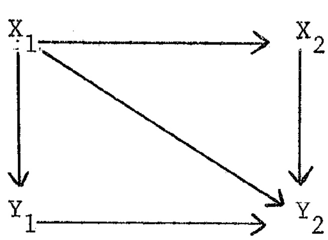
$\hat{r}_{X_2Y_1\cdot} =$

Fig. 2.--Causal Model Predicting Zero-order Cross-lag



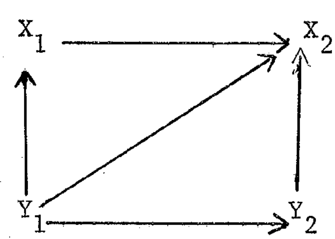
$\hat{r}_{X_1Y_2} = 0$

Fig. 3.--Causal Model Predicting Zero-order Cross-lag



$\hat{r}_{X_2Y_1} = r_{X_1Y_1} r_{X_2X_1}$

Fig. 4.--Causal Model Predicting Partial Cross-lag



$\hat{r}_{X_1Y_2} = r_{X_1Y_2} r_{Y_2Y_1}$

Fig. 5.--Causal Model Predicting Partial Cross-lag

identical to Figure 2 with the exception that Y is assumed to be the cause of X and the predicted value of $r_{X_1Y_2} = 0$. We are now in a position to compare the predicted values of the cross-lagged correlations with the observed. If $r_{X_1Y_2} > r_{X_2Y_1}$ then the model of Figure 2 provides a "better fit" than the model diagrammed in Figure 3 and we should infer that X is the cause of Y.

A hypothetical example may help to clarify this. Suppose that X is an intelligence test score and Y is a school grade point average. Most people would argue that intelligence is the cause of grades rather than grades being the cause of intelligence. Suppose that both are measured at two points in time for a sample of children. In the model of Figure 2 intelligence (X) is assumed to cause grades (Y). Since there is assumed to be no causal connection between Time 1 intelligence and Time 2 grades, either direct or indirect, the predicted correlation between them is zero. In the model of Figure 3 by contrast grades are assumed to cause intelligence and the predicted correlation between Time 1 intelligence and Time 2 grades is zero. If the correlation of intelligence at 1 with grades at 2 was larger than the correlation of grades at 1 with intelligence at 2, the model of Figure 2 would be a better fit and we would infer that intelligence causes grades.

What assumptions have been made in connection with this inference? In addition to the above-mentioned general assumptions of linearity, recursiveness, and independence of error terms, these particular models assume that causal relations are as diagrammed and <u>assume that</u> X_1 <u>and</u> Y_1 are independent, in our example that first time intelligence and first time grades are independent. This last assumption is made explicit by the lack of an arrow between them in the diagrams. This assumption is testable by simply computing the correlation between them. Since the instances in which we would want to assume that X_1 and Y_1 are not correlated are practically nonexistent, these models are clearly inadequate.

The simplest improvement in the models is the addition of an arrow between X_1 and Y_1. This has been done in Figures 4 and 5. Note, however, that the addition of this arrow changes the predicted values of the cross-lagged correlations, $r_{X_2Y_1}$ and $r_{X_1Y_2}$. In Figure 4, for example, there is now a spurious correlation between Y_1 and X_2, grades 1 and intelligence 2, whereas in the previous model (Figure 2) there was no correlation whatever, direct, indirect, or spurious. The predicted value of $r_{X_2Y_1}$ in this model is the product of $r_{X_1Y_1}$ and $r_{X_2X_1}$:

$$\hat{r}_{X_2Y_1} = r_{X_1Y_1} r_{X_2X_1} \tag{3}$$

In the example, the predicted value of the correlation between grades at 1 and intelligence at 2 is the product of the Time 1 correlation between grades and intelligence and the correlation between intelligence at 1 and intelligence at 2. Similarly the predicted value of $r_{X_1Y_2}$ in Figure 5 is:

$$\hat{r}_{X_1Y_2} = r_{X_1Y_1} r_{Y_2Y_1} \tag{4}$$

In the example, the predicted value of the correlation between intelligence at 1 and grades at 2 is the product of the Time 1 correlation between grades and intelligence and the correlation between grades at 1 and grades at 2.

Now the model shown in Figure 4, where it is assumed that X causes Y, intelligence causes grades, will give a better fit if the deviation of the actual from the predicted value of $r_{X_2Y_1}$ is smaller than the deviation of the actual from the predicted value of $r_{X_1Y_2}$. We should infer that X causes Y if:

$$r_{X_1Y_2} - \hat{r}_{X_1Y_2} > r_{X_2Y_1} - \hat{r}_{X_2Y_1} \tag{5}$$

Substituting the predicted values as given in expressions (3) and (4) into expression (5) gives:

$$r_{X_1Y_2} - r_{X_1Y_1} r_{Y_2Y_1} > r_{X_2Y_1} - r_{X_1Y_1} r_{X_2X_1} .$$

Since $r_{X_1Y_1}$ appears on both sides we write it as a constant and have:

$$r_{X_1Y_2} + kr_{X_2X_1} > r_{X_2Y_1} + kr_{Y_2Y_1} . \tag{6}$$

From Formula (6) we see that the causal inference depends not only on the relative size of the cross-lagged correlations, but also on the <u>relative stabilities of X and Y</u>. Substantively we might say that the more stable Y is over time the less subject it is to the influence of X. Applied to our example Formula (6) suggests that the causal inference depends not only on whether the correlation between intelligence at 1 and grades at 2 is larger than the correlation between grades at 1 and intelligence at 2, but it also depends on whether intelligence is more stable than grades. Again, the more stable grades are over time the less subject they are to the influence of intelligence.

Under what conditions will the comparison of the cross-lagged correlations alone lead to the correct inference under the model of Figure 4? From inequality (6) we see that:

$$r_{X_1Y_2} > r_{X_2Y_1},$$

under the condition that:

$$r_{X_2X_1} \geq r_{Y_2Y_1}.$$

This shows that if we assume that X is not less stable than Y, and that intelligence is not less stable than grades, and if the correlation of X_1 with Y_2 is greater than the correlation of Y_1 with X_2, then we should infer that X is the cause of Y, intelligence is the cause of grades. The assumption that X is at least as stable as Y is testable simply by comparing $r_{X_2X_1}$ with $r_{Y_2Y_1}$. In sum, the comparison of zero-order cross-lagged correlations is valid under this model if the independent variable is at least as stable as the dependent variable.

The reader has probably already observed that, although the use of <u>zero-order</u> cross-lagged correlations involves a limiting assumption about the relative stabilities of the variables, the use of <u>partial</u> cross-lagged correlations does not involve this assumption. Figure 4 leads to the prediction that:

$$\hat{r}_{X_2Y_1} = r_{X_1Y_1} r_{X_2X_1}.$$

This is equivalent to the prediction that:

$$\hat{r}_{X_2Y_1 \cdot X_1} = \frac{r_{X_1Y_2} - r_{X_1Y_1} r_{Y_2Y_1}}{\sqrt{1-r^2_{X_1Y_1}}\sqrt{1-r^2_{Y_2Y_1}}} = 0. \tag{7}$$

In our example, the prediction is that the partial correlation between grades at 1 and intelligence at 2, controlling for intelligence at 1, will be zero. Similarly, Figure 5 predicts that:

$$\hat{r}_{X_1Y_2 \cdot Y_1} = \frac{r_{X_1Y_2} - r_{X_1Y_1} r_{Y_2Y_1}}{\sqrt{1-r^2_{X_1Y_1}}\sqrt{1-r^2_{Y_2Y_1}}} = 0. \tag{8}$$

In our example the prediction is that the partial correlation between intelligence at 1 and grades at 2, controlling for grades at 1, will be zero.

In other words the absence of an arrow from Y_1 to X_2 in Figure 4 implies that the partial correlation between Y_1 and X_2 goes to zero when X_1 is controlled. Thus without any limiting assumptions about relative stabilities we should infer that X is the cause of Y under this model if:

$$r_{X_1Y_2 \cdot Y_1} > r_{X_2Y_1 \cdot X_1} \tag{9}$$

In the example, if the partial correlation of first time intelligence with second time grades, holding constant first time grades, is larger than the partial correlation of first time grades with second time intelligence, holding constant first time intelligence, we would properly conclude that intelligence causes grades.

An objection which might be raised to the models shown in Figures 4 and 5 is that they assume direction of causation between X_1 and Y_1 and between X_2 and Y_2, when in fact we might not wish to make such assumptions. Although it is necessary to indicate a correlation between X_1 and Y_1, we shall show that it is not necessary to assume a direction of causation, moreover, we shall show that it is not necessary to connect X_2 and Y_2 with a direct causal path.

How is it that the direction of the path between X_1 and Y_1 need not be indicated? Let us examine Figure 4. The interpretation of the correlation between Y_1 and X_2 is that it is spurious. According to this model, X_1 is the cause of both Y_1 and X_2 giving rise to the correlation between them. X_1 is "antecedent" to Y_1 and X_2. In the example, intelligence at 1 is the cause of both grades at 1 and intelligence at 2. Intelligence at 1 is antecedent to grades at 1 and intelligence at 2.

Suppose we reverse the direction of the arrow between Y_1 and X_1 so that Y_1 is now the "cause" of X_1, grades at 1 are the "cause" of intelligence at 1, but the other arrows are left unchanged. <u>The predicted value for</u> $r_{X_2Y_1}$ <u>is not affected</u>. However, the <u>meaning</u> of $r_{X_2Y_1}$ is changed The correlation between Y_1 and X_2 is now indirect rather than spurious. Y_1 is now a cause of X_2, grades at 1 now cause intelligence at 2, but only indirectly, through X_1, intelligence at 1 X_1 is now "intervening"[1] between Y_1 and X_2, intelligence 1 is now intervening between grades at 1 and intelligence at 2.

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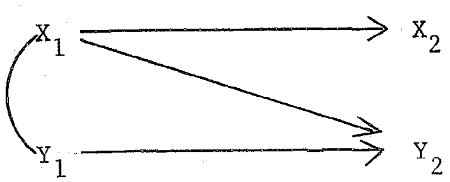
[1] For a full discussion of antecedent and intervening variables see Hyman, <u>op. cit</u>., pp. 242-274.

This discussion shows that, (1) it is not necessary to assume a direction of causation between X_1 and Y_1 in order to make causal inferences about the time period between T_1 and T_2, (2) the inferences made only apply to this time period. They are consistent with quite different causal processes going on at other times.

Figures 6 and 7 are arranged so as to show no direction of causation between X_1 and Y_1. They also show no direct causal link between X_2 and Y_2. The presence or absence of the arrow between X_2 and Y_2 does not affect the predicted value of the cross-lagged correlation. If an arrow is put in however, it must point to the dependent variable.



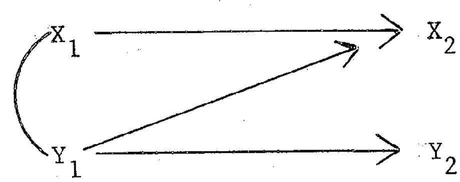
(1) $\hat{r}_{X_2Y_1} = r_{X_1Y_1} r_{X_2X_1}$

or $\hat{r}_{X_2Y_1 \cdot X_1} = 0$

(2) $\hat{r}_{X_2Y_2} = r_{X_1Y_2} r_{X_2X_1}$

or $\hat{r}_{X_2Y_2 \cdot X_1} = 0$

Fig. 6.--Causal Model Predicting Partial Cross-lag and Time 2 Cross-sectional Correlation



(1) $\hat{r}_{X_1Y_2} = r_{X_1Y_1} r_{Y_2Y_1}$

or $\hat{r}_{X_1Y_2 \cdot Y_1} = 0$

(2) $\hat{r}_{X_2Y_2} = r_{X_2Y_1} r_{Y_2Y_1}$

or $\hat{r}_{X_2Y_2 \cdot Y_1} = 0$

Fig. 7.--Causal Model Predicting Partial Cross-lag and Time 2 Cross-sectional Correlation

If the arrow is omitted, the model contains an additional prediction. In Figure 6, for example, the correlation between X_2 and Y_2 is spurious and is due to the effects of the antecedent variable, X_1, which is the cause of both X_2 and Y_2. In our example, the second time correlation between grades and intelligence is spurious and is due to the effects of the antecedent, intelligence 1, which is the cause of both grades 2 and intelligence 2. Conversely, in Figure 7, the correlation between X_2 and Y_2 is spurious, and is due to the effects of the antecedent Y_1, grades 1. Thus we have the following new predictions from Figures 6 and 7:

$$\hat{r}_{X_2Y_2} = r_{X_1Y_2} r_{X_2X_1},$$

or

$$\hat{r}_{X_2Y_2 \cdot X_1} = 0; \tag{10}$$

conversely,

$$\hat{r}_{X_2Y_2} = r_{X_2Y_1} r_{Y_2Y_1},$$

or

$$\hat{r}_{X_2Y_2 \cdot Y_1} = 0. \tag{11}$$

Now we should infer under these models that X is the cause of Y if Figure 6 is a better fit than Figure 7, i.e., if:

$$r_{X_2Y_2} - r_{X_2Y_1} r_{Y_2Y_1} > r_{X_2Y_2} - r_{X_1Y_2} r_{X_2Y_1}.$$

This reduces to:

$$r_{X_1Y_2} r_{X_2X_1} > r_{X_2Y_1} r_{Y_2Y_1}. \tag{12}$$

Expression (12) indicates that the causal inference depends on the relative size of the cross-lagged correlations and the relative stabilities of the two variables. Although the form of the mathematical function is different, this is the same conclusion (encouragingly) that was reached by our previous procedure. Inequality (6) is reproduced here for comparison with inequality (12).

$$r_{X_1Y_2} + kr_{X_2X_1} > r_{X_2Y_1} + kr_{Y_2Y_1}. \tag{6}$$

Comparison of the cross-lagged partial correlations is thus an <u>additive</u> function of cross-lagged correlations and stabilities, while comparison of the partial X_2Y_2 correlations when X_1 and Y_1 are alternatively controlled, is a <u>multiplicative</u> function of cross-lagged correlations and stabilities. Since we are dealing with inequalities, these two procedures must lead to the same inferences, and the additional prediction obtained by omitting a direct causal link between X_2 and Y_2 is redundant.

The Pelz and Andrews Model

Pelz and Andrews[1] proposed a causal model somewhat similar to the types we have been discussing here, although their development was not at all formal. Figures 4 and 5 are similar to the Pelz-Andrews model with the exception that,

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[1]Pelz and Andrews, <u>op. cit</u>.

under their assumptions, no direction need be given to the arrows between X_1 and Y_1. They base the causal inference on comparison of $r_{X_1Y_2}$ with $r_{X_2Y_1}$ and assume the following:

(1) $r_{X_2X_1} = r_{Y_2Y_1}$, i.e., the variables are equally stable, in our example intelligence and grades are equally stable.

(2) The independent variable has a cross-lagged correlation of unity, i.e., if X is the cause of Y, then $r_{X_1Y_2} = 1.00$, in our example intelligence at 1 is perfectly correlated with grades at 2.

(3) $r_{X_1Y_1} = r_{X_2Y_2}$, i.e., the correlation between X and Y is about the same at Time 1 and Time 2.

If these assumptions could be met with any actual data, the comparison of $r_{X_1Y_2}$ with $r_{X_2Y_1}$ would lead to the correct inference under the model. However, it is extremely unlikely that data could be found which would satisfy these assumptions.

Let us consider one implication of assumption (2) which Pelz and Andrews do not discuss. If $r_{X_1Y_2} = 1.00$, it must follow that $r_{X_1Y_1} = r_{Y_2Y_1}$. Since X_1 and Y_2 are one and the same, a third variable, Y_1, must correlate the same with each, and the stability of the dependent variable must equal the Time 1 correlation between the variables. In the example, if intelligence at 1 is perfectly correlated with grades at 2, it must follow that the first time correlation between grades and intelligence is exactly equal to the stability of grades. It is extremely unlikely that such a circumstance would be found in actual data.

In any case, we have shown previously that assumptions 2 and 3 are not necessary, and although the assumption of equal stability in X and Y

is necessary for comparing the zero-order cross-lagged correlations, it is unnecessarily restrictive, since the partials can be compared without any assumptions whatever about stability.

Pelz and Andrews do extend their model to cover more than one time period. In the case of the models presented in Figures 4, 5, 6, and 7, it can also be shown that if adjacent time periods both suggest the inference that X causes Y, then the total time span covered by both these time periods will also suggest the inference that X is the cause of Y.

The conclusion which emerges from the discussion to this point can be summarized in the following sentence. Under the assumptions of a group of formal causal models (Figures 4, 5, 6, and 7) direction of causation is a function of (1) the relative size of cross-lagged correlations; (2) the relative stability over time of the variables.

Measuring Change

Campbell[1] has observed that measures of "change" in longitudinal data are beset by problems of "statistical regression" arising from errors of measurement. Statistical regression can be thought of as arising from "error" in the sense that we discussed error above, i.e., in the sense of imperfect correlation. The fact that the correlation over time in a variable--the stability of the variable--is less than unity gives rise to statistical regression.

"Change" in a variable Y is normally measured by the difference between an individual's score at Time 2 and his score at Time 1. Symbolically:

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[1] Campbell, op. cit.

$$c_Y = Y_2 - Y_1, \tag{13}$$

where c_Y is change (gain) in Y.

However, unless the correlation between Y_2 and Y_1 is unity, Y_1 is not the best prediction of Y_2. The best prediction of Y_2 under the usual least squares criterion is:

$$\hat{Y}_2 = bY_1 + a, \tag{14}$$

where b is the slope of the least squares regression line and a is the Y_2 intercept. Let us assume that $\sigma_{Y_2} \cong \sigma_{Y_1}$. Now referring to Figure 8, we observe the following: Since the points tend, on the average, to fall near the regression line, $Y_2 = bY_1 + a$, the difference, $Y_2 - Y_1$, will, on the average, be positive for points below the mean of Y_1, and will, on the average, be negative for points above the mean of Y_1. Careful study of Figure 8 will help to clarify this notion.

Another way to express these facts is to observe that scores which were, at Time 1, below the $\bar{\bar{Y}}$ will on the average move up by Time 2; while those scores which were, at Time 1, above the $\bar{Y}$ will, on the average have gone down by Time 2. Both sets of scores will, on the average, have "regressed toward the mean."

This phenomenon has no substantive importance. It should be considered an artifact of the imperfect correlation between Y_2 and Y_1. The point of this discussion is that the measure, $c_y = Y_2 - Y_1$, is subject to misinterpretation due to regression effects.

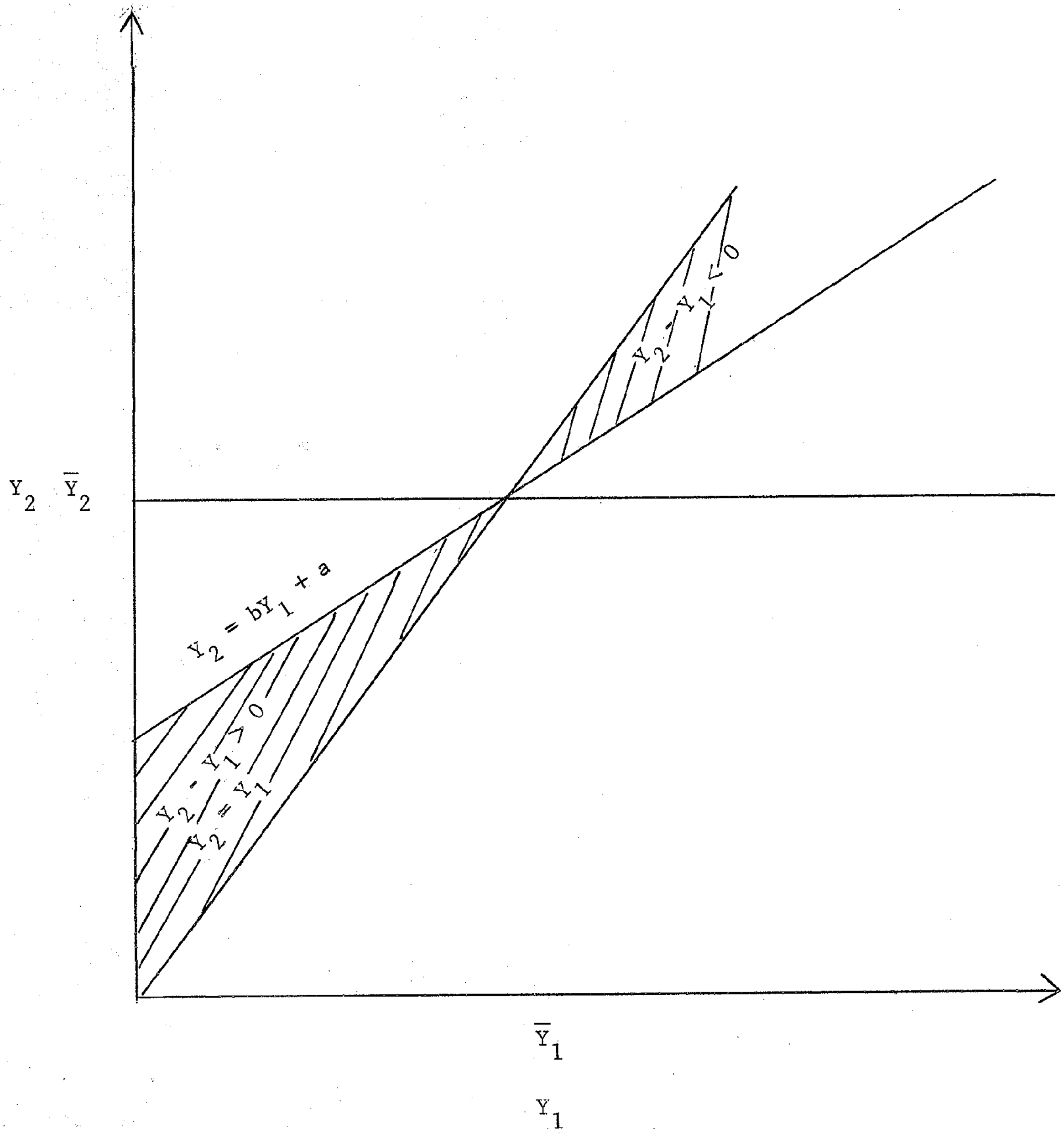

Fig. 8.--Illustration of Regression Effects

Suppose, however, that change is conceived in the following way:

$$c'_Y = Y_2 - \hat{Y}_2 \qquad (15)$$

where

$$\hat{Y}_2 = bY_1 + a$$

This has been termed by Duncan[1] "deviational change." It is the difference between Y_2 and the value of Y_2 which is predicted by Y_1 according to least squares regression. In other words, it is the "residual" from the regression of Y_2 on Y_1. This measure is free of regression toward the mean.

Correlates of Deviational Change

Suppose that we wish to correlate another variable such as X_1 with deviational changes in Y. It can be proven[2] that:

$$r_{X_1 c'_Y} = r_{X_1 (Y_2 - \hat{Y}_2)} = \frac{r_{X_1 Y_2} - r_{X_1 Y_1} r_{Y_2 Y_1}}{\sqrt{1 - r^2_{Y_2 Y_1}}} \qquad (16)$$

Formula (16) is strikingly similar to the partial correlation of X_1 with Y_2 controlling for Y_1. The numerator is, in fact, identical to the numerator of the partial and:

$$r_{X_1 c'_Y} = r_{X_1 c'_Y Y_2 . Y_1} \sqrt{1 - r^2_{X_1 Y_1}} . \qquad (17)$$

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[1] Otis Dudley Duncan, Ray P. Cuzzort, and Beverly Duncan, Statistical Geography (Glencoe, Ill.: The Free Press, 1961), p. 163.

[2] Robert W. Hodge of NORC deserves the credit for verifying this proof.

The square root factor is simply the square root of variance in X_1 which is unrelated to variance in Y_1.

We might wish to assess direction of causation by comparing the correlation of X_1 with deviational change in Y and the correlation of Y_1 with deviational change in X. Since the numerators of these two correlations are identical to the numerators of the cross-lagged partial correlations, $r_{X_1Y_2.Y_1}$ and $r_{Y_1X_2.X_1}$, this procedure leads to exactly the same conclusions as are reached comparing the cross-lagged partials. Thus, a comparison of $r_{X_1c'_Y}$ with $r_{Y_1c'_X}$ leads to a correct causal inference under the causal models of Figures 4, 5, 6, and 7.

Let us return to our hypothetical example of intelligence and grades to clarify what has been said. Deviational change in Y, grades, is the residual from the regression of grades 2 on grades 1, and deviational change in X, intelligence, is the residual from the regression of intelligence 2 on intelligence 1. Suppose we correlate intelligence at 1 with deviational changes in grades then correlate grades at 1 with deviational changes in intelligence. If the first of these coefficients is larger than the second we shall correctly concluded, under the assumptions of the causal models shown in Figures 4, 5, 6, and 7, that intelligence is the cause of grades.

An Interpretation of Rosenberg's Approach

The above discussion leads to an interpretation of Rosenberg's[1] analysis of the 16-fold table. Suppose, to follow Rosenberg, that we exclude from the analysis those who changed both viewing and buying habits between

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[1]Rosenberg, op. cit.

Time 1 and Time 2. Although we feel that approaches which exclude certain cells of the 16-fold table should be avoided, the numbers of cases involved in this exclusion will generally not be large enough to affect the results. We shall include, for the present, those who changed neither viewing nor buying habits. Now let us ask whether the initial viewers are more likely to increase their buying, than are the initial nonviewers. In other words let us look at the correlation between initial viewing and change in buying.

Conversely let us look at the correlation between initial buying and change in viewing. These comparisons are shown in Tables 4 and 5 respectively.

Now if the degrees of association in Tables 4 and 5 are computed from the extreme cells i.e., if the "no change" groups are omitted from the computation, we have duplicated Rosenberg's method.

In the previous discussion we saw that correlating deviational changes in the dependent variable with the initial state of the independent variable leads to causal inferences which are correct under our models. To the extent that Rosenberg's method is similar to this procedure it is also consistent with our models. Rosenberg's method will, in general, lead to the same results as our previous methods. In some cases, however, the results might differ due to the following factors:

1. Rosenberg's exclusion of "double changers."

2. The method of measuring association, i.e., estimating the degree of association by percentage differences between the extreme cells.

3. The effects on Rosenberg's change measures of statistical regression.

TABLE 4

INITIAL VIEWING BY INCREASE IN BUYING

("Double Changers" Excluded)

	Buying				
	T_1	T_2	Increase	No Change	Decrease
Viewing	Yes	Yes	57	573	53
	No	No	81	995	80

TABLE 5

INITIAL BUYING BY INCREASE IN VIEWING

("Double Changers" Excluded)

	Buying		
	T_1	Yes	No
	T_2	Yes	No
Viewing	Increase	27	219
	No Change	186	1,302
	Decrease	31	231

The "Harmonizing" Approach

The one approach which we have not considered from the standpoint of formal causal models is the "harmonizing approach" used by Lazarsfeld.[1] It will be recalled that this approach led, in the viewing and buying example to the inference that buying was the cause of viewing, while all other approaches led to the opposite inference. Thus we know that, at least under certain circumstances, Lazarsfeld's approach leads to inferences which are incorrect under our causal models. Since Lazarsfeld and his colleagues fail to make clear what precise criteria they use in reaching a decision, it is rather difficult to generalize the circumstances under which this approach leads to the correct inferences under our models.

Lazarsfeld's approach was limited to those who were at the first time "inconsistent" in buying and viewing habits, excluding all "consistent" cases. He asks, do those who become consistent change viewing habits or buying habits more often? Lazarsfeld went on to exclude cases who did not "become consistent." We can rephrase the question as follows and proceed without excluding those who did not "become consistent": Among those who were at Time 1 inconsistent, which habit is more stable?

If buying is more stable then we infer that it is the cause of viewing. In our present example, buying is, indeed, more stable than viewing, and for this reason Lazarsfeld's approach leads to an inference opposite to that of the other approaches.

Figure 9 illustrates this approach generalized to continuous variables. Point A_1 is located at some distance from a regression line for the Time 1

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[1] Lipset, Lazarsfeld _et al._, _op. cit._

scatter plot of X and Y. An individual located at point A_1 is "inconsistent" and an individual who is located close to the regression line (point B_1) is "consistent." If point A_1 moves, through time, toward the regression line horizontally, the value of Y is stable while the value of X changes. If, on the other hand, point A moves vertically toward the line, the value of Y changes while X remains stable.

Suppose we arbitrarily define some region not close to the regression line as an "inconsistent" region. We should infer that X is the cause of Y if, within the inconsistent region:

$$r_{X_2X_1} > r_{Y_2Y_1}.$$

In other words, if X is more stable than Y among those who were originally "inconsistent," we should infer that X is the cause of Y.

<u>What, however, should we expect among those who were consistent at the first time</u>? Lazarsfeld fails to make this clear.

Let us consider two possibilities: (1) If X is the cause of Y, X is more stable than Y both among those who were originally consistent and also among those who were originally inconsistent, i.e., in both cases $r_{X_2X_1}$ is greater than $r_{Y_2Y_1}$. (2) If X is the cause of Y, X is <u>more stable</u> than Y among those who were originally inconsistent but X is <u>less stable</u> than Y among those who were originally consistent. Substantively, the second alternative argues that for those who are consistent there is no reason for Y to change because it is already consistent with X. X, however, is free to change inasmuch as it is caused by factors other than Y.

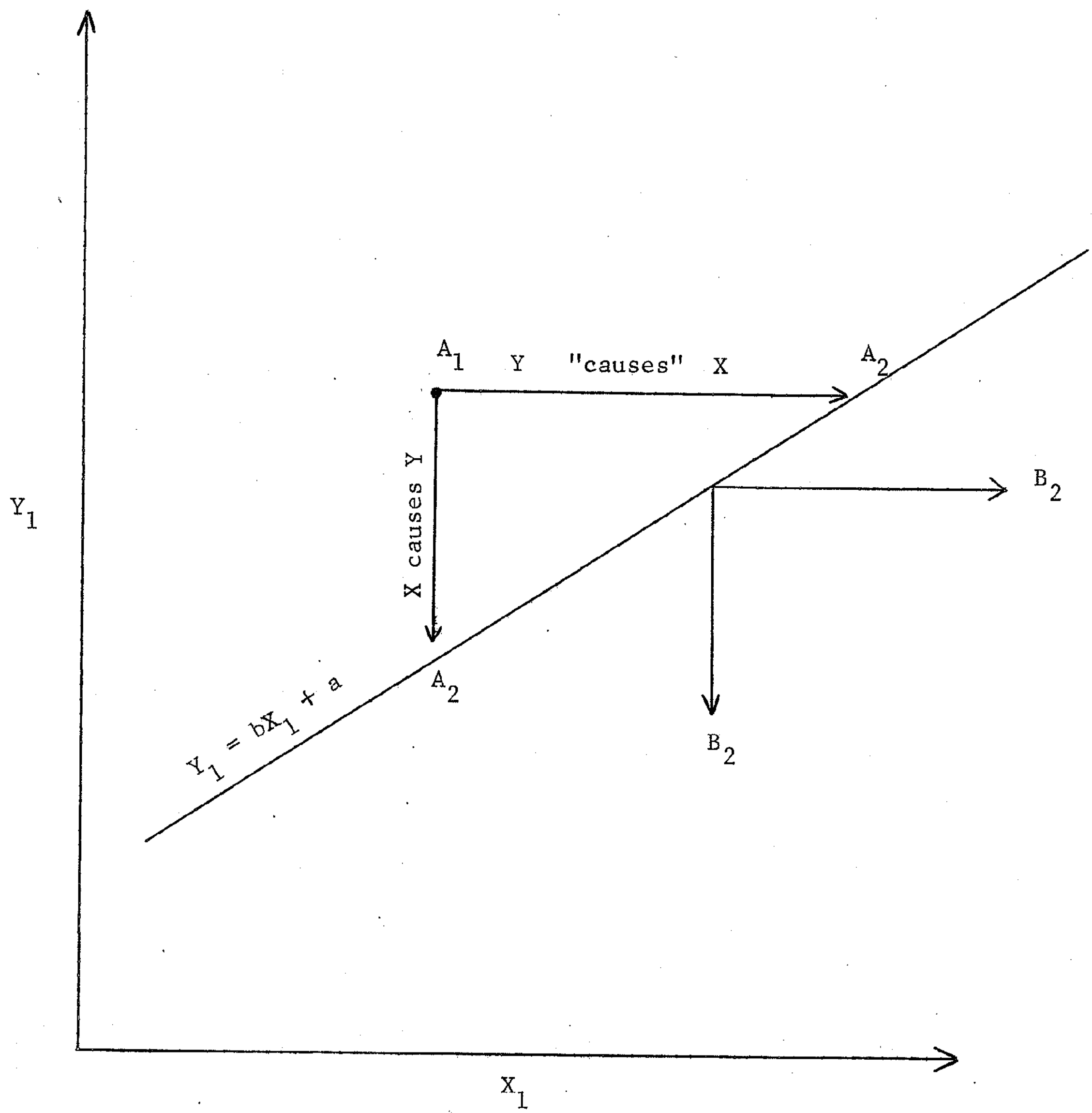

Fig. 9--"Harmonizing" Approach for Continuous Variable

Figures 10 and 11 may help to clarify these alternatives. In these diagrams stability is conceived of as the regression of X_2 on X_1 and the regression of Y_2 on Y_1. If the slope of the total sample regression line is steeper in Figure 10 than it is in Figure 11, then $r_{X_2X_1}$ is greater than $r_{Y_2Y_1}$ and X is more stable than Y.

Suppose now that we divide the sample into two groups according to some arbitrary criterion involving deviations from the regression line (or lines) of the scatter plot for X_1 and Y_1 (Figure 9), i.e., we define groups which were originally consistent or inconsistent. We can compute for each of these groups separately the values of $b_{X_2X_1}$ and $b_{Y_2Y_1}$. The b's are the slopes of the regression lines for predicting X_2 from X_1 and for predicting Y_2 from Y_1, and reflect the relative stabilities of X and Y.

Using analysis of covariance[1] it is possible to test the hypothesis that the "total" line will fit the separate lines for consistent and inconsistent groups in both Figures 10 and 11. This amounts to testing the hypothesis that for each variable the consistent group does not differ in its stability from the inconsistent group. We shall consider the implications of two possible outcomes of these tests.

1. One possible outcome, and we feel the most likely outcome, is that the total line fits both the inconsistent and consistent groups for both X and Y. If this is the case the subgroups don't differ in stability and it can be shown that the control for consistency has negligible effect on the zero-order correlations $r_{X_2X_1}$ and $r_{Y_2Y_1}$. Consistency, defined in terms of

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[1] See Helen M. Walker and Joseph Lev, Statistical Inference (New York: Holt, Rinehart, and Winston, 1953), pp. 393-395.

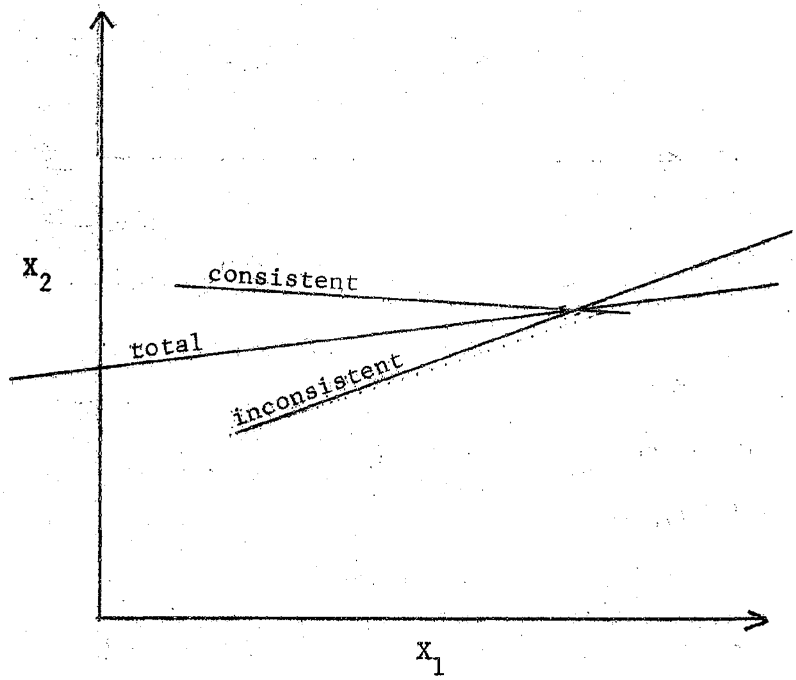

Fig. 10.--Regression Lines for Independent Variable

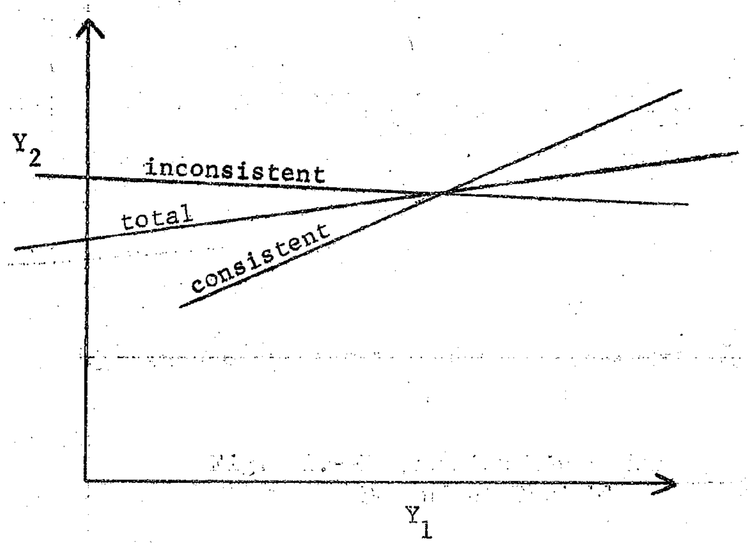

Fig. 11.--Regression Lines for Dependent Variable

deviations from the regression lines, $\hat{Y}_1 = bX_1 + a$ or $\hat{X}_1 = bY_1 + a$, is statistically independent of Y_1 and X_1 and controlling for it can hardly affect the zero-order stabilities.

In this case we may dismiss the notion of consistency and infer that X is the cause of Y if:

$$r_{X_2X_1} > r_{Y_2Y_1}.$$

This shows that under this outcome Lazarsfeld's approach depends solely on the relative stabilities of the variables. Under our models this comparison is valid if we assume that:

$$r_{X_1Y_2} \geq r_{X_2Y_1},$$

i.e., if we assume that the independent variable has a cross-lagged correlation at least as high as the dependent variable.

This assumption is necessary because under our models the causal inference depends on both the relative stabilities and the relative size of cross-lagged correlations, whereas Lazarsfeld's approach, in this case, depends only on the relative stabilities.

2. Another possible outcome of the tests (we imagine relatively rare in actual data) is shown in Figures 10 and 11. Here we should infer under Lazarsfeld's method that X is the cause of Y since the line for the inconsistents has a steeper slope in Figure 10 than in Figure 11, i.e., X is more stable than Y, and the line for consistents has a steeper slope in Figure 11 than in Figure 10, i.e., Y is more stable than X.

Under these circumstances it is not possible (at least for this writer) to specify an algebraic relation to our causal models. In case of this outcome we are unable to determine on mathematical grounds whether Lazarsfeld's approach leads to inferences consistent with our models. Of course for a particular body of data an empirical determination would answer the question.

In sum we feel that the "harmonizing" approach reflects, in general, the relative stabilities of the variables, although this may not be the case for all bodies of data. It is consistent with our causal models only if we are willing to make a restrictive assumption about the relative size of cross-lagged correlations.

Partials and Prediction

The reader will have perceived by this time that we favor the use of cross-lagged partials. It is possible to view the use of these measures from perspectives not contingent on our causal models. In the discussion of Zeisel's approach to the 16-fold table we noted that the use of cross-lagged partials could be considered an analogy to a simple experimental situation. An additional interpretation can be made in the language of "prediction." For such an interpretation, no assumptions about causal relations need be more (however, no causal inferences can be made without making the assumptions). In terms of simple prediction the partial, $r_{X_1Y_2 \cdot Y_1}$ tells us whether we can predict Y_2 any better by using X_1 in addition to Y_1 as a predictor than we could by using Y_1 alone. In other words, how much we gain by throwing X_1 into a multiple regression equation with Y_1 in order to predict Y_2.

Conversely, the partial $r_{X_2Y_1 \cdot X_1}$ measures how much would be gained by predicting X_2 from Y_1 in addition to X_1 rather than from X_1 alone.

The information concerning prediction which these partials provide, without doubt, is of practical value quite apart from any causal implications which may be involved.

Additional Problems

Despite its ambitious title, this chapter by no means exhausts the problem of causal inferences from longitudinal data. In particular, various problems in connection with time intervals have not been discussed systematically. For example, our observed time interval may bear only an imperfect relation to the so-called "interval of causation," our time interval may obscure cyclic phenomena occurring at shorter or longer time intervals, or, in general, it may be an unrepresentative "sample" of time.[1]

We have, moreover, largely ignored the problem of what happens when other variables are taken into consideration.[2] These problems are only a few of the ways in which the present analysis needs to be extended and modified.

Summary and Conclusion

In summary, we advocate the use of cross-lagged partial correlations in making causal inferences from longitudinal data, although there are a number of related procedures which will, starting from the same assumptions, lead to the same inferences. Our approach is based on a causal model which assumes the following state of affairs:

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[1]For further discussion of these problems see Duncan *et al*., *op. cit*., pp. 160-174; and Pelz and Andrews, *op. cit*.

[2]Problems of the effect of outside variables on causal models are dealt with at length in Blalock, *op. cit*.

1. Relationships among the variables are linear.

2. Causation is recursive.

3. "Errors" are uncorrelated.

4. The variables, X and Y, are correlated at Time 1.

5. X_1 has a causal influence on X_2.

6. Y_1 has a causal influence on Y_2.

7. The independent variable at Time 1 has a direct causal influence on the dependent variable at Time 2.

8. The dependent variable at Time 1 does not have a direct causal influence on the independent variable at Time 2.

9. Either the independent variable at Time 2 has a direct causal influence on the dependent variable at Time 2; or there is a spurious Time 2 correlation between the variables.

We hope that what has been accomplished is to give the reader some basis for evaluating our own procedures and to make a start toward an analysis of longitudinal data which is less ad hoc, and more carefully considered.

CHAPTER III

OCCUPATIONAL VALUES AND CAREER CHOICES AT COLLEGE GRADUATION

In this chapter we shall be concerned with identifying patterns of values which are consistent with choice of various careers. Our procedure in this is essentially empirical. Patterns of values are used as a predictor of career choice and the attempt is made to obtain a fairly high association between each career and its consistent values.

At the same time we shall attempt to treat the value measures in a way which allows us to say something about what the values are that are consistent with each career. We should like to be able to say not only that there are values consistent with a particular career but we should also like to specify what those values are.

The Measurement of Career Choice

It will be recalled that by the spring of 1963, NORC had sent three questionnaires to the respondents of the College Senior Study, the first in June, 1961, just prior to graduation, the second in June, 1962, one year after graduation, and the third in the spring of 1963 after the second post-graduate year. In each of these questionnaires respondents were asked to select "your anticipated long-run career field and ignore any school, stop-gap job, or temporary military service which might precede it." Selections were made from a detailed list of approximately 100 careers.

In this analysis related careers in the detailed list have been combined in order to reduce the total number of careers to a manageable number. Two separate lists of careers have been employed in the analysis. In preliminary work with a 10 per cent random sub-sample with N = 1,712, a list of ten career categories was used. In the major analysis of the full sample of 15,850 males a list of twenty-one career categories has been used.

The decision to employ as many as twenty-one career categories in the major analysis arose from our desire to have a sufficient number of careers to permit some analysis of variations in our findings by career. In assigning detailed titles to the twenty-one categories we tried to establish more or less homogeneous groups which would be neither too small for analysis nor so large that most of the cases would fall in one or two categories. We did not however design categories with a view to maximizing the correlations with value patterns. As will be seen later, value patterns have been constructed in part so as to obtain high associations with career choices but the career choice categories were not manipulated in this fashion. The reader may wish to refer to Appendix A which gives the detailed career titles subsumed under each of the twenty-one categories.

Table 6 shows the distribution of the sample by career choice at college graduation. The largest career is business which was chosen by 23.9 per cent of the sample and the smallest is social work selected by 0.6 per cent of these men. The residual category which could not be classified under a specific title constitutes 9.9 per cent of the sample. The three largest careers, business, engineering, and teaching, comprise almost half (47.6 per cent) of the sample.

TABLE 6

DISTRIBUTION OF CAREER CHOICES
AT COLLEGE GRADUATION

Career	Per Cent
Business	23.9
Engineering	14.5
Teaching (elementary or secondary)	9.2
Law	6.0
Physical sciences (except chemistry)	5.2
Medicine	4.6
Humanities	3.4
Social sciences	3.1
Religion	3.0
Chemistry	2.6
Agriculture	2.2
Biological sciences	1.9
Educational administration	1.9
Physical education	1.8
Vocational education	1.5
History	1.3
Journalism, communications	1.2
Military service	1.2
Dentistry	0.9
Social work	0.6
Not elsewhere classified	9.9
Total	99.9

N.	(23,519)
NA, DNA	437
Total weighted N.	23,956

The Measurement of Occupational Values

The third wave questionnaire contained no measure of occupational values. The first two waves, however, do contain such items. In both of the first two waves respondents were asked the following question: "Which of these characteristics would be very important to you in picking a job or career? (Circle as many as apply.)

1. Making a lot of money.
2. Opportunities to be original and creative.
3. Opportunities to be helpful to others or useful to society.
4. Avoiding a high pressure job which takes too much out of you.
5. Living and working in the world of ideas.
6. Freedom from supervision in my work.
7. Opportunities for moderate but steady progress rather than the chance of extreme success or failure.
8. A chance to exercise leadership.
9. Opportunities to work with people rather than things.
10. None of the above."

Table 7 gives the proportion in each career who endorse each of the above values. It shows that there is considerable variation across careers in the frequency with which these values are endorsed. For example, 79 per cent of those planning careers in social work or religion express an interest in working with people while 14 per cent of prospective physical scientists and only 13 per cent of prospective chemists express such an interest. These figures can be contrasted with the proportion endorsing the value, "people," in the sample as a whole. This is 45 per cent. Thus social workers and

TABLE 7

VALUES AND CAREER CHOICES

(Per Cent Endorsing Each Value)

Career	Values									
	People	Helpful	Original	Ideas	Money	Leadership	Freedom	Steady	Pressure	None
Vocational education . . .	47	72	46	32	22	45	16	46	24	2
Physical education . . .	67	67	21	19	17	49	9	34	15	2
Education administration.	75	82	43	30	12	61	14	32	11	2
Teaching.	57	79	47	39	12	37	19	33	20	1
Religion.	79	94	40	42	0	49	9	17	7	1
History	54	75	55	70	8	33	27	19	20	1
Humanities. . . .	41	64	83	74	17	27	35	23	20	2
Social science. .	54	71	67	67	18	46	28	27	15	0
Social work . . .	79	87	32	28	12	40	19	48	14	0
Journalism. . . .	49	43	79	60	31	42	26	22	12	4
Law	60	66	42	42	51	61	34	15	8	1
Business.	52	41	39	24	48	60	21	37	16	2
Military.	50	50	34	20	22	90	7	38	6	2
Engineering . . .	17	39	65	43	34	50	17	41	20	2
Physical science.	14	42	72	60	29	33	30	30	24	2
Chemistry	13	45	75	47	28	32	23	35	19	1
Dentistry	54	77	39	16	44	24	56	18	20	2
Medicine.	64	92	45	33	24	33	42	14	7	1
Biological sciences	17	67	62	46	20	21	28	29	22	2
Agriculture . . .	21	49	37	21	20	42	27	48	27	2
NEC	50	64	49	40	28	48	24	35	17	1
All Careers .	45	57	51	38	31	48	23	32	16	2
Average Deviation .	17.4	17.0	14.8	14.6	12.8	12.6	9.0	8.9	5.2	0.8

ministers are considerably more interested in working with people than is the total sample and chemists and engineers are very uninterested in working with people.

To take another example, 51 per cent of the future lawyers and 48 per cent of the future businessmen express an interest in money, while less than one half of one per cent of those planning careers in religion express such an interest. For the sample as a whole 31 per cent endorse the value, "money."

In general, the substantial variations that occur by career in the proportions endorsing the several values suggest that the value items can be used to differentiate or predict career choices.

Are all the values equally useful in predicting career choice, or do some of them produce substantial variation by career while others produce little? In order to provide a rough answer to this question we computed and entered in the bottom row of Table 7 an "average deviation" of each value. This was computed by subtracting the percentage endorsing the value for the sample as a whole from the percentage endorsing it for each particular career. summing the absolute value of these deviations across careers and dividing by the number of careers. The "not-elsewhere classified" career category was omitted from these computations because it is a heterogeneous residual group and to try to predict this category using the value measures has little justification.

The average deviations indicate that the values are not all equally useful in predicting career choices. "People" and "helpful" appear to produce the greatest variation by career while "avoid pressure," on the average, produces little variation. "None" shows almost no variation at all by career.

Basing our decision on the average deviations, we retained, for the subsequent analysis, the six values, "people," "helpful," "original," "ideas," and "leadership," considering them to be relevant to career choice. The values, "freedom," "steady," "pressure," and "none," have been omitted from subsequent analysis as less relevant to career choice.

Having selected six values for further analysis we wanted to know the extent to which the six values measured different aspects or dimensions of psychological reality. On the one hand it might be that the values measure six separate factors while on the other hand they might all measure a single factor. Realistically the answer should lie somewhere between these two extremes and can be approached by investigating the extent to which the six value items are statistically independent of one another.

Table 8 gives the associations (Yule's Q) among the values at college graduation for the random sub-sample of 1,712 men. It is obvious at once that they are not all independent of one another. The association of +.69 between "ideas" and "original" suggests that these two values tap a common dimension. We have called this dimension "intellectualism" although the reader might prefer to think of it as "creativity" and it is also similar to Rosenberg's[1] "self-expression" value complex.

The structure of associations among the four values, "helpful," "people," "leadership," and "money," might be interpreted as fitting either a one dimensional or a two dimensional model. In the one dimensional model the structure of associations is viewed as a Guttman Simplex. A line has been drawn above "helpful" in Table 8; the Guttman Simplex is composed of the six coefficients below the line. Note that the coefficients along the lower

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[1]Rosenberg, op. cit.

diagonal tend to be large but become smaller as one moves away from this diagonal in any direction. Finally the coefficient in the upper right hand corner becomes negative.

TABLE 8

ASSOCIATIONS (Q) AMONG SELECTED OCCUPATIONAL VALUES AT COLLEGE GRADUATION*

	Original	Helpful	People	Leadership	Money
Ideas	+.69	+.28	+.06	+.15	-.03
Original		+.12	-.07	+.26	+.03
Helpful			+.47	+.13	-.13
People				+.45	+.14
Leadership					+.41
Money					

*Based on random sub-sample of 1,712 males.

The interpretation is that the four values, "helpful," "people," "leadership," and "money," form a continuum with "helpful" at one end and "money" at the other. The associations between adjacent values on the continuum are high but become smaller for nonadjacent values. Each respondent can be assigned a single location along the continuum. At one extreme would be those endorsing only the value, "helpful," next would be those choosing both "helpful" and "people," next those choosing only "people," and so on down to those choosing only "money." From a substantive point of view one might consider the "helpful" end of the continuum as orientation to others and the "money" end as orientation to self.

This one dimensional model requires that "helpful" and "money" be negatively related since they are supposed to be at opposite ends of the continuum.

But since the association between them is only -.13 it can be argued that they are not negatively related but rather are independent. If they are in fact independent then we should be well advised to interpret the structure of associations among the four values as two dimensional rather than one dimensional. In the two dimensional model "helpful" and "people" would be one dimension and the second would be "leadership" and "money." These two dimensions would be considered as independent of one another.

It can be objected that the two dimensional model requires a low association between "people" and "leadership" since they are supposed to be independent while in fact the association between them is moderately high ($Q = +.45$).

It appears that one can make a fair case for either a one dimensional or a two dimensional model. At the same time it appears that an objection can be raised to either interpretation. In order to resolve this dilemma we asked which model provided greater differentiation among careers. We found that the one dimensional continuum failed to predict law which is high on both "helpful" and "money" and failed to predict the natural sciences which are low on both "helpful" and "money." The two dimensional model, however, does allow for these contingencies, and we therefore decided to use it in the subsequent analysis.

In all then we decided to use three dimensions of value orientation, namely "intellectualism" which is made up of the values, "ideas" and "original," "people orientation" which is made up of the values, "helpful" and "people," and "enterprise" which is made up of the values "money" and "leadership."

These dimensions are similar to dimensions employed by Davis[1] and by Rosenberg.[2] What we have called intellectualism corresponds to Rosenberg's "self-expression," our enterprise corresponds to Rosenberg's "extrinsic-reward-orientation," and our people orientation is identical to Rosenberg's "people orientation."

It was our feeling that since there are only two value items entering into each of three indexes of value orientation, the reliability of these indexes might be rather low. In order to improve the reliability we tried to find in the questionnaire other attitudinal items which would be highly correlated with the value items and would predict choice of the same careers as the value items making up a particular index.

This effort was not very successful. Although we were able to find a number of items in the first wave questionnaire which met the criteria, most of these items were not repeated on the second wave. The mose useful items proved to be a checklist of self-descriptive adjectives which was repeated on both waves one and two. From this checklist two adjectives met the criteria, "intellectual," and "ambitious."

The association of the adjective, "intellectual" with the value, "ideas" is +.59 and with the value, "original" is +.44. These three items comprise the Intellectualism Index. A respondent is classified as high on intellectualism if he checked at least two of the three items.

The association of "ambitious" with the value, "leadership," is +.32 and with the value "money," is +.21. These three items comprise the Enterprise

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[1]Davis, Undergraduate Career Decisions.

[2]Rosenberg, op. cit.

Index. A respondent is classified as high on enterprise if he checked at least two of the three items.

No adjectives were found which were highly correlated with "people orientation." The People Orientation Index is thus composed of only the two values, "helpful" and "people." A respondent is classified as high on people orientation only if he checked both values.

When the three indexes are all dichotomized into high and low groups the association between enterprise and intellectualism is $Q = +.15$, between enterprise and people orientation is $Q = +.15$, and between intellectualism and people orientation is $Q = +.10$.[1] On the basis of these small associations we may say that the three value dimensions are relatively independent of one another.

Although the use of two or three items generally increases the reliability of an index over what it would be if only one item were use, it does not necessarily increase the predictive validity. Because of our concern with obtaining good predictive validity, i.e., high associations between value measures and career choices, two empirical checks on predictive validity were made in the course of constructing the value indexes. The first has been mentioned before. It involved selecting only those items which differentiated among careers for use in the value indexes. The second empirical check was that the individual items entering the value indexes must contribute both separately and in combination with the other items to the prediction of particular career choices, i.e., the association of the item with choice of career must not be removed or reversed in the presence of other items.

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[1]These computations were performed on the random sub-sample with N = 1,712.

For example, the adjective, "intellectual" and the values, "original" and "ideas" are each related to choice of physical sciences. It should be the case that "intellectual" still has a positive partial association with physical sciences even when the two value items are used as controls. Similarly each value item should also have a positive partial association with physical sciences in combination with the other two items entering this index.

These checks were performed for each index by simultaneously cross-tabulating the items entering the index by the career choice categories using the random sub-sample with N = 1,712. In no case was the predictive contribution of an individual value item or adjective completely removed or reversed in the presence of the other items in the same index.

In summary, the criteria used in the construction of the value indexes were as follows:

1. The value items must be relevant to career choice, i.e., must differentiate among careers.

2. The separate items entering an index must be associated with one another.

3. Each item entering the index must be associated with the same careers as are the other items entering the index.

4. The associations between value items and careers must not be removed or reversed in the presence of the other items entering the index.

A definition of a value pattern or value configuration can now be specified. When each of the three value indexes is dichotomized into high and low groups there are eight (2 x 2 x 2 = 8) logically possible combinations of positions on the three indexes. A respondent can be high on all three indexes, high on people orientation and enterprise but not intellectualism, high on people orientation and intellectualism but not enterprise, and so forth. Each of these combinations is considered to be a value configuration or value pattern.

Consistency between Values and Career Choices

What value patterns are consistent with a given career? Conversely, what career choices are consistent with a given pattern of values? We have taken an empirical approach to the definition of consistency. Specifically we shall define as consistent with a given career those value patterns which are statistically associated with that career. This amounts to saying that a value pattern which predicts choice of a given career is consistent with that career. The other side of this same coin is that a career which predicts the holding of a particular pattern of values is consistent with those values.

Table 9 illustrates the computation of the association between career choice for medicine and the value pattern defined by a "high" classification on all three of the indexes. Of the total of 23,479 weighted respondents who answered both the career choice and value questions, 1,077 are planning careers in medicine and 1,648 are classified as high on all three value indexes. When career choices are cross-tabulated by value patterns we find that 119 respondents both chose medical careers and at the same time are classified as high on all three value indexes. The remaining three cell entries of the 4-fold table shown in Table 9 can now be completed by subtraction from the margins. Thus 958 respondents (1,077 - 119 = 958) chose medical careers but were not classified high on all three indexes, 1,529 respondents (1,648 - 119 = 1,529) did not choose medicine but were classified as high on all three indexes, and

20,873 respondents (23,479 - 119 - 958 - 1,529 = 20,873) neither chose medicine nor were they classified high on all three indexes.

TABLE 9

MEDICINE BY HIGH ON ALL THREE VALUE INDICES

Career	Value Pattern		Total
	Yes	No	
Yes.	119	958	1,077
No	1,529	20,873	22,402
Total . . .	1,648	21,831	23,479
	$Q = +.26$		

The coefficient of association, Q, for Table 9 is $Q = +.26$ indicating a modest association between medicine and the value pattern indicated by a classification as high on all three indexes. This pattern and career choice for medicine are, therefore, considered consistent with one another.

Since there are twenty careers[1] and eight value patterns, 160 (8 x 20 = 160) 4-fold tables similar to Table 9 were prepared. The resulting Q coefficients are presented in Table 10. Those value patterns which are considered consistent with a given career are indicated by an asterisk. The criterion of consistency was arbitrarily chosen as $Q \geq +.20$ indicative of at least a moderate degree of association.

[1]The twenty-first career choice category is "not elsewhere classified" which is a very heterogeneous residual category. For this reason value and career change data are not presented for this group. It is however included in certain tables as a part of the group which is <u>not</u> in a particular career at a particular time.

TABLE 10

ASSOCIATIONS (Q) BETWEEN VALUE PATTERNS
AND CAREERS AT COLLEGE GRADUATION

Value Patterns and Careers	Association							
People orientation.	High	High	High	High	Low	Low	Low	Low
Enterprise.	High	High	Low	Low	High	High	Low	Low
Intellectualism . .	High	Low	High	Low	High	Low	High	Low
Medicine.	+.26*	+.26*	+.27*	+.55*	-.43	-.61	-.13	-.21
Physical education.	+.04	+.28*	-.36	+.44*	-.70	-.43	-.85	+.30*
Educational administration. .	+.15	+.52*	+.10	+.52*	-.75	-.50	-.48	+.17
Dentistry	-.36	+.48*	-.44	+.38*	-.50	-.26	-.29	+.03
Law	+.39*	+.32*	-.11	-.04	-.03	+.16	-.47	-.28
Military.	-.13	+.37*	-.88	-.35	+.16	+.37*	-.79	-.11
Business.	-.11	+.18	-.66	-.33	-.13	+.55*	-.63	+.01
Agriculture	-.82	-.26	-.47	-.26	-.13	+.08	-.27	+.45*
Engineering	-.55	-.59	-.73	-.74	+.45*	+.13	+.21*	+.17
Journalism.	+.26*	-.59	-.02	-.45	+.42*	-.30	+.32*	-.11
Chemistry	-.68	-.67	-.89	-.46	+.46*	-.10	+.48*	+.09
Physical science. .	-.56	-.67	-.42	-.59	+.36*	-.25	+.58*	.00
Biological science.	-.57	-.62	-.16	-.34	+.02	-.36	+.47*	+.26*
Humanities.	+.20*	-.76	+.60*	-.50	+.05	-.76	+.64*	-.30
History	+.34*	-.26	+.55*	-.04	-.56	-.86	+.51*	-.15
Social science. . .	+.41*	-.25	+.53*	-.05	+.05	-.65	+.41*	-.35
Vocational education	+.08	+.12	+.31*	-.03	-.23	-.30	-.50	+.27*
Religion.	+.29*	+.34*	+.60*	+.60*	-.90	-.93	-.55	-.21
Teaching.	+.15	-.01	+.42*	+.46*	-.61	-.24	-.16	+.09
Social work	+.28*	+.27*	+.49*	+.63*	-.89	-.74	-.83	-.16

*Indicates that the career and value pattern in this cell are considered "consistent." The criterion is $Q \geq +.20$.

One may read Table 10 either vertically or horizontally. We shall be mainly interested in which value patterns are consistent with a given career, but it is also possible to determine which careers are consistent with a given pattern of values. The first thing we shall seek to determine from Table 10 is whether career choices can be predicted better using combinations or patterns of values than they could by using the value indexes separately. In other words we should like to know whether the concept of a pattern of occupational values as distinct from the simpler concept of an occupational value is a useful one. The answer is that it is indeed useful.

Considering business for example, if the value indexes were used separately the best predictor of business would be a high score on the Enterprise Index. However, among those with a high score on the Enterprise Index, it is only those who are also low on both people orientation and intellectualism who are particularly likely to choose business. Thus the value pattern of high enterprise, low people orientation, and low intellectualism predicts choice of business considerably better than the Enterprise Index used by itself.

As another example, high enterprise is also the single best value predictor of choice for law. People orientation, however, is also a predictor of law and it is in fact the combination of a high score on enterprise with a high score on people orientation which really predicts law. A high score on either of these indexes in the absence of a high score on the other affords prediction hardly better than chance. Again it is knowledge of a particular configuration of values which enables us to best predict the career choice.

Reading the table the other way let us consider the People Orientation Index. Used by itself this index is consistent with choice for several different careers including social work, humanities, law, and dentistry. These careers however can be differentiated from one another by the use of combinations of values. Social work is best predicted by high people orientation combined with low intellectualism and low enterprise, humanities is best predicted by high people orientation combined with high intellectualism and low enterprise, dentistry is best predicted by high people orientation combined with low intellectualism and high enterprise, and law is best predicted by the combination of high scores on all three indexes.

A useful device for the presentation of findings on the relation between career choices and value patterns is to view the three value orientations as defining a three dimensional "space" and to characterize each career by its location in that space. For each career the greatest concentration of its members will be located at some point in the space (the most consistent value pattern), a relatively high concentration of members in regions "close" to that point (other consistent value patterns) and a low concentration in distant (inconsistent) regions.

James A. Davis[1] has devised a visual aid for representing such a three dimensional "attribute space" in two dimensions. It is a chart in the form of a clock or wheel. Figure 12 illustrates this chart. The smaller circle in the center is divided into two regions of the attribute space--in our case the value space. These are the regions representing the combination of high scores on all three value orientations and the region

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[1]Davis, Undergraduate Career Decisions.

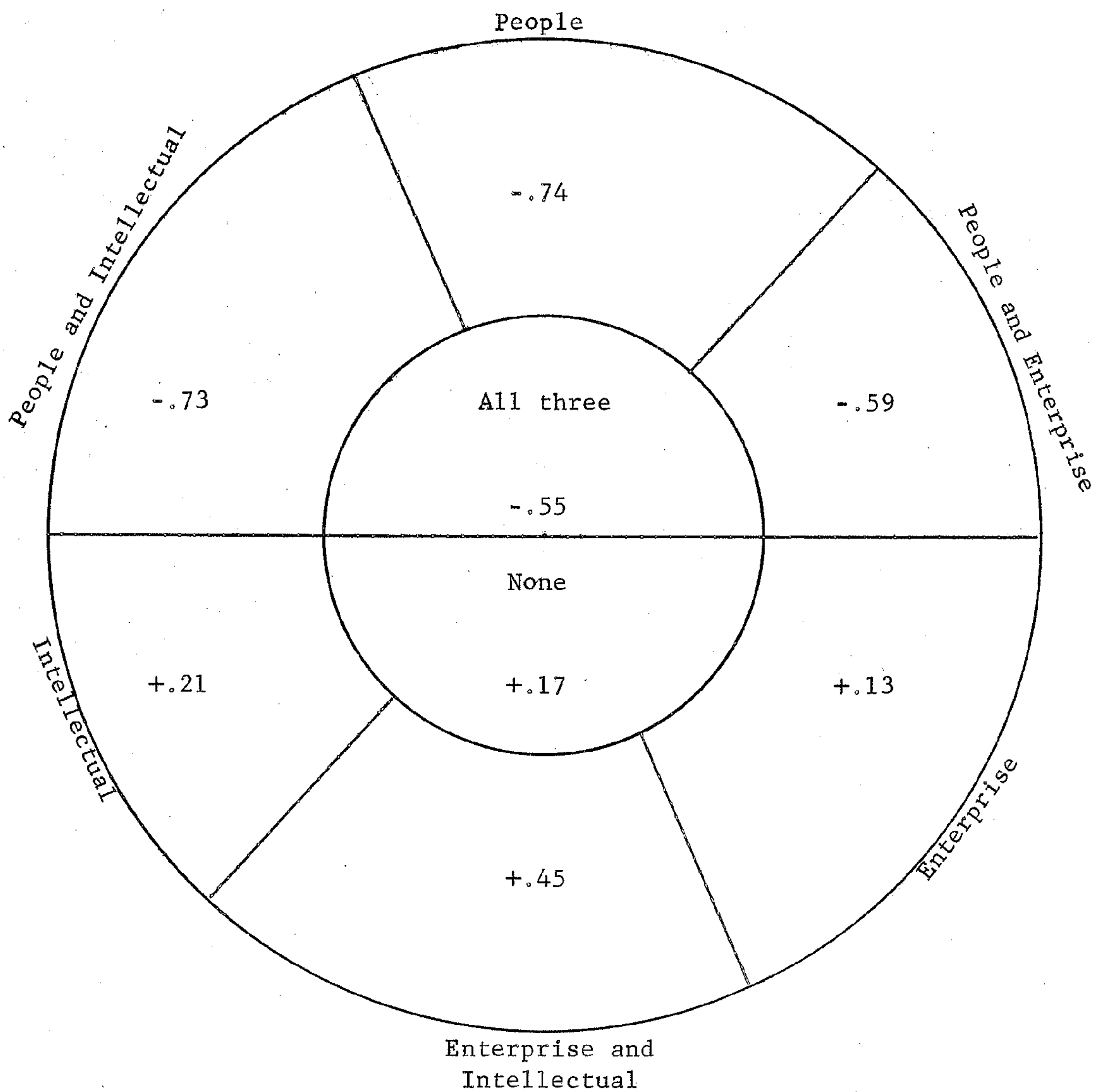

Fig. 12.--Associations (Q) between Value Patterns and Engineering at College Graduation

representing the combination of low scores on all three value orientations. Around the outer circle are sectors representing the remaining six regions in the value space. At the top is the region representing people orientation by itself, i.e., the combination of a high score on people orientation with low scores on enterprise and intellectualism. Moving clockwise the next sector represents people orientation in combination with enterprise, next--enterprise alone, next--enterprise combined with intellectualism, next--intellectualism alone, and finally intellectualism combined with people orientation completes the circle.

The coefficients of association between the career choice for engineering and each of the eight value patterns have been entered upon this clock for illustrative purposes. The clock shows that the pattern most consistent with engineering is the combination of enterprise with intellectualism. Also consistent is the adjacent pattern, intellectualism alone. The non-adjacent patterns involving people orientation are very inconsistent with engineering. The most inconsistent pattern is people orientation alone ($Q = -.74$) which is located farthest from the combination of enterprise with intellectualism. In terms of the value space, engineering is best located in the region where enterprise and intellectualism combine. A number of engineers are found in adjacent regions of intellectualism alone or enterprise alone. Almost no engineers are found in the most distant region of the space, namely people orientation alone.

In the case of engineering the coefficients become more negative in a regular progression without reversals as one moves away from the most consistent region. In other words, the further one moves in the value space the less consistent the values are with the career of engineering. This suggests that engineering can validly be assigned to a single location in the space, that location being where the values are most consistent.

This is generally true for careers other than engineering as well. Considering the six sectors of the outer clock, the average for the twenty careers of the coefficients of association for the most consistent sector is +.47. For the two sectors adjacent to the most consistent sector the average association is +.06. For the next most distant two sectors the average association across the twenty careers is -.39. Finally, for the most distant sector, on the opposite side of the clock, the average association is -.79. This indicates that on the average, the degree of consistency declines in a regular fashion as one moves to more distant regions in the value space.

Regarding the most distant region in the space, it should correspond to the least consistent value pattern which it does for fourteen of the twenty careers. The six exceptions are vocational education, physical education, medicine, dentistry, journalism, communications, and chemistry. For all but one (vocational education) of these exceptional cases the least consistent sector is adjacent to the most distant region in the space.

Regarding the progression of coefficients as one moves from the most to the least consistent regions, for sixteen of the twenty careers there are no reversals in the regular progression from large positive to large negative associations. The exceptions are vocational education, dentistry, chemistry, and religion. For all but one (vocational education again) of these exceptional cases the reversals occur in the inconsistent region of the space, i.e., among coefficients of negative sign.

In no case would we be able to argue on the basis of these minor irregularities that a career has two or more nonadjacent locations in the value space.

In general then, careers have a single location in the three dimensional value space. As one moves away from this location the values tend to become less consistent and to be least consistent in the region most distant in the space.

One career, vocational education, fails to conform to these generalizations. Figure 13 gives the coefficients for vocational education so that the reader may see for himself the extent of our failure to find a sensible pattern of values for this career.

How large a region in the value space shall we term "consistent"? It will be recalled that we chose $Q \geq +.20$ as indicating at least a moderate positive association between a value pattern and a career. For the career of engineering this definition gives two "consistent" sectors in the value space. On the average there are 2.5 value patterns consistent with each career by this definition. For the careers of medicine, religion, and social work[1] there are four consistent value patterns by this definition. For the careers of business and agriculture there is only one consistent value pattern in each case. For business it is enterprise alone and for agriculture it is the combination of low scores on all three value indexes.

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[1]In each of these three cases the four consistent patterns are the four patterns which involve people orientation. Thus medicine, religion, and social work are consistent with any people oriented pattern of values.

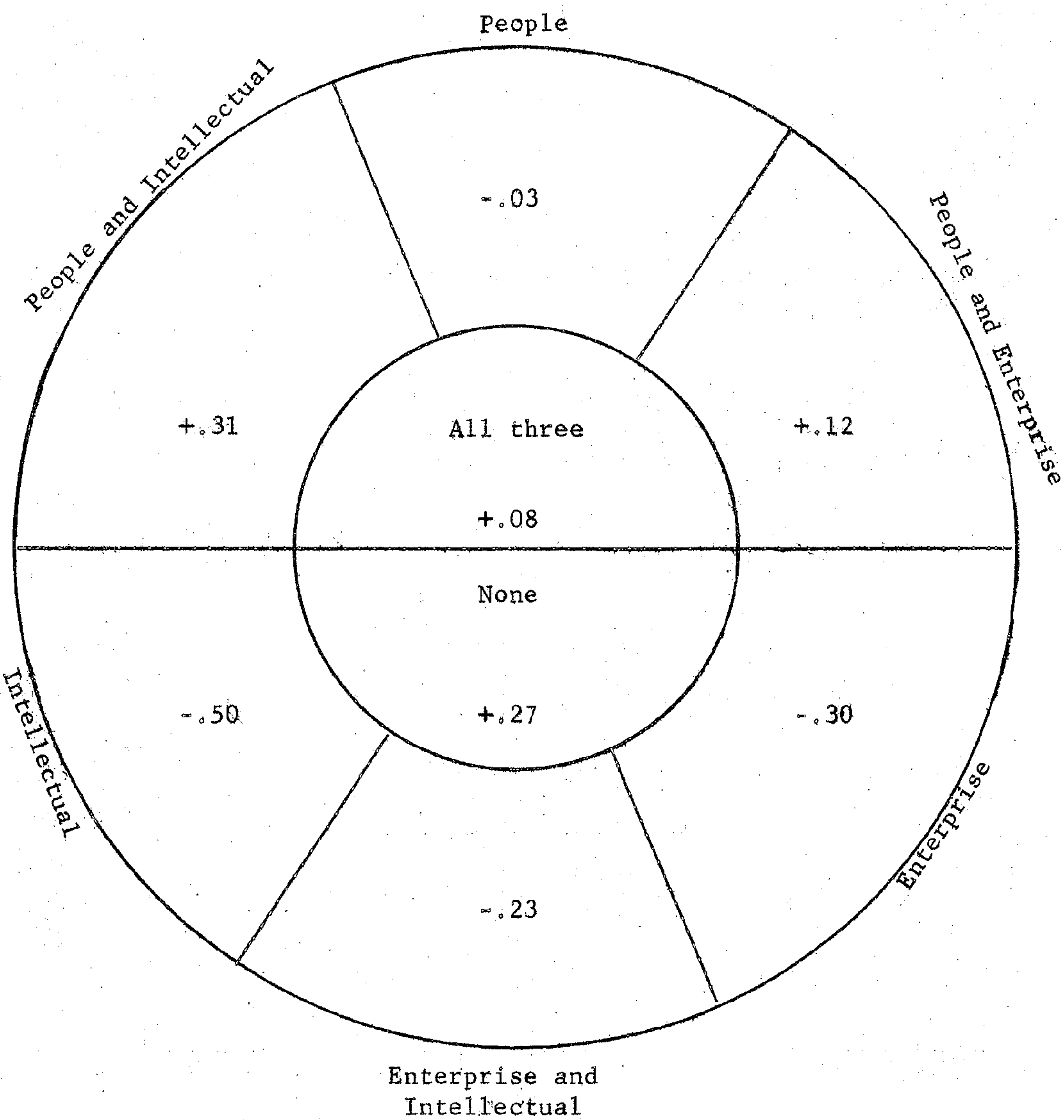

Fig. 13.--Associations (Q) between Value Patterns and Vocational Education at College Graduation

We have seen, however, that consistency can be viewed in terms of a more or less continuous movement through a value space and need not be dichotomized into consistent and inconsistent groups. If it is dichotomized there are other cutting points different from the one that we have used which might be fully as reasonable. Some might prefer a more inclusive definition of consistency, while others might prefer a less inclusive definition. In any case the cutting point will be arbitrary.

Figure 14 shows the best single location of each career in the value space and is intended as a capsule summary of the data in Table 10. Beginning at 12 o'clock in the purely people oriented sector we have medicine. Moving clockwise in the direction of increasing enterprise we have physical education and educational administration. In the region where people orientation and enterprise combine are dentistry and law. The sector of enterprise alone contains prospective businessmen and military men. Moving into the region where enterprise combines with intellectualism and at the greatest distance from people orientation we find engineering and journalism. Moving away from enterprise to intellectualism alone we find the natural sciences and humanities. Close to humanities but more people oriented are history and the social sciences. Also located in the region where people orientation and intellectualism combine is vocational education. Finally, becoming less intellectual and returning to the purely people oriented sector we have religion, teaching, and social work.

Agriculture is the only career that is best located in the center rather than on the outer circle. It is best located in the sector which combines low scores on all three value indexes. If one wished to locate

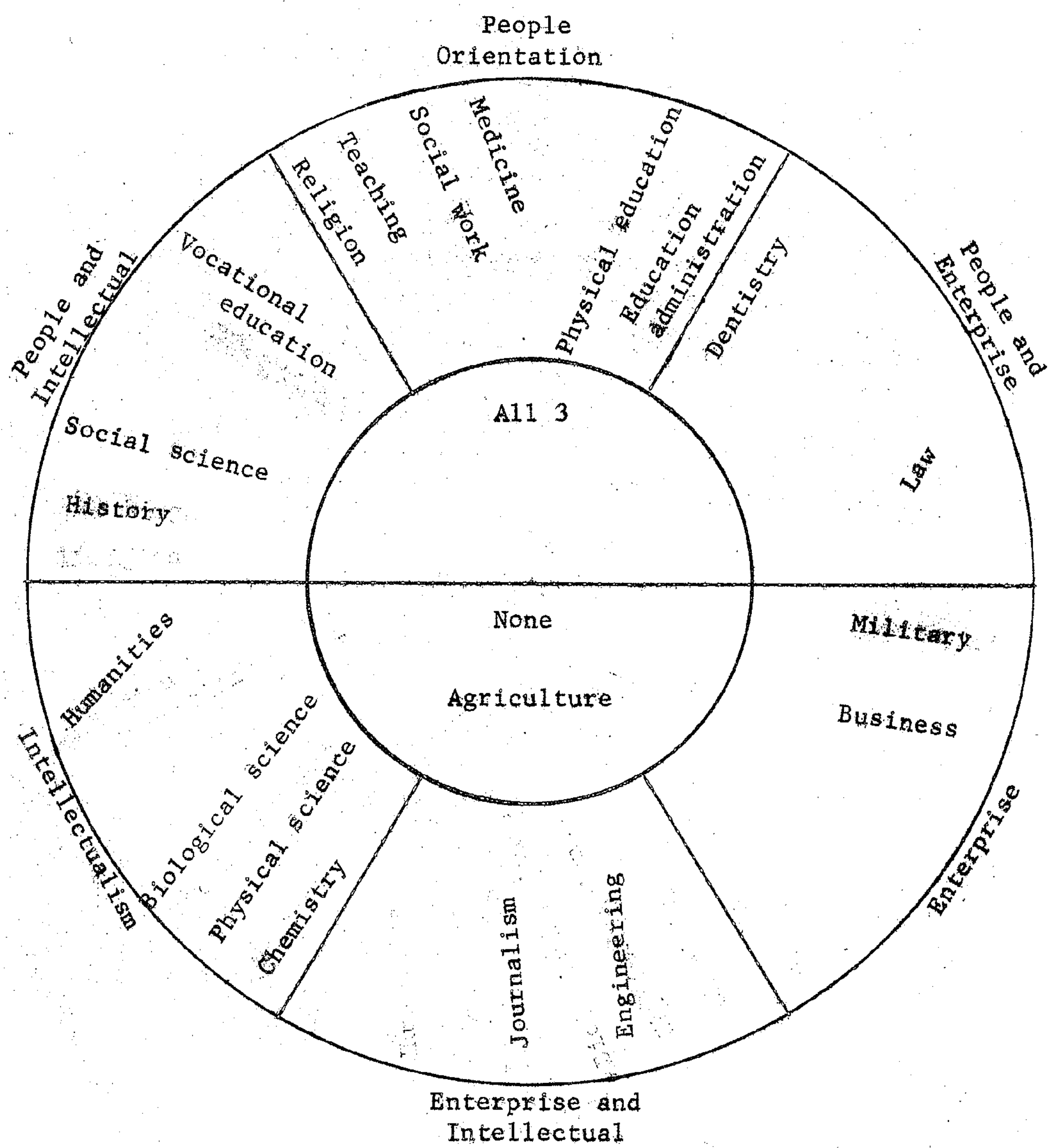

Fig. 14.--Location of Careers in the Value Space at College Graduation

agriculture on the outer clock it would best be placed at 4 o'clock in the enterprise sector. But the coefficient of association even for this sector is only +.08.

What is the usefulness of Figure 14 and the discussion which we have devoted to it? The concept of a value space and its illustration in Figure 14 should be viewed as a device for understanding the qualitative nature of the value differences among careers in terms of our three indexes of value orientation. Figure 14 does not tell us how great the differences among careers are, nor does it tell us whether there are differences among careers in values or other characteristics which are not measured by these three indexes. Business and law, for example, differ in that law tends to be more people oriented than business. How great is this difference? Does it have any practical importance? Do law and business differ in other ways not indicated by these value indexes?

For another example, the fact that medicine and social work have practically identical locations in this value space is more an indication that we have failed to tap an important value dimension than it is a finding of an identity in values between the members of these two careers. In this case what we have failed to measure is an "interest in science" dimension which has been found in various past studies of vocational interests. It is one of the trails of secondary analysis that we knew the importance of this dimension, but did not have any measures of it available on the second or third wave questionnaires and thus had to omit it from the analysis.

Future social workers and physicians, in fact, differ in "interest in science" with the social workers scoring low and the physicians scoring high. Similarly humanities and natural sciences can be distinguished on this dimension as can journalism and engineering. It is clear that in future studies of the occupational values of college students items should be added to measure interest in science.

Apart from these limitations, the concept of a value space is quite useful for demonstrating the patterns in the data of Table 10. For example, engineering is located in the value space about half way between business and the natural sciences suggesting that engineering combines the values of these very different career fields. It may be that some engineers are a "business type" while others are a "scientific type" or it may be that most engineers have both business and scientific inclinations at the same time.

Another interesting illustration is history. It is located in the value space between the humanities and the social sciences. It thus reflects, in the value orientations of its members, the substantive conflict within the field concerning whether the subject matter of history belongs in humanities or in social sciences.

The social sciences and social work have different locations in the value space. The difference is that the social scientists profess more intellectualism. Similarly, the social sciences and the natural sciences have different locations. The difference here is that the social sciences are more people oriented.

Although many other interesting facts can be noted in Figure 14 we shall leave it at this point with the observation that this approach has proved very useful in characterizing differences in values among careers.

Prediction of Career Choice

When the different "consistent" value patterns are combined for a given career how good a prediction do we get of choice for that career? In other words, how good is the prediction when the value space is dichotomized into a consistent and inconsistent region?

The average coefficient of association between a career and its consistent values is $Q = +.548$ indicating a substantial degree of association. These coefficients range from +.37 for vocational education to +.75 for religion. The standard deviation is .112.

This indicates that although we have done a fairly good job of predicting choice for all the careers, there is enough variation in predictability that we shall have to be alert to this source of variation in subsequent analysis where careers are the unit of analysis.

Regression Effects

It will be recalled that in constructing the value indexes and defining consistent values for each career we have followed procedures which were in part designed to obtain high associations. Specifically, we did the following:

1. Selected value items which showed a high degree of differentiation among careers.

2. Constructed value indexes on the basis of the size of associations among items and between items and careers.

3. Defined as consistent those value patterns which showed the highest associations with each career.

Since research data are subject to measurement and sampling error, it is very likely that when a large number of coefficients of association are examined, some of them are too high (and some too low) due to sampling and measurement error. When procedures are used which select high associations and group them together for one or another reason, error makes it probable that this particular set of selected associations will, on the average, be lower in a replication study. This does not mean that if a new set of associations were selected on the replication it would not, on the average, be as high or higher. It means that the same identical set will tend to be lower. This is because those associations which were originally too high due to error will tend to regress to their true values.

Usually the researcher is in no position to test the seriousness of such effects upon his findings. In panel analysis, however, one can assess the seriousness of one kind of error. Since our value and career measures have been repeated on separate administrations of the questionnaire we can make some reasonable inferences about regression effects due to measurement error. Since, however, the sample consists of the same respondents at the two times we are not able to assess regression effects due to sampling error.

We shall be concerned with changes in the relationship of careers and values from the first administration of the questionnaire to the second and we shall ask two specific questions:

1. To what extent do careers have the same location in the value space one year after college that they have at college graduation?

2. Is there a substantial reduction in our ability to predict career choice from the selected "consistent values"?

For the first of these two questions, it is possible that the changes which occur could be real movements of a career in the value space rather than regression effects. However, past investigations provide no theoretical or empirical reason to believe that one set of values would be consistent with a career at college graduation and a different set one year later, the careers involved in the minor shifts which do occur are all relatively small careers, and the shifts show no systematic patterns. All this suggests that an interpretation in terms of regression effects is more tenable.

Changes in the location of careers in the value space are minor. Only five of the twenty careers move by as much as one hour on the clock chart. No career moves by more than one sector. Figure 15 diagrams the movements of these five careers. An arrow for each career originates at the initial location and points to the final location. The name of the career involved is placed at its final location. The specific changes are as follows:

1. Vocational education becomes less intellectual.
2. Military service becomes more people oriented.
3. Biological sciences become slightly higher in enterprise.
4. Journalism becomes lower in enterprise.
5. Religion becomes more intellectual.

The changes in degree of association between particular careers and their consistent values are relatively more serious. The average coefficient of association between a career and its consistent values decreases from +.548 to +.510, while the standard deviation increases from .112 to .170. This change in the average degree of association is not very large but the change in the standard deviation of the association is considerable. There

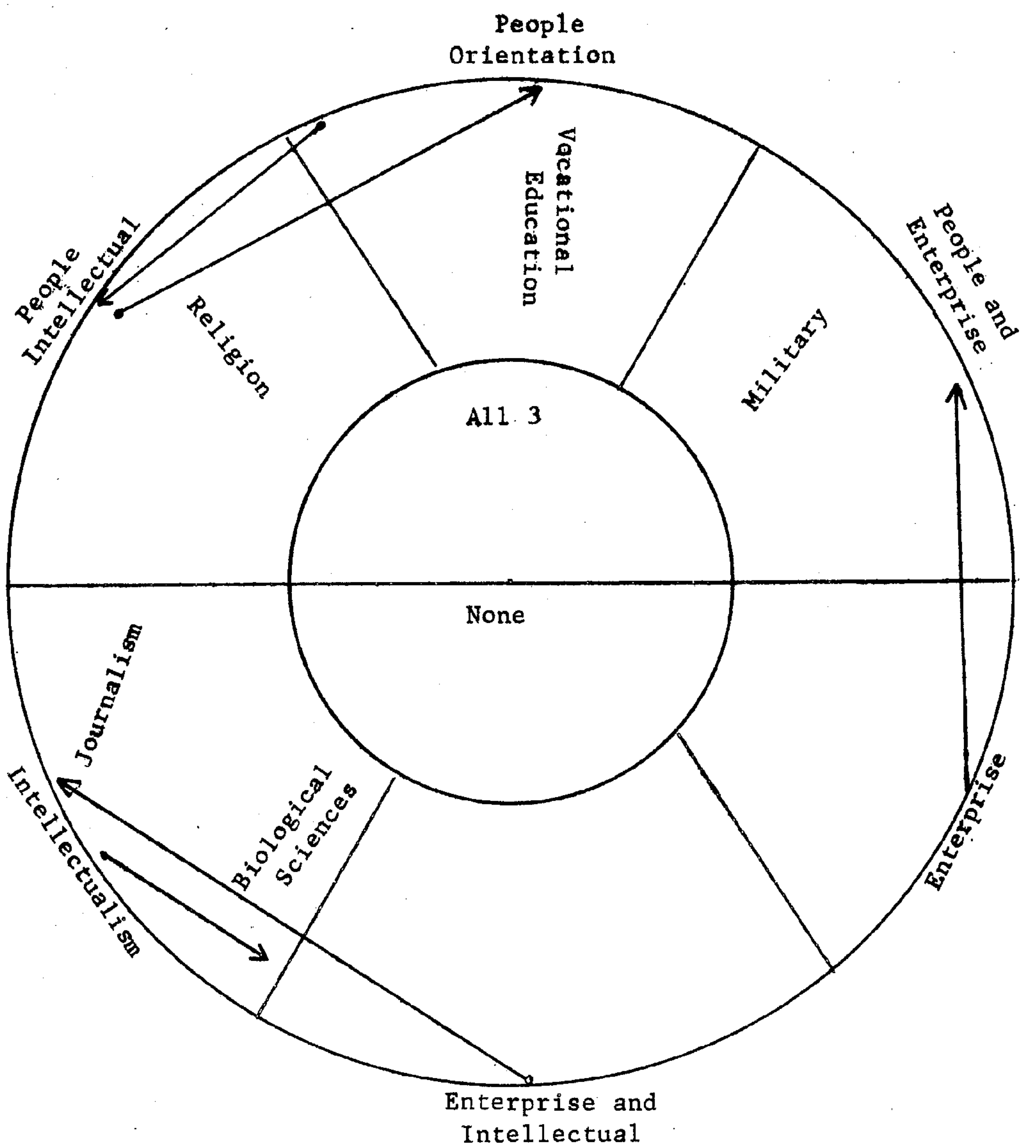

Fig. 15.--Changes of Location of Careers in the Value Space from College Graduation to One Year Later

is considerably more variation around the average at the second time than there is at the first.

This means that, on the average, we are only slightly less successful at predicting career choice on the second wave but our success is more uneven. It is very good for some careers and rather poor for others.

The most serious failure is our former nemesis, vocational education, which has an association of only +.06 with its "consistent values" at the second time. This is a decline of .31 from the first time association of +.37. In the case of vocational education the "consistent values" are worthless for predicting career choice.

Three other careers have associations below +.40 at the second time with their consistent values. These are educational administration (+.36), social sciences (+.37), and biological sciences (+.37). The decreases in degree of association for these careers between the first and second times are .31, .28, and .14 respectively.

Overall these findings suggest that regression effects do not disturb our findings greatly. This analysis does suggest however, that we shall have to pay close attention to variations in the degree of predictability of the careers in those subsequent analyses where the career is the unit of analysis.

Summary

In this study career choice is measured using a detailed list of approximately 100 careers. This detailed list has been collapsed into twenty-one career choice categories by combining related titles.

The measurement of values is more complex. From a list of ten occupational values and from a self-descriptive adjective checklist, six values and two adjectives were selected which were found to be related to the choice of particular careers. From the six values and two adjectives three relatively independent dimensions of value orientation, people orientation, enterprise, and intellectualism, were constructed.

The criteria used in constructing these indexes demanded that the separate items entering an index be associated with one another, that each item entering the index be associated with the same careers as the other items entering the index, and that these associations must obtain both separately and in combination with the other items entering the index.

A cross-tabulation of the three value indexes was interpreted as a three dimensional "value space." The association between each career and each region of the value space was computed and a consistent location in the value space was thus determined for each career.

The average association at college graduation between a career and its "consistent" values was +.548 with a standard deviation of .112. When these data were recomputed for the same respondents one year after college graduation the changes in location of careers in the value space were very minor. However, the average association between a career and its consistent values declined slightly to +.510 while the standard deviation increased to .170. These changes were interpreted as "regression effects" arising from the analytic procedures rather than changes with any substantive meaning.

CHAPTER IV

THE RELATIVE EFFECTS OF CAREERS AND VALUES

This chapter concerns the central problem of the report. Does career choice determine values, or do values determine career choice, or are both these processes occurring?

The basic finding that there are strong associations between values and career choices implies: (1) There are variations across careers in the proportions endorsing various values. (2) There are variations across value patterns in the proportions entering various careers. These two implications are not separate findings but rather they are alternative modes of expressing the same finding--the finding of substantial associations.

There is not, however, a one-to-one relation between a particular career and a particular pattern of values. For example, a people-oriented respondent can find a number of different careers which are consistent with his values including medicine, teaching, or social work. Conversely, more than one value pattern may be consistent with a given career. Law, for example, accommodates either an intellectual or a nonintellectual orientation about equally well.

Since there is not a one-to-one relation between career choices and value patterns, we are faced with a decision about whether data should be aggregated by career or by value pattern. If we are to speak of the values consistent with a given career, we must usually speak of more than one value pattern. On the other hand, if we are to speak of the careers consistent with a particular set of values, we must usually speak of more than one career. Thus, there are two different analytic strategies which might be used.

Rosenberg's[1] strategy was to define an aggregation of different careers as consistent with a particular value. He speaks, for example, of "people-oriented" occupations or of "self-expressive" occupations. We have chosen the alternative strategy of defining an aggregation of value patterns as consistent with a particular career. This enables us to speak of "business values" or of "education values." While Rosenberg's approach permits examination of variations by values in the nature of the relationship between career choices and values, our approach permits examination of variations by career in the nature of this relationship. We shall see whether values play a greater role in career change for some careers than they do for others.

Matrix Adaptation of Causal Models

Under the assumptions of the causal models developed in Chapter II, comparison of cross-lagged partial correlations will lead to correct causal inferences. Given a causal relation between two correlated variables, comparison of cross-lagged partial correlations enables one to distinguish cause and effect.

The models of Chapter II, however, were developed in terms of the correlation coefficient, r, for use when variables are continuous. The career choice and value measures are not continuous variables but rather are

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[1]Rosenberg, op. cit.

treated as dichotomous attributes. A person either chooses or does not choose a particular career at a particular time and his values are classified as either consistent or not consistent with that career at that time. We therefore need a means by which the models of Chapter II can be adapted for use with dichotomous attributes. Some simple matrix algebra applied to matrices of conditional probabilities will answer to this need.

When measures are taken at two points in time, a respondent can be classified, with respect to each career and its consistent values, in terms of four dichotomous attributes, career at Time 1, career at Time 2, values at Time 1, and values at Time 2. Among these four attributes are six logically possible zero-order associations:

1. The cross-sectional association between career and values at Time 1.

2. The cross-sectional association between career and values at Time 2.

3. The association between career at Time 1 and career at Time 2 which indicates stability or turnover in the career.

4. The association between values at Time 1 and values at Time 2 which indicates stability or turnover in values.

5. The cross-lagged association between career at Time 1 and values at Time 2.

6. The cross-lagged association between values at Time 1 and career at Time 2.

It is possible to represent each of the six zero-order associations by a matrix of conditional probabilities (P). Such a matrix is nothing more than a simple table of percentages each row of which adds to a total of 1.00. Figure 16 shows schematically the six possible zero-order associations for a particular career and its consistent values at two times. Each relation is identified as P with subscripts indicating career (C) or values (V) and time (1 or 2). $P_{C_1V_1}$ represents the relations between career and values at Time 1. $P_{C_2V_2}$ is the same relation at Time 2. $P_{C_1V_2}$ and $P_{C_2V_1}$ are the cross-lagged relations and $P_{C_2C_1}$ and $P_{V_1V_2}$ are the turnover tables or stability relations.

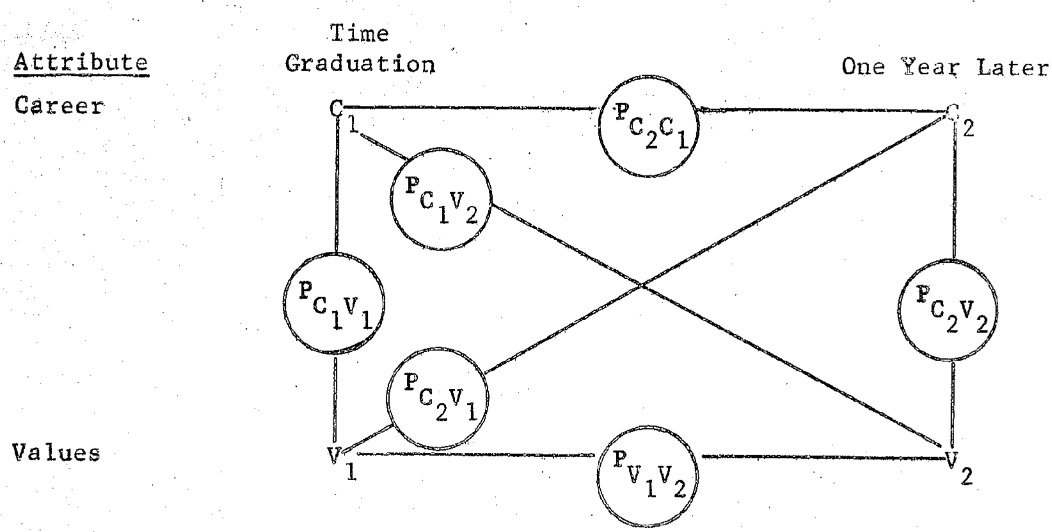


Fig. 16.--Conditional Probability Matrices (P)

Table 11 is included as an example. It shows the conditional probability matrices (P) for the career of engineering. As a measure of degree of association between the two attributes in each matrix, a difference in proportions (d) has been computed and entered below the matrix.

The reader will note that in the $P_{C_2C_1}$ matrix, we report the conditional probabilities that a respondent will (or will not) be in engineering

TABLE 11

CONDITIONAL PROBABILITY MATRICES (P)
FOR ENGINEERING

$P_{C_1V_1}$

	V_1	$\overline{V}_1$	
C_1	.367	.633	1.000
$\overline{C}_1$	.204	.796	1.000

$d_{C_1V_1} = .163$

$P_{C_2V_2}$

	V_2	$\overline{V}_2$	
C_2	.430	.570	1.000
$\overline{C}_2$	.213	.787	1.000

$d_{C_2V_2} = .217$

$P_{C_1V_2}$

	V_2	$\overline{V}_2$	
C_1	.428	.572	1.000
$\overline{C}_1$	.213	.787	1.000

$d_{C_1V_2} = .215$

$P_{C_2V_1}$

	V_1	$\overline{V}_1$	
C_2	.353	.647	1.000
$\overline{C}_2$	.206	.794	1.000

$d_{C_2V_1} = .147$

$P_{C_2C_1}$

	C_1	$\overline{C}_1$	
C_2	.844	.156	1.000
$\overline{C}_2$	.023	.977	1.000

$d_{C_2C_1} = .821$

$P_{V_1V_2}$

	V_2	$\overline{V}_2$	
V_1	.539	.461	1.000
$\overline{V}_1$	.158	.842	1.000

$d_{V_1V_2} = .381$

at Time 1 given that he is (or is not) in engineering at Time 2. This is a departure from the conventional presentation in which one computes the conditional probabilities of the respondent's state at <u>Time 2</u> given his state at <u>Time 1</u>. The conventional time order arrangement is also reversed in $P_{C_2V_1}$ matrix. $P_{C_2V_1}$ gives the conditional probabilities that a person will (or will not) have engineering values at Time 1 given that he is (or is not) in engineering at Time 2. These reversals are based on two considerations. In the first place, we wanted to be able to compare the differences (d) from one matrix to another. Since the average proportions choosing a particular career are considerably smaller than the average proportions endorsing consistent values, differences in matrices which report the proportions in a career are not really comparable with differences in matrices which report the proportions having consistent values. This is because the variance of difference between two proportions which are very small is considerably smaller than the variance of a difference between two proportions in the range, say, from .30 to .70. We therefore, decided to compute for each matrix the proportion having (or not having) the values, rather than in one matrix computing the proportions choosing the career and in another matrix the proportions having the values.

The second consideration has to do with the demands of matrix multiplication. Specifically, if the $P_{C_2C_1}$ matrix is to be postmultiplied by the $P_{C_1V_1}$ matrix, the career choice at Time 1 must be located in the columns of $P_{C_2C_1}$ and in the rows of $P_{C_1V_1}$. The reasons why one would want to perform this particular multiplication will be explained on the following page.

The matrices of Table 11 give the zero-order associations among engineering choices and engineering values at the two times. It is necessary to develop cross-lagged partial associations from these. Let us consider, as an example, the association between Time 1 career and Time 2 values. This is shown in the $P_{C_1V_2}$ matrix. In order to find the cross-lagged partial, we must control for or hold constant Time 1 values. The problem amounts to asking what the association is between career at 1 and values at 2 net of the association between career at 1 and values at 1 and the association between values at 1 and values at 2.

To obtain a solution, we begin by assuming that the cross-lagged partial is zero, i.e., that the association between engineering at 1 and engineering values at 2 is the result of the association between career at 1 and values at 1 and the association between values at 1 and values at 2. From this assumption, it follows that the probability that a person who is in this career at Time 1 will have these values at Time 2 can be found as the product of two independent probabilities, namely the probability that a person in this career has (or does not have) the values at 1 times the independent probability that a person who has (or does not have) the values at 1 also has the values at 2.

From the $P_{C_1V_1}$ matrix, the probability that a respondent who chooses engineering at 1 will have engineering values at 1 is .367, and from the $P_{V_1V_2}$ matrix the probability that a respondent having engineering values at 1 will also have them at 2 is .532. Under the assumption of zero partial association, these two probabilities are independent and their product,

(.367) (.539) = .198, is the conditional probability that a respondent in engineering at 1 will have engineering values at 2 given that he had engineering values at 1.

Similarly, the conditional probability that a respondent in engineering at 1 will have engineering values at 2 given that he did <u>not</u> have such values at 1 (.633) (.158) = .100, is found as the product of the probability that a respondent in engineering at 1 does not have the values at 1 (.633) times the probability that a respondent who does not have the values at 1 will have these values at 2 (.158).

The total probability that a respondent who chose engineering at Time 1 will have engineering values at Time 2 is then found as the sum of the two mutually exclusive conditional probabilities calculated above.

$$.198 + .100 = .298$$

The result, .298, may be interpreted as an expected value for the upper left hand cell of the $P_{C_1V_2}$ matrix on the assumption that the association between career at 1 and values at 2 is due entirely to the common dependence of these two attributes on values at 1, i.e., the partial association is zero.

Translating this argument into the language of matrix algebra, the expected value for the upper left hand cell of $P_{C_1V_2}$ is the product of the first row vector in $P_{C_1V_1}$ multiplied by the first column vector in $P_{V_1V_2}$. When this approach is extended to obtain an expected value for each cell, the expected value for the matrix $\hat{P}_{C_1V_2}$ is simply the product of $P_{C_1V_1}$ postmultiplied by $P_{V_1V_2}$:

$$P_{C_1V_1} \times P_{V_1V_2} = \hat{P}_{C_1V_2} \qquad \text{or,}$$

$$\begin{pmatrix} .367 & .633 \\ .204 & .796 \end{pmatrix} \times \begin{pmatrix} .539 & .461 \\ .158 & .842 \end{pmatrix} = \begin{pmatrix} .298 & .702 \\ .236 & .764 \end{pmatrix}$$

If the cross-lagged partial association is zero, the observed $P_{C_1V_2}$ matrix will be equal to the expected $\hat{P}_{C_1V_2}$ computed by the above multiplication. The difference between the observed and the expected matrices gives a measure of the degree of association remaining when values at 1 are controlled.

$$P_{C_1V_2} - \hat{P}_{C_1V_2} = P_{C_1V_2 \cdot V_1} \qquad \text{or,}$$

$$\begin{pmatrix} .428 & .572 \\ .213 & .787 \end{pmatrix} - \begin{pmatrix} .298 & .702 \\ .236 & .764 \end{pmatrix} = \begin{pmatrix} +.130 & -.130 \\ -.023 & +.023 \end{pmatrix}$$

In this case, the difference between the observed and expected matrices is large enough to warrant the conclusion that values at 1 do not account for the association between career at 1 and values at 2 and that there is in fact a positive partial association between them.

This approach is simply one method of determining the partial association between two attributes when a third attribute is held constant. Although our career and value measures each have but two categories, this approach is applicable to attribute data classified into any number of categories. The general procedure involves: (1) Arrange the tables so that the <u>row</u> probabilities add up to 1.00. (2) In performing the matrix multiplication place the categories of the control attribute in the columns of the left hand matrix and in the rows of the right hand matrix. In the two by two case, each matrix has only 1 degree of freedom and this allows a considerable simplification of procedures utilizing the difference in proportions, d, from each matrix. This difference is a convenient measure of the degree of association in the matrix. Returning to Table 11, the d's are:

$$d_{C_1V_1} = +.163$$

$$d_{V_1V_2} = +.381$$

$$d_{C_1V_2} = +.215$$

The expected value for $d_{C_1V_2}$ is simply the product of $d_{C_1V_1}$ and $d_{V_1V_2}$:

$$d_{C_1V_1} \times d_{V_1V_2} = \hat{d}_{C_1V_2} \quad \text{or,}$$

$$.163 \times .381 = .062$$

The identical result is also obtained through the more complicated procedure of performing the matrix multiplication and then taking the difference in proportions in the expected matrix.

The deviation of the observed $d_{C_1V_2}$ from the expected $\hat{d}_{C_1V_2}$ is taken directly:

$$d_{C_1V_2} - \hat{d}_{C_1V_2} = d_{C_1V_2 \cdot V_1} \quad \text{or,}$$

$$.215 - .062 = +.153$$

Again, the identical result is obtained by the more complicated procedure of subtracting the expected matrix from the observed matrix and then taking the difference in proportions in the resulting matrix.

It may be of interest to note that this procedure is equivalent to "demographic standardization." In demographic standardization, the probability or rate of occurrence of an attribute is compared among different populations. Differences between these populations in other characteristics associated with the attribute in question are equalized through standardization. In our case, we are concerned with the probability of holding engineering values at Time 2 among those in engineering at 1 and those not in engineering at 1. These two groups, however, differ in the holding of engineering values at Time 1 which is related to holding these values at Time 2. The differences in values at Time 1 are equalized through standardization.

In standardization, the difference between two probabilities or rates can be broken down into two components. One component is that portion of the difference which is related to differences in "composition" between the two groups--in this case value composition at Time 1. The second component is that portion of the difference which is not due to differences in composition between the two groups. Symbolically:

$$d_{C_1V_2} = \hat{d}_{C_1V_2} + d_{C_1V_2 \cdot V_1} \quad \text{or,}$$

$$.215 = .062 + .153$$

The total zero-order cross-lagged association, .215, is broken down into components. The first component, .062, is that portion of the association which is due to differences in values at Time 1 and the second component, .153 is that portion of the association which is not due to value differences at Time 1. In other words, the second component is that portion of the association which is net of values at 1 or is the partial association. The partial association in turn measures the effect of choice for engineering upon engineering values over the time period between Time 1 and Time 2.

The development of the "value effect" partial, $d_{C_2V_1 . C_1}$, is based on a similar rationale but is computed with the conventional time order reversed. Rather than working from values at 1 to career at 1 to career at 2, we work in reverse from career at 2 to career at 1 to values at 1. In more formal terms, we are concerned with developing an expected value, e.g., the probability that a person who is in engineering at Time 2 had engineering values at Time 1. On the assumption of zero partial association when career at 1 is controlled, this expected value is found as the product of two independent probabilities, namely the probability that a person was (or was not) in the career at 1 times the independent probability that a person who was (or was not) in the career at 1 had the values at 1. The two mutually exclusive conditional probabilities thus computed are summed to give the desired expected value.

Extending this procedure, the expected value for the $P_{C_2V_1}$ matrix is the product of $P_{C_2C_1}$ postmultiplied by $P_{C_1V_1}$. The procedure can be further simplified, as above, by multiplying the d's for each matrix thus obtaining the expected d for $P_{C_2V_1}$.

The Relative Effect of Career and Values for Engineering

Continuing with the example of engineering, Table 12 shows the matrix operations and gives their results for both cross-lagged partial associations; first, $d_{C_1V_2 \cdot V_1}$ which measures the effect of choice for engineering upon engineering values, then in the lower portion of the table, $d_{C_2V_1 \cdot C_1}$, which measures the effect of engineering values upon choice for engineering.

The partial, $d_{C_1V_2 \cdot V_1} = +.153$, which has already been discussed in the previous section, measures the association between engineering at 1 and engineering values at 2, net of any influence of engineering values at 1. The "value effect" partial, $d_{C_2V_1 \cdot C_1} = +.013$, has been developed by a similar rationale and measures the association between holding engineering values at 1 and choosing an engineering career at 2, net of the effect of engineering choice at 1.

Comparison of these partials shows that for engineering, values have virtually no effect on career. Career, by contrast does have an effect on values and thus is the stronger of the two attributes.

Let us examine these findings in terms of the causal models developed in Chapter II. Figures 17 and 18 present alternative causal models for engineering along with the respective degrees of fit for the two associations predicted by each model. In Figure 17, choice for engineering is assumed to cause engineering values while in Figure 18, the values are assumed to cause choice for engineering.

Each model provides two predictions. In Figure 17, the prediction for the cross-lagged association is $\hat{d}_{C_2V_1} = .134$. This is very close to the observed $d_{C_2V_1} = .147$, the discrepancy being:

TABLE 12

DERIVATION OF CROSS-LAGGED PARTIAL ASSOCIATIONS
FOR ENGINEERING

"Career Effect"

$$\overset{P_{C_1V_1}}{\begin{pmatrix} .367 & .633 \\ .204 & .796 \end{pmatrix}} \times \overset{P_{V_1V_2}}{\begin{pmatrix} .539 & .461 \\ .158 & .842 \end{pmatrix}} = \overset{\hat{P}_{C_1V_2}}{\begin{pmatrix} .298 & .702 \\ .236 & .764 \end{pmatrix}}$$

$$d_{C_1V_1} = .163 \qquad d_{V_1V_2} = .381 \qquad \hat{d}_{C_1V_2} = .062$$

$$\overset{P_{C_1V_2}}{\begin{pmatrix} .428 & .572 \\ .213 & .787 \end{pmatrix}} - \overset{\hat{P}_{C_1V_2}}{\begin{pmatrix} .298 & .702 \\ .236 & .764 \end{pmatrix}} = \overset{P_{C_1V_2 \cdot V_1}}{\begin{pmatrix} +.130 & -.130 \\ -.023 & +.023 \end{pmatrix}}$$

$$d_{C_1V_2} = .215 \qquad \hat{d}_{C_1V_2} = .062 \qquad d_{C_1V_2 \cdot V_1} = +.153$$

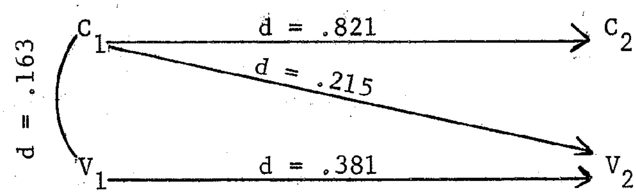
"Value Effect"

$$\overset{P_{C_2C_1}}{\begin{pmatrix} .844 & .156 \\ .023 & .977 \end{pmatrix}} \times \overset{P_{C_1V_1}}{\begin{pmatrix} .367 & .633 \\ .204 & .796 \end{pmatrix}} = \overset{\hat{P}_{C_2V_1}}{\begin{pmatrix} .342 & .658 \\ .208 & .792 \end{pmatrix}}$$

$$d_{C_2C_1} = .821 \qquad d_{C_1V_1} = .163 \qquad \hat{d}_{C_2V_1} = .134$$

$$\overset{P_{C_2V_1}}{\begin{pmatrix} .353 & .647 \\ .206 & .794 \end{pmatrix}} - \overset{\hat{P}_{C_2V_1}}{\begin{pmatrix} .342 & .658 \\ .208 & .792 \end{pmatrix}} = \overset{P_{C_2V_1 \cdot C_1}}{\begin{pmatrix} +.011 & -.011 \\ -.002 & +.002 \end{pmatrix}}$$

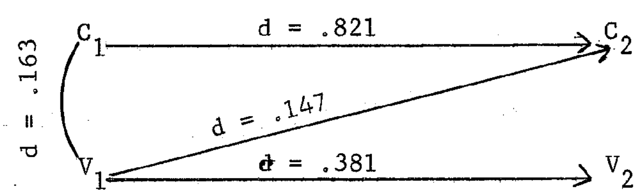
$$d_{C_2V_1} = .147 \qquad \hat{d}_{C_2V_1} = .134 \qquad d_{C_2V_1 \cdot C_1} = +.013$$



$$\hat{d}_{C_2V_1} = (.163)\ (.821) = .134;\ d_{C_2V_1} - \hat{d}_{C_2V_1} = .147 - .134 = +.013$$

$$\hat{d}_{C_2V_2} = (.215)\ (.821) = .177;\ d_{C_2V_2} - \hat{d}_{C_2V_2} = .217 - .177 = +.040$$

Fig. 17.--Causal Model for Engineering and Values Consistent with Engineering from College Graduation to One Year Later



$$\hat{d}_{C_1V_2} = (.163)\ (.381) = .063;\ d_{C_1V_2} - \hat{d}_{C_1V_2} = .215 - .063 = +.153$$

$$\hat{d}_{C_2V_2} = (.147)\ (.381) = .056;\ d_{C_2V_2} - \hat{d}_{C_2V_2} = .217 - .056 = +.161$$

Fig. 18.--Causal Model for Engineering and Values Consistent with Engineering from College Graduation to One Year Later

$$d_{C_2V_1} - \hat{d}_{C_2V_1} = +.013$$

The prediction for the Time 2 cross-sectional association, $d_{C_2V_2} = +.177$, is similarly quite close to the observed $d_{C_2V_2} = .217$, the discrepancy being:

$$d_{C_2V_2} - \hat{d}_{C_2V_2} = +.040.$$

Figure 18 by contrast does not fit the data as well. The prediction for the cross-lagged association is $\hat{d}_{C_1V_2} = .063$. This is not very close to the observed $d_{C_1V_2} = .215$, the discrepancy being:

$$d_{C_1V_2} - \hat{d}_{C_1V_2} = +.153.$$

Also the prediction for the Time 2 cross-sectional association, $\hat{d}_{C_2V_2} = .056$ departs considerably from the observed $d_{C_2V_2} = .217$. The discrepancy here is:

$$d_{C_2V_2} = \hat{d}_{C_2V_2} = -.161.$$

By any of these tests, the model of Figure 17 is a better fit than the model of Figure 18 and we should infer that, for engineering, the career causes the values rather than the reverse.

In these models, we derived predictions not only for the cross-lagged associations but also for the cross-sectional association between career and values at Time 2. In Chapter II, it was proved that this additional set of predictions must lead to the same causal inference that is made by comparing the cross-lagged partials and thus is redundant. In subsequent analysis, we shall present for each career only the cross-lagged partials[1]--the formal rationale being implicit rather than explicit.

The reader will recall from Chapter II that under the formal causal models, causal inference in a case such as this depends upon (1) the relative size of cross-lagged associations, (2) the relative stabilities of the attributes. Returning to Table 11, we note that while the zero-order cross-lagged associations differ by only 7 percentage points, the career of engineering is more stable than the engineering values by 44 percentage points. It is this large difference in stability which, mathematically, produces the difference in cross-lagged partials leading to the inference that for engineering, career is the strpnger of the two attributes. This does not necessarily mean that substantively career stability causes the value effect to be low. Alternatively, it may be the case that because the value effect is low, the career is stable. We shall consider this question further in the next chapter.

Relative Effects of Careers and Values for Particular Careers

We are now ready to turn to Table 13 which gives the relative strength of career and value effects for each of the twenty careers. The careers have been ordered according to the strength of career effects as opposed to value

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[1]The raw data for these computations have been obtained from "16-fold tables" tabulated for each career. A 16-fold table results from the cross-tabulation of four dichotomous items, career at 1, career at 2, values at 1, and values at 2. There are sixteen logical combinations of four dichotomous attributes (2 x 2 x 2 x 2 = 16) and hence sixteen cells in the table. If the reader wishes to check our results by alternative procedures or otherwise, refer to the 16-fold tables; they are contained in Appendix B.

TABLE 13

RELATIVE STRENGTH OF CAREERS AND VALUES BY CAREER IN THE YEAR FOLLOWING COLLEGE GRADUATION

Career	T_1 Relation	Stability		Cross-lagged		Expected Cross-lag		Partial Cross-lag		Difference
	$d_{C_1V_1}$	$d_{C_2C_1}$	$d_{V_1V_2}$	$d_{C_1V_2}$	$d_{C_2V_1}$	$\hat{d}_{C_1V_2}$	$\hat{d}_{C_2V_1}$	$d_{C_1V_2 \cdot V_1}$	$d_{C_2V_1 \cdot C_1}$	CP
Dentistry	.255	.858	.279	.230	.194	.071	.219	+.159	-.025	+.184
Chemistry	.240	.886	.381	.259	.209	.091	.213	+.168	-.004	+.172
Medicine	.314	.911	.449	.314	.291	.141	.286	+.173	+.005	+.168
Physical sciences	.301	.743	.381	.342	.289	.115	.224	+.227	+.065	+.162
Engineering	.163	.821	.381	.215	.147	.062	.134	+.153	+.013	+.140
Law	.142	.775	.351	.208	.139	.050	.110	+.158	+.029	+.129
Religion .	.438	.810	.449	.389	.440	.197	.356	+.192	+.085	+.107
Business .	.213	.739	.225	.150	.197	.048	.157	+.102	+.040	+.062
Agriculture	.218	.813	.219	.127	.195	.048	.177	+.079	+.018	+.061
Teaching .	.177	.609	.352	.188	.178	.062	.108	+.126	+.070	+.056
Biological sciences.	.271	.603	.311	.147	.177	.084	.163	+.063	+.014	+.049
Journalism.	.257	.633	.377	.195	.217	.097	.163	+.098	+.054	+.044
Military .	.230	.453	.273	.182	.189	.063	.104	+.119	+.085	+.034
Humanities.	.407	.637	.396	.349	.423	.161	.259	+.188	+.164	+.024
Physical education	.345	.771	.316	.224	.384	.109	.266	+.115	+.118	-.003
Educational admin. .	.327	.298	.279	.149	.160	.091	.097	+.058	+.063	-.005
Social sciences.	.297	.548	.396	.224	.277	.118	.163	+.106	+.114	-.008
Vocational education	.187	.652	.204	.011	.108	.038	.122	-.027	-.014	-.013
Social work	.416	.491	.449	.274	.319	.187	.204	+.087	+.115	-.028
History . .	.342	.580	.396	.258	.368	.135	.198	+.123	+.170	-.047
X . . .	.277	.682	.343	.222	.245	..	..	+.123	+.059	+.064
S . . .	.086	.160	.078	.087	.097	..	..	.058	.056	.073
$r_{X.(CP)}$	-.31	+.75	+.14	+.35	-.20	..	..	..	..	..

effects. Career is strongest relative to values for dentistry followed by chemistry, then medicine and so on down to history which is weakest relative to its values.

The first three columns of Table 13 give the zero-order associations which are used in computing expected cross-lagged associations. In the first column is the cross-sectional association between career at 1 and values at 1. In the second column is the career stability association. In the third column is the value stability association.

The fourth and fifth columns give the observed zero-order cross-lagged associations. The eighth and ninth columns give the deviations from expectation, i.e., the cross-lagged partial associations.

In the final column, the partial measuring value effects, $d_{C_2V_1 \cdot C_1}$, has been subtracted from the partial measuring career effects, $d_{C_1V_2 \cdot V_1}$, in order to obtain a single measure of the predominance of career effects over value effects. This will subsequently be called "career predominance" (CP). Where CP is positive, career has more effect, and where CP is negative, values have more effect.

In summarizing the results, we may simply note that career appears stronger for fourteen of the twenty careers while values appear stronger for six. Although career is stronger for most careers, the finding depends on what career is being considered. The results, in other words, vary by career.

We may examine career variations in the results further by referring to the numerical value of CP rather than to just the sign. CP ranges from a high of +.184 for dentistry indicating substantial career predominance to a low of -.047 for history indicating a modest value predominance. The average CP for the twenty careers is +.064 suggesting modest career predominance and the standard deviation is .071.

Using a "weighted" average rather than a simple average makes little difference. If the results for each career are "weighted" by the size of that career at Time 1, the weighted average CP is +.084 as opposed to the unweighted average CP of +.064.

In view of our general finding of relatively weaker value effects, one might ask whether there are values other than those which were, at Time 1, consistent which might have a stronger effect. While this is conceivable for values other than those measured in our study, it is unlikely that any value patterns we have measured would show stronger effects. This is because those value patterns which are consistent at college graduation remain consistent one year later. If there were a tendency for new value patterns to have effects for particular careers after college graduation one would expect some movements of careers in the value space. This, as we showed in Chapter III, did not occur.

At the bottom of Table 13 are given means and standard deviation for several of the columns. These may be used with caution in summarizing the contents of the table. Two particular points of caution should be mentioned. First, the "observations" upon which these means and standard deviations are computed are not completely independent of one another. Each "observation" is in fact a measure of association based on our entire sample and all these measures are computed on the same sample. The results for one career depend to some extent upon the results for other careers. The precise extent and implications of this dependence are difficult to assess.

The second point is that the means of two columns which are multiplied will not crossfoot corectly, e.g., the mean for the $\hat{d}_{C_1V_2}$ column <u>cannot</u> be obtained by multiplying the mean of $d_{C_1V_1}$ times the mean of $d_{V_1V_2}$. This is because the product of means is not generally equal to the mean of products.

With these cautions in mind, let us examine the zero-order associations. The causal inference depends upon (1) the relative size of cross-lagged association, (2) the relative stabilities of the attributes. Table 13 shows that the zero-order cross-lagged associations generally do not differ greatly, although for two careers, history and physical education, they differ by 10 percentage points or more. Interestingly, such differences as do occur generally favor $d_{C_2V_1}$ which contributes to the value effects rather than the career effects; $d_{C_2V_1}$ is in fact larger than $d_{C_1V_2}$ for thirteen of the twenty careers. The stability measures by contrast do generally differ considerably. Career is more stable than values for every career. The average difference between the two associations is 34 percentage points. In general then, it is the fact that careers are more stable than values that, mathematically, produces stronger career effects for most careers. However, as we said in our discussion of engineering, more information is needed to determine whether because a career is stable it therefore is less subject to the influence of values or on the other hand because it has not been greatly affected by values it therefore is stable.

With respect to variations by career, Table 13 shows that career stability also varies more by career than does value stability. The standard deviation for career stability is .160 while for value stability it is only .078. The standard deviations for the zero-order cross-lagged associations do not differ greatly. Both are smaller than .100 and thus both cross-lagged associations are less variable than is career stability. In the bottom row of Table 13, we have comupted and entered the correlation (r) between each of the zero-order associations and the career predominance column. Again these results show that it is variations in career stability more than anything else which "explain" variations by career in the degree of career predominance. The correlation between career stability and career predominance is $r = +.75$ meaning that career stability explains 56 per cent of the variance in career predominance or alternatively, career predominance explains 56 per cent of the variance in career stability. None of the other correlations are very large. The largest is the $d_{C_1V_2}$ column which correlates +.35 with career predominance. Thus only about 12 per cent of the variance in career predominance is "explained" by variations in the association of career at 1 with values at 2. Other correlations are lower yet. What we have found then is that career predominance varies by career and that these variations are related to the stability of the careers.

The Relation of Career Effects to Value Effects

Having begun with the question of whether career choices determine values or values determine career choices, we have been led to the conclusion that even though career is stronger for most careers still the answer depends on what career is being considered. For example, career is stronger for dentistry, medicine, and the physical sciences while for history and social work values are stronger.

One may ask whether the best way to present and elaborate this finding is in terms of a single continuum indicating the degree of "career predominance" for each career, or whether a more elaborate typology involving combinations of career and value effects is in order. As an example, consider the careers of physical education and educational administration. These careers show virtually identical CP scores both very close to zero. But for physical education, both the partials are about +.12 indicating some effect of careers upon values and of values upon careers, while for educational administration both the partials are about +.07 indicating relatively weaker effects of careers upon values and values upon careers. Is it generally useful to make distinctions of this sort or does it not matter?

This question can be answered by computing the correlation across careers between the career effects partial, $d_{C_1V_2 . V_1}$, and the value effects partial, $d_{C_2V_1 . C_1}$. Suppose first that the correlation is large and positive. This outcome would mean that for careers where career effects are strong, value effects are also strong and conversely for careers where career effects are weak, value effects are also weak. In this case, a single dimension or continuum would be appropriate for summarizing the results.

However, such a positive correlation would also strongly suggest the possibility that the findings were artifactual. That is, there would be a strong possibility that career variations in findings were simply a function of variations in our success at obtaining high associations between career choices and values in the first place. Fortunately, this is not the case in our data. As an additional check on the influence of variations in predictability, the correlation between the $d_{C_1V_1}$ and the CP columns of Table 13 has been computed. The correlation is modest with $r = -.31$. Thus original variations in predictability do not have an appreciable effect upon variations in career predominance.

Suppose for a second possibility that the correlation between career effects and value effects is large and negative. This outcome would mean that the careers with strong career effects have, at the same time, weak value effects and conversely that the careers with weak career effects have, at the same time, strong value effects. This would suggest in turn, that career effects and value effects are separate indications of the same phenomenon and that the single dimension of career predominance would be an appropriate summary of the findings. This is the outcome we expected on the basis of preliminary tabulations using a list of seven career categories and the RSS of 1,712 cases. However, with the full sample and the final list of twenty careers, this expectation proved wrong.

The final possibility, and this is what we actually found, is that career effects and value effects are relatively independent of one another. This means that strong value effects may, but need not, be found in the same careers with strong career effects. Conversely, weak value effects may, but need not, be found in the same careers with weak career effects. The correlation across careers between $d_{C_1V_2 \cdot V_1}$ and $d_{C_2V_1 \cdot C_1}$ is $r = +.17$, indicating that the two effects are relatively independent, and may be considered as separate phenomena.

A Typology of Career and Value Effects

Since career effects and value effects are relatively independent, a two dimensional typology of careers may be constructed. Normally, if the two "effect" variables are dichotomized, such a typology involves four types, the logically possible combinations of two dichotomous attributes being (2 x 2 = 4) four. In the present case, however, the value effects variable is lower on the average than the career effects variable, and rather than dichotomize both variables at the median, we have arbitrarily chosen to dichotomize them both at +.100. A partial association greater than or equal to +.100 is considered to show a relatively "strong" effect and a partial less than +.100 is considered to show a relatively "weak" effect.

The resulting classification is shown in Figure 19 where the reader will observe that "weak" career effects combine with "strong" value effects for only one career, social work. For social work, $d_{C_1V_2.V_1} = +.087$ and $d_{C_2V_1.C_1} = +.115$. These partials are so close together that it may be more reasonable to classify social work under "mutual effects" rather than under "value predominant." If this is done, there are only three types of careers rather than four.

The largest type is "career predominant." These careers have relatively strong career effects and weak value effects. Ten of the twenty careers are classified as career predominant. They are dentistry, chemistry, medicine, physical sciences, engineering, law, religion, business, teaching, and military service.

	Value Effects	
Career Effects	Strong[1]	Weak
Strong[1]	"<u>Mutual Effects</u>" Humanities Physical education Social sciences History (Social work)[2]	"<u>Career Predominant</u>" Dentistry Chemistry Medicine Physical sciences Engineering Law Religion Business Teaching Military service
Weak	"<u>Value Predominant</u>" (Social work)[2]	"<u>Indeterminate</u>" Agriculture Biological sciences Journalism Educational adminis- tration Vocational education

Fig. 19--Typology of Career and Value Effects

[1]A strong effect is arbitrarily defined as having a partial $\geq +.100$.

[2]For social work $d_{C_1V_2 . V_1} = +.087$ and $d_{C_2V_1 . C_1} = +.115$. These partials are so close together that it may be more reasonable to classify social work under "Mutual Effects" than under "Value Predominant."

The second type is "mutual effects." These careers have relatively strong effects of both kinds. The four careers so classified are humanities, physical education, social sciences, and history. It may also be reasonable to include social work in this type.

The third type is "indeterminate." These careers show weak effects of both kinds. The five indeterminate careers are agriculture, biological sciences, journalism, educational administration, and vocational education.

The advantage of this formulation over the single CP continuum lies in separating the "mutual effects" type of career from the "indeterminate" type of career. Physical education, to use a previous example, shows mutual effects while educational administration is indeterminate. Similarly humanities shows strong effects of both kinds while journalism shows weak effects of both kinds.

On the other hand, the single CP continuum has the advantage that it allows a precise answer to the question of which of the two effects is stronger for a particular career and gives a numerical indication of how much stronger. For many purposes, we may want to use the single CP continuum. It appears that for those careers with high CP scores, i.e., above about +.05, career effects are strong and value effects are weak. Thus, high scores on CP correspond to the "career predominant" type. Low scores indicate either of the two remaining types. Either both effects are strong and we have a "mutual effects" career or neither effect is strong and we have an "indeterminate" type of career. We shall need to be alert to these considerations in subsequent analysis of career predominance.

Consideration of Possible Methodological Objections

Although we have discussed several methodological problems involved in our procedures as we went along, there remain several specific methodological problems which need further consideration. Specifically, we shall consider in this section the following four questions:

1. Do the cross-lagged partial associations conceal statistical interactions such that the findings will depend on whether a person was initially in or not in the career or initially had or did not have the values? For example, might values affect loyalty to a career but not recruitment or might career affect value retention but not adopting of new values?
2. Would more reliable measurement of values change the findings?
3. Is the "sample" of careers adequately constructed?
4. Is the sample of time adequate?

Statistical Interactions in Cross-lagged Partials

When we say that a career has an effect upon values, we are actually speaking of two different situations. For a person who has appropriate values, the question is whether being in the career influences him to retain those values. On the other hand, for a person with inappropriate values, the question is whether the career influences him to adopt more appropriate values.

Similarly, to say that values affect career implies two possible situations. If a person is already in the career, the values ought to promote his loyalty. If, on the other hand, he is not in the career, then the values ought to contribute to his recruitment.

Till now, we have employed a single measure of career effect, the partial association, $d_{C_1V_2 \cdot V_1}$, and a single measure of value effect, $d_{C_2V_1 \cdot C_1}$. However, it is possible to view each of these measures as a weighted average of the separate effects in the two different situations described above.

If the two separate associations that are averaged in this fashion do not differ greatly from one another, we say that there is no "interaction" in the effects of the independent and the control attributes upon the dependent attribute, e.g., the effect of values upon career loyalty is the same as the effect of values on career recruitment. If, however, the two associations do differ greatly, then there is an "interaction," or in another manner of speaking, a "specification," of the relationship. The association is "specified" as occurring to a greater extent within one of the categories of the control attribute, e.g., if the effect of values is specified to occur more greatly among those not in the career, then values would have more effect on recruitment than on loyalty.

We shall be concerned first of all about the extent to which such interactions occur and secondly, how they affect our judgment on whether career or values is the stronger variable.

Table 14 gives, in the first four columns, cross-lagged partial associations computed separately for each category of the control attribute. In the fifth column is the difference between the two career effect measures and in the sixth column is the difference between the two value effect measures. Taking a difference of .10 or more as an indication of a specification, there are specifications of the career effect measure for ten of the twenty

TABLE 14

PARTIAL ASSOCIATIONS $d_{C_1V_2 \cdot V_1}$ and $d_{C_2V_1 \cdot C_1}$ FOR SEPARATE CATEGORIES OF CONTROL ATTRIBUTES BY CAREER

(Percentage Differences, d)

Partial	$d_{C_1V_2 \cdot V_1}$		$d_{C_2V_1 \cdot C_1}$		$d_{C_1V_2 \cdot V_1}$	$d_{C_2V_1 \cdot C_1}$
Effect on	Retention	Adopting	Loyalty	Recruitment	Difference	Difference
Dentistry	.15	.17	-.11	-.03	-.02	-.08
Chemistry	.13	.21	-.02	.02	-.08	-.04
Medicine	.11	.27	.07	-.01	-.16	+.08
Physical sciences .	.24	.23	.16	.11	+.01	+.05
Engineering	.16	.16	.02	.06	.00	-.04
Law	.17	.15	.08	.07	+.02	+.01
Religion	.12	.42	.15	.35	-.30	-.10
Business	.12	.11	.05	.11	+.01	-.06
Agriculture	.14	.03	.01	.09	+.11	-.08
Teaching	.08	.15	.12	.11	-.07	+.01
Biological sciences	.33	.03	.05	.01	+.30	+.04
Journalism	.05	.15	-.04	.18	-.10	-.22
Military	.12	.12	.17	.10	.00	+.07
Humanities	.15	.26	.15	.36	-.11	-.21
Physical education	.12	.12	.10	.40	.00	-.30
Educational administration. .	.01	.11	.05	.07	-.10	-.02
Social sciences . .	.03	.20	.24	.12	-.17	+.12
Vocational education	-.07	.01	-.11	.07	-.08	-.18
Social work	.05	.20	.22	.13	-.15	+.09
History	.18	.04	.32	.17	+.14	+.15
r with "net" partial	+.49	+.74	+.64	+.55		

careers. For seven of the ten specifications, the effect of career on value adopting is stronger than the effect of career on value retention. These seven careers are medicine, religion, journalism, humanities, educational administration, social sciences, and social work. The effect of career on value retention is stronger than the effect of career on value adopting for three careers--agriculture, biological sciences, and history.

There are specifications of the value effect for seven of the twenty careers. For five of these seven, the effect on recruitment is stronger than the effect on loyalty. These five are religion, journalism, humanities, physical education, and vocational education. For two careers, the value effect on loyalty is greater than on recruitment. These are social sciences and history.

Specifications then, do occur. Career generally affects adopting more than retention of values and values generally affect recruitment more than loyalty. Do these specifications modify our judgment as to whether career or values is the stronger variable over time?

For a career like engineering, the answer is clearly no, both sub-group partials measuring the effect of careers on values are larger than either of the sub-group partials measuring the effect of values on career. We conclude, as we did before, that for engineering the career is stronger than the values. For some other careers, the results are mixed depending on what two partials are compared. In such a case, the best way to get a single answer is to do what we have already done above--take an average of the career effects and compare it with an average of the value effects.

We concluded previously that for most careers, the career is stronger than the values. This conclusion is not affected by differences in the sub-group partials. If one compares the career effect on value retention with the value effect on career loyalty, career is stronger in twelve of twenty comparisons. Comparing the career effect on value retention with the value effect on career recruitment, career is stronger in eleven of twenty comparisons. Comparing the career effect on value adopting with the value effect on career loyalty, career is stronger in fifteen of twenty comparisons. Finally, comparing the career effect on value adopting with the value effect on career recruitment, career is stronger in thirteen of the twenty comparisons. In each case career is stronger in a majority of the comparisons.

Considering variations by career, we should like to know how good the net partial is as an indicator of the sub-group partials. The correlation, across the twenty careers, between each sub-group partial and the relevant net partial has been computed and the coefficients entered in the bottom row of Table 14. The correlations range from +.49 to +.75. We would have more confidence that the net partials adequately summarize the sub-group partials if these correlations were higher.

Another way to approach the problem is to ask whether the specifications which occur in sub-group partials are related to the career predominance measure used previously. If they are not, then we cannot be harmed too seriously by disregarding them in subsequent analysis of career predominance.

The correlations across the twenty careers between the career predominance measure and columns five and six of Table 14--those columns indicating the degree of specification of career and value effects respectively--are -.075 and +.025 indicating that the specifications are independent of career predominance. Thus, we shall be safe in disregarding specifications in the analysis of the next chapter.

Inadequate Measurement of Values

We have seen that for most careers career has a stronger effect than values and that this comes about because careers tend to be about twice as stable as value patterns. The average stability of values is d = +.34 over the one year period. We would have no particular reason to doubt the reliability of this result were it not for the fact that studies of the Strong Vocational Interest Blank in which "vocational interests" are measured with 400 items, have shown a higher degree of stability. Bloom[1] reports stabilities of greater than +.70 (r) for comparable age groups and for time spans up to ten or twenty years on various scales from this test.

If we scored value consistency on a continuous scale rather than a dichotomy and computed r rather than d, we would obtain a higher stability than +.34 over the one year period. But it would still not be as high as +.70. In view of the fact that we used only nine items in constructing the value indices, it seems likely that the use of more items would lead to a greater stability of values.

Would more stable values, obtained through improved measurement (adding more items) lead to stronger value effects and possibly reverse our findings? If the cross-lagged associations did not change as a result of these operations, then, indeed, increasing the stability of values through improved measurement could reverse or at least equalize the findings.

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[1]Benjamin S. Bloom, Stability and Change in Human Characteristics (New York: John Wiley and Sons, 1964).

There is reason to believe, however, that better measurement of values would not only increase value stability, it would also change the other associations as well. Our data can shed some indirect light on this matter. We note that there are some variations by career in value stability within our sample. We can thus see whether, for those careers with relatively greater value stability, career predominance tends to be less.

In Table 13 at the bottom of the $d_{V_1V_2}$ column, the correlation across careers between value stability and career predominance is given. The question of concern is whether increasing value stability leads to lower career predominance, i.e., whether there is a substantial negative correlation. In fact, the correlation is mildly positive ($r = +.14$). In our sample then, increasing value stability does not modify the findings and is in fact independent of career predominance.

In Table 15, we have divided the careers into three groups of high, medium, and low relative value stability with six, seven, and seven careers respectively. We have computed for each level of value stability the average of each measure used in computing career predominance. Table 15 shows that there is actually a curvilinear relation between value stability and career predominance. Those careers which are intermediate in value stability tend to be highest in career predominance. The reason for this apparently is that the most stable careers tend to be intermediate in value stability. The two extremes of value stability are about equal in career predominance so that except for the effect of variations in career stability, value stability appears unrelated to career predominance.

How can this be? Table 14 shows that as value stability increases so does every other association entering into the computation of career

TABLE 15

RELATIVE EFFECTS OF CAREERS AND VALUES
BY VALUE STABILITY

(Average d's)

Measure	Value Stability		
	High	Medium	Low
$d_{V_1V_2}$	.42	.36	.26
$d_{C_1V_1}$	.37	.23	.24
$d_{C_2C_1}$	.66	.75	.63
$d_{C_1V_2}$	.30	.23	.14
$d_{C_2V_1}$	.35	.22	.18
$d_{C_1V_2 \cdot V_1}$	.14	.15	.08
$d_{C_2V_1 \cdot C_1}$	.11	.05	.03
CP	.03	.10	.05
N	6	7	7

predominance except career stability. In other words, where values are more reliably measured every association involving a value measure tends to be higher. Although value effects do indeed increase with increasing value stability, so do career effects and the net result is no difference in career predominance.

It is worth noting that value stability depends in part on what values are involved. The people-oriented value patterns are most stable, the intellectual patterns next, and the enterprise patterns are least stable.[1]

In sum, we do not really know what the effect on our findings would be of increasing value stability through more reliable measurement. However, the indirect evidence we have been able to muster gives us no reason to expect that this would change the findings and some reason to expect that all relevant correlations would be raised as a result with no net effect on the degree of career predominance.

"Sampling" of Careers

Our list of twenty careers is not really a sample of careers. It is a categorization of the entire population of careers which are chosen by college graduates. Another investigator might well group this population into a larger or smaller number of categories and would almost certainly produce a somewhat different assignment of specific career choices to the various categories regardless of how many there are.

We shall concern ourselves with the possibility that if a different list of careers were used, our general finding that career choice is stronger than values would prove wrong.

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[1] Degree of career predominance is to some extent related to what value pattern is involved. Where the values involved are people orientation in combination with enterprise or to a lesser extent people orientation alone, value effects are greater and hence career predominance is less.

Examination of Table 13 shows that it would, in fact, be possible to combine heterogenous careers together in such a way that value effects would appear stronger or at least equal. In the extreme, if all the careers where career is predominant were combined into a single category while all careers where values are predominant were left as they are, then value effects would appear stronger for most careers.

However, it is hard to imagine that such a grouping of careers would actually occur except through deliberate attempts to distort the data.

We reasoned that the use of a "weighted" average, with the finding for each career weighted by the size of that career would provide some protection against distortion due to peculiar findings for small careers. Small careers are the ones which would be most likely to be combined together in other categorization schemes.

Using the relative size of each career one year after college graduation as the weighting factor, we computed several such weighted averages. The weighted average of the career effect measures is +.132 as compared to an unweighted average of +.123, a difference of about one percentage point. The weighted average of value effects is +.046 as against the unweighted +.059 again a very small difference. The weighted average career predominance is +.084 as against the unweighted average of +.064. It is apparent that a weighting adjustment has no effect on the results. Thus, it is unlikely that different groupings of careers, in particular different combinations of small career categories, would lead to different conclusions than we have obtained.

To summarize, while it is conceivable that a different career categorization could modify our results, we do not think it very likely.

Is the Sample of Time Adequate?

It is possible that the nature of the relationship between careers and values is different at different stages of an individual's development. In high school or college, for example, values may have a stronger effect upon career choices than they do in the post-graduate years. Our data show that in the year after college graduation career choice is a more potent factor than values, but we are in no position to generalize to other stages of the career choice process. We speculate that as an individual approaches closer to actual labor market participation reality factors such as investment in specialized career preparation impose constraints on freedom of movement among careers thereby increasing the stability of career plans and reducing the effect of values upon choice.

Since we sent questionnaires to our respondents at the end of their second post-graduate year as well as their first, we shall be able to extend a part of our analysis to the second year after college and determine whether the process is essentially any different in this period. We unfortunately have no measure of values at Time 3, the end of the second year, but we do have the career choice measures. It can thus be determined whether value effects are any different in the second year than they are in the first but it cannot be determined whether career effects are any different.

Table 16 gives the results. The first two columns give the associations used in computing the expected cross-lagged partial, namely, the association between career and values at Time 2 and the stability of career

TABLE 16

THE EFFECT OF VALUES OR CAREER IN THE SECOND YEAR FOLLOWING COLLEGE GRADUATION BY CAREER

(Percentage Differences, d)

Career	T_2 Relation $d_{C_2V_2}$	Stability $d_{C_3C_2}$	Cross-lagged $d_{C_3V_2}$	Expected Cross-lag $\hat{d}_{C_3V_2}$	Partial Cross-lag $d_{C_3V_2 \cdot C_2}$	First Year Partial Cross-lag $d_{C_2V_1 \cdot C_1}$
Dentistry	.190	.873	.188	.166	+.022	-.025
Vocational education . . .	-.003	.659	-.072	-.002	-.070	-.014
Chemistry	.272	.885	.301	.241	+.060	-.004
Medicine	.342	.943	.334	.323	+.011	+.005
Engineering . . .	.217	.885	.225	.192	+.033	+.013
Biological sciences	.176	.738	.195	.130	+.065	+.014
Agriculture . . .	.160	.812	.147	.130	+.017	+.018
Law	.192	.858	.199	.165	+.034	+.029
Business	.160	.764	.149	.122	+.027	+.040
Journalism . . .	.315	.683	.275	.215	+.060	+.054
Educational administration.	.155	.560	.160	.087	+.073	+.063
Physical sciences	.358	.745	.329	.267	+.062	+.065
Teaching	.226	.632	.239	.143	+.096	+.070
Religion	.421	.899	.412	.378	+.034	+.085
Military	.189	.547	.130	.103	+.027	+.085
Social sciences .	.194	.653	.239	.127	+.112	+.114
Social work . . .	.406	.569	.295	.231	+.064	+.115
Physical education . . .	.237	.721	.225	.171	+.084	+.118
Humanities . . .	.375	.695	.353	.261	+.092	+.164
History	.348	.682	.366	.237	+.129	+.170
$\overline{X}$	.246	.740	.236	.186	+.050	+.059
				S	.048	.056

choices from Time 2 to Time 3. The third column gives the observed cross-lagged association between values at Time 2 and career at Time 3. The fourth column gives the expected value for this cross-lagged association and the fifth column gives the difference between observed and expected, i.e., the partial cross-lagged association between Time 2 values and Time 3 career. The final column is taken from Table 13. It shows the comparable cross-lagged partial for the earlier year. The careers have been arranged in increasing order on the first year value effect.

The bottom rows of the table give the averages of the various measures and the standard deviations of the two value effect partials. The average measures provide a convenient way of summarizing what has occurred between the two years.

On the average, there has been no change in value effects from the first to the second post-graduate year. The cross-lagged partial declined by about 1 percentage point as does its standard deviation. The largest change in the average situation is that the stability of careers increases by 4 percentage points between the two years (from .682 to .740). While this is not a large enough change in career stability to bring about a decline in value effects if the careers continue to become more stable in succeeding years value effects would eventually be reduced.

Regarding changes in value effects for particular careers, the correlation across careers, for the value effect measures in the two different years, is .72 suggesting rather similar orderings. No career changes by as much as 10 percentage points. There are, however, seven careers which change by as much as 5 percentage points. For two of these seven careers, value effects increase. These are chemistry and biological sciences. For five careers, vocational education, religion, military service, social work, and humanities value effects decline. The two careers for which value effects increased were relatively low in the first place while four of the five careers for which value effects declined were relatively high in the first place (the exception is vocational education). These movements may be described as movements away from the extremes and toward the mean. The movements thus can be viewed as probably due to statistical regression arising from imperfection in our measures rather than to processes having substantive importance.

These results give us little reason to believe that the overall findings concerning career predominance would be very different in the second post-graduate year than they are in the first. Value effects have not changed to any significant extent and it is unlikely that career effects would change either. Over the long run, however, it might be the case that value effects would decline while career effects became increasingly more potent.

Summary

In this chapter, we have considered the central problem of the dissertation, whether career choice determines values or value orientations determine career choices. Data on changes over the one year period following college graduation were presented for twenty careers and patterns of values consistent with each career.

The effect of career upon values was measured by the partial association of Time 1 career with Time 2 values, controlling for Time 1 values. The effect of values upon career was measured by the partial association of Time 1 values with Time 2 career, controlling for Time 1 career. The difference between these partials was taken as a measure of the degree of career predominance for each career.

Although both career and values have some effect upon one another, for most careers the effect of career on values is greater than the effect of values on career.

When findings for particular careers are considered, we find that, across careers, the effects of career and values are independent of one another. This leads to a typology of effects. Ten careers are classified as "career predominant" having strong career effects and weak value effects. Five careers are classified as showing "mutual effects." These careers showed strong effects of both types. Finally, five careers are classified as "indeterminate" having weak effects of both types. There was no career for which value effects clearly predominated.

The single measure of career predominance provides a good one dimensional summary since the "career predominant" careers score high on it, the "mutual effects" careers score low, and the "indeterminate" careers score in between.

Several methodological problems were considered and some attempt was made to bring empirical evidence to bear on each. First with respect to statistical interactions in cross-lagged partials, they do occur. Career generally affects adopting more than retention of values and values generally affect recruitment more than loyalty to a career. However, these results do not affect our finding that for most careers, career is stronger than values. Specifications, moreover, are independent of the degree of career predominance and thus should not influence further analysis of career predominance.

Secondly, we considered the possibility that more reliable measurement of values might increase value stability and hence increase value effects relative to career effects. We found, however, that within our sample, variations in value stability were unrelated to the degree of career predominance. There was some reason to believe that increased reliability of value measures would lead to increases in all relevant associations with no net effect on the degree of career predominance.

Third, we considered the possibility that different career categorizations could lead to different conclusions and decided that this was unlikely.

Finally, we extended the analysis of value effects to the second post-graduate year finding that value effects did not change to any significant extent in the second year. Over the long run, however, it is possible that value effects would decline as career choices became more stable.

CHAPTER V

VARIATIONS IN CAREER PREDOMINANCE

In this chapter, we shall make some attempt toward explanation of the variations across careers in the nature of the relationship between careers and values. In the previous chapter, we found that for most careers the effect of career choice on change in values was somewhat greater than the effect of values on change of career plans. However, we also found that the nature of these relations depends on what career is being considered. Some careers showed strong career effects and weak value effects, while other careers showed strong effects of both types and still others manifested weak effects of both types. How do these careers differ? What is it that produces variations in the strength of career and value effects?

We shall attempt to "explain" these variations both in statistical and in a substantive sense. Among the factors to be considered are the nature of patterns of movement and stability among the various careers, the effects of academic ability, the role of attendance at graduate school, the prestige of various careers, and the investment of time and energy involved in career preparation.

Stability and Movement among Careers

There are two senses in which careers can be considered stable or unstable. On the one hand, one can ask whether careers change in size.

We shall refer to the absence of changes in size as "structural stability." On the other hand, one may ask, quite apart from changes in size, whether there is a great deal of turnover in the personnel of a career from one time to another. We shall refer to low turnover as "individual stability." The relations between structural and individual career change will be considered subsequently.

Structural stability.--Table 17 gives the career distribution of our sample at three points in time and is intended to show the structural stability of career choices over the two years following college. The table shows that the career distribution is highly stable over this period. The relative sizes of the careers have changed hardly at all. Comparing Time 1 with Time 3, only 4 per cent of the respondents would have to change their careers in order to make the distributions identical. Only three careers grow by as much as one-half of 1 percentage point. These are business, which increases by about 2 percentage points, military service, which increases by about 1 percentage point, and social work which increases by one-half of 1 percentage point. The increases for military service and social work are proportionately rather large since both of these careers were quite small in the first place. The only category to decline by as much as one-half of 1 percentage point is the NEC, or residual, group which declined by about one and one-half points. Thus, apart from the NEC decline, the gains to business, military service, and social work are provided by fairly uniform and very small losses to the remaining careers.

In general, it appears that careers do not change in size in the two years after college, and that structural stability as we have defined

TABLE 17

CAREER DISTRIBUTION AT THREE TIMES

Career	College Graduation	One Year after College	Two Years after College
Business	23.9	24.6	25.8
Engineering	14.5	15.1	14.3
Teaching	9.2	8.1	8.9
Law	6.0	6.1	5.9
Physical sciences	5.2	4.8	5.1
Medicine	4.6	4.6	4.4
Humanities	3.4	3.6	3.7
Social sciences	3.1	3.2	2.9
Religion	3.0	3.2	3.2
Chemistry	2.6	2.4	2.3
Agriculture	2.2	2.1	2.0
Biological sciences	1.9	2.1	2.0
Educational administration	1.9	2.6	1.9
Physical education	1.8	1.4	1.6
Vocational education	1.5	1.2	1.3
History	1.3	1.0	0.9
Journalism	1.2	1.2	1.2
Military	1.2	1.6	2.2
Dentistry	0.9	0.8	0.8
Social work	0.6	0.7	1.1
Not elsewhere classified	9.9	9.7	8.5
Total	99.9	100.1	100.0
N	(23,519)	(22,814)	(23,499)
NA, DNA	437	1,142	457
Total weighted N	23,956	23,956	23,956

it is high. It might be asked whether this distribution remains stable because respondents stubbornly persist in choosing careers for which there is no labor market demand or whether it is stable precisely because it reflects the structure of labor market demand for the talents of these college graduates. It is highly plausible that the aggregate distribution of college graduate career choices is determined to a large extent by the labor market either directly in the form of available jobs or indirectly through the availability of various types of graduate training. Labor market demand might well explain the structural stability of career choices. The question amounts to asking how realistic the career choice distribution is. Realistic implementation would provide one indication.

In an attempt to find evidence bearing on this question, we have compared the distribution of career choices at Time 3 with the distribution of jobs which respondents actually held at or prior to Time 3, and with the distribution by field of graduate study for those respondents enrolled in school at Time 3. Roughly one-fourth of the respondents appear in both these distributions since these respondents combined, in one way or another, school with work.

Table 18 gives the results of these comparisons. Although there is a good deal of similarity of career choices to each of the other distributions, there are some discrepancies. The coefficient of dissimilarity between the job held distribution and the career choice distributions is 26 per cent, indicating that 26 per cent of the respondents would have to change career choices to make the two distributions identical.

Practically the same degree of dissimilarity, 25 per cent, exists between the career choice and graduate field distributions. These discrepancies,

TABLE 18

DISTRIBUTION OF CAREER CHOICES, CURRENT JOBS, AND FIELDS OF GRADUATE STUDY TWO YEARS AFTER COLLEGE GRADUATION

Career	Career Choice	Current (or Most Recent) Job	Graduate Field
Business	25.8	25.0	11.1
Engineering	14.3	16.1	10.6
Teaching	8.9	14.0	11.1
Law	5.9	0.6	10.2
Physical sciences	5.1	2.4	8.2
Medicine	4.4	0.1	8.2
Humanities	3.7	1.0	5.9
Social sciences	2.9	0.6	6.0
Religion	3.2	1.3	4.9
Chemistry	2.3	1.4	3.5
Agriculture	2.0	1.6	0.8
Biological sciences	2.0	0.6	3.6
Educational administration. .	1.9	0.3	1.9
Physical education	1.6	1.7	1.4
Vocational education	1.3	1.9	1.6
History	0.9	0.1	2.0
Journalism	1.2	1.0	0.6
Military	2.2	20.4	0.0
Dentistry	0.8	0.0	1.4
Social work	1.1	1.2	0.7
Not elsewhere classified. . .	8.5	8.8	6.3
Total	100.0	100.1	100.0
N	(23,499)	(17,892)	(11,726)
NA, DNA	457	6,064	12,230
Total weighted N	23,956	23,956	23,956

however, are not as serious as they might, at first, appear. The job held and graduate field distributions are in a sense complementary. For careers such as business, engineering, and teaching, graduate study is not necessary to obtain ultimate employment in the career and career plans may appropriately be implemented by employment upon graduation. For this type of career, we expect a degree of overrepresentation in the jobs held distribution. In contrast, for careers like medicine and law, graduate training is the appropriate implementation of the career choice. For these careers we expect an underrepresentation of the job held distribution and an overrepresentation in the graduate field distribution.

Another way of expressing these ideas is to state that if career plans are a realistic reflection of labor market demand, it should be the case that the number of people ultimately planning careers in a given field is approximately the sum of the number not enrolled in school who have jobs in the field plus the number enrolled in school for study in that field plus an adjustment for the number serving in the armed forces who will return to that career. The proportion of people planning careers in a given field should thus tend to fall between, as a weighted average, the comparable proportions in the other two distributions.

Table 18 shows that this in general tends to be the case, the most notable exceptions being military service (for obvious reasons), business, agriculture, journalism and the teaching professions. The teaching professions appear to employ more people than have indicated long run choice of teaching, but the other discrepancies are best understood as due to the large proportion (20 per cent of those listing a job) who are serving in the armed forces, but not planning to be professional military men.

In sum, it appears that with appropriate correction for military service, and combining of job fields with graduate study fields, we obtain a distribution of actual employment and career preparation activities, which is very similar to the distribution of long-range career plans. Our estimate of the precise degree of similarity is above 90 per cent. It thus appears that the distribution of career choices is not only stable but also it is being realistically implemented through actual employment and career preparation activities. These considerations suggest but do not prove conclusively that the number of people choosing a career is determined by the number of slots available to that career in the occupational structure. We shall assume, for the purposes of subsequent analysis, that this is the case. More exactly, we shall assume that the size of a career, i.e., the total number choosing it, is not determined by the choices people make, it rather helps to determine those choices.

Individual stability.--Individual stability is related to structural stability by a very simple "accounting formula." The number of people in a career at Time 2 is equal to the number in it at Time 1, minus the number who defect from it, plus the number who are recruited to it. Symbolically:

$$n_1 - D + R = n_2,$$

where: n_1 is the total size with subscripts indicating time, D is the number of defectors, and R is the number of recruits. Rearranging the formula, we have:

$$R = D + (n_2 - n_1).$$

This says that the number of recruits to a career is equal to the number of defectors plus the increase in size. Where structural stability is high, as it is in our data, there tends to be no change in size, and the number of recruits is simply equal to the number of defectors.

Assuming that the total size is fixed and unaffected by the choices of individuals, it must be the case that if there are no defectors from a career, there can be no recruits. On the other hand, if many people leave the career, it must be the case that many more come in to take their place. Thus careers may vary in amount of defection and recruitment, i.e., in amount of turnover. Since the number loyal plus the number who defect gives the total number in the career at Time 1, turnover can be measured by simply taking the proportion who remain loyal to the career from one time to the next. Of our careers, medicine commands most loyalty and educational administration least.

For medicine and other high loyalty careers, there are very few defectors, hence very few recruits, and the career is effectively closed. For educational administration and other low loyalty fields conversely, there are many defectors, and many recruits. These fields are not only open, but people <u>must</u> enter them. "Must" is emphasized because it has both a mathematical and substantive meaning. Mathematically, the number of recruits must equal the number of defectors because the career does not change in size. Substantively, a relatively large rate of defection creates a demand which must be met through high recruitment.

The "accounting formula" given above can be arranged into a 4-fold "turnover table." Figure 20 illustrates such a table symbolically. Such tables are sometime treated as though they involved 2 degrees of freedom. That is, the probability of recruitment is sometimes treated as though it varied independently of the probability of loyalty (or defection). This treatment is justified if and only if it can be assumed that the total number in the career at Time 2 is the result rather than a determinant of loyalty and recruitment.

	C_2	$\bar{C}_2$	
C_1	L	D	n_1
$\bar{C}_1$	R	$\bar{L}$	$N - n_1$
	n_2	$N - n_2$	N

C = Career

n = Number in career

L = Loyalists

D = Defectors

R = Recruits

I = In career at neither time

Fig. 20.--Turnover Table

We assumed that the total number in the career is a determinant rather than a result of these processes, and in so doing "fixed the marginals" leaving to the Table 1 degree of freedom and not 2. Relating this statistical argument to its substantive implications, we assumed that the marginals are determined by labor market processes and in so doing took away a degree of freedom from the career choices of individuals. Individuals are not completely free to choose whatever career they might like. They cannot go where there is no room. They must enter a career which has openings for their particular abilities or preparations. It follows that recruitment is not independent of loyalty and there is only one piece of information in a career turnover table. This piece of information is whether there is a low or a high degree of turnover. In other words, it is the "individual stability" of the career.

How is individual stability measured? If the turnover table is percentaged so that each of the rows totals 1.00, the resulting table is a matrix of "transition probabilities" or a "transition matrix." Table 19 gives an example of such a matrix for the career of engineering. It shows that for those who chose the career of engineering at college graduation, the probability of choosing engineering a year later is .870, while for those who did not choose engineering at Time 1, the probability of choosing it a year later is .028. In this case the proper measure of stability or turnover is the difference, $d_{C_1C_2}$, between those two probabilities which is,

$$d_{C_1C_2} = .870 - .028 = .842.$$

This difference measures the association between engineering at Time 1 and engineering at Time 2, so that the degree of "individual stability" or turnover, is simply the degree of association between the initial career choice and the later career choice.

TABLE 19

TRANSITION MATRIX FOR ENGINEERING FROM COLLEGE GRADUATION TO ONE YEAR AFTER COLLEGE

	C_2	$\bar{C}_2$	
C_1	.870	.130	1.000
$\bar{C}_2$	.028	.972	1.000

However, when we examine variations across careers in individual stability, it is the case in our data that the correlation between $d_{C_1C_2}$ and the probability of loyalty (.879 for engineering) is almost perfect ($r = +.992$). Thus, although the individual stability should technically be considered to be the difference between the probability of loyalty and the probability of recruitment, for all practical purposes, it may be measured by the probability of loyalty alone. For a given career, the more stable it is the more loyalty it commands, and the correlation between loyalty and stability is almost perfect.

The probability of loyalty for each career is given in the diagonal cell of Table 20, which is a transition matrix for all twenty careers. The average probability of loyalty for the twenty careers is .682, with a standard deviation of .136. Least stable is educational administration with a probability of loyalty of .424, and most stable is medicine with a probability of loyalty of .901.

Let us consider the relation of the whole transition matrix (Table 20), to the more simple 4-fold transition matrices illustrated in Table 19. For each career, the probability of loyalty is given in the diagonal cell entry of the large matrix. The probability of defection is simply the sum of all the non-diagonal cells in the relevant <u>row</u> of the large matrix. In the case of engineering, the probability of defection, .130, can be found by adding all the non-diagonal cells in the engineering row of the table. It could also, of course, be found by simply subtracting the diagonal cell from 1.000.

TABLE 20

CAREER 1 TO CAREER 2 TRANSITION MATRIX

	Career	Vocational Education	Physical Education	Educational Administration	Teaching	Religion	History	Humanities	Social Science	Social Work
Educational	Vocational education . . .	52.9	1.8	11.7	3.9	-	-	-	-	-
	Physical education	.8	66.7	10.1	8.3	-	-	-	-	.3
	Educational administration	4.9	2.1	42.4	27.6	1.4	.9	.7	1.2	.7
	Teaching	.1	.8	8.8	59.5	1.8	3.1	4.3	1.5	.7
Humanistic	Religion	-	-	.1	5.6	84.4	.1	2.1	.6	1.0
	History	-	2.1	3.9	17.4	3.2	48.2	5.7	4.3	-
	Humanities	.1	-	.7	12.3	2.5	.1	66.3	1.6	.3
	Social sciences	-	-	.9	3.1	1.9	1.0	1.6	56.8	1.4
	Social work	4.2	1.4	-	2.1	2.1	-	-	6.3	56.6
Pragmatic	Journalism	-	.4	1.4	5.4	.7	-	6.8	1.4	-
	Law	.1	.2	.4	1.3	.5	.3	.8	2.7	.1
	Business	.9	.1	.9	.8	.3	-	.5	1.1	.2
	Military	-	.4	-	1.8	-	.4	.4	1.8	-
Scientific	Engineering	-	.1	.1	.3	-	-	.2	.1	-
	Physical sciences	.1	-	1.1	3.9	.2	.1	.3	.8	-
	Chemistry	-	-	-	1.2	.2	.2	.3	-	-
	Dentistry	-	3.1	-	3.1	-	-	-	-	.5
	Medicine	-	-	-	.9	-	.1	.6	.3	-
	Biological sciences . . .	-	-	.2	5.9	-	-	.2	1.5	.2
	Agriculture	-	-	.2	1.4	-	-	-	.4	-
	Not elsewhere classified .	.2	.4	2.6	3.6	.9	.4	3.1	5.2	1.3
	Per cent recruited over all	.4	.3	1.8	3.1	.6	.4	1.3	1.4	.4

TABLE 20--Continued

Journalism	Law	Business	Military	Engineering	Physical Sciences	Chemistry	Dentistry	Medicine	Biological Sciences	Agriculture	Not Elsewhere Classified	Total Per Cent	Weighted N
.3	.3	9.6	.9	6.0	-	-	-	-	.9	-	11.7	1.00	(333)
-	-	1.6	.5	.8	.3	-	-	-	1.1	1.1	8.5	1.00	(375)
-	.2	2.6	.7	.9	1.4	-	1.4	-	2.8	.2	7.7	1.00	(427)
.3	.4	3.8	.4	.5	3.5	.5	.1	.2	2.0	.2	7.8	1.00	(1,975)
-	.7	1.6	.1	.4	-	-	-	.4	-	-	2.6	1.00	(682)
.7	3.2	5.3	.7	-	.7	-	-	.7	-	-	3.9	1.00	(282)
3.5	.8	3.1	.5	.4	.5	-	-	.3	-	.8	6.3	1.00	(766)
.9	3.6	8.9	1.1	.4	.9	-	-	-	.4	.4	16.7	1.00	(699)
-	.7	11.9	.7	-	-	.7	-	-	-	2.1	11.2	1.00	(143)
59.9	2.5	11.8	-	2.5	.7	-	-	.4	-	-	6.1	1.00	(279)
.2	79.6	8.7	.4	1.3	.6	-	.1	.3	-	.1	2.4	1.00	(1,357)
.7	2.4	81.6	1.3	3.8	.5	.1	-	.1	-	.3	4.3	1.00	(5,380)
.4	1.8	19.6	58.0	5.1	.7	.4	.4	-	-	.4	8.7	1.00	(276)
-	.5	5.6	.7	87.0	2.1	.1	-	.4	.1	.3	2.4	1.00	(3,278)
-	.3	5.9	1.0	8.9	71.1	2.1	.1	.1	.7	.1	4.3	1.00	(1,168)
-	.2	1.5	.8	2.0	4.2	81.2	-	1.0	5.0	-	2.3	1.00	(600)
1.5	-	5.1	.5	.5	1.5	3.1	75.0	3.1	.5	-	2.6	1.00	(196)
-	1.5	.7	.1	.4	-	.3	.8	90.1	2.5	-	1.9	1.00	(1,050)
-	-	1.7	1.7	1.7	.7	1.0	-	5.9	70.7	3.0	5.4	1.00	(406)
-	1.2	7.1	.2	1.2	.2	-	-	-	6.0	77.0	5.2	1.00	(504)
.4	2.3	15.5	1.6	4.8	1.4	.3	.2	1.0	1.1	1.2	52.5	1.00	(2,229)
.4	1.4	6.5	.9	2.8	1.2	.3	.1	.4	.8	.4	4.9	..	..

N . . . . . . = 22,405
NA . . . . . = 1,551

Total N = 23,956

The probability of recruitment is found as the weighted average of the non-diagonal cells in the relevant <u>column</u> of the large matrix, the "weight" being the total number of cases in each row. In order to make this understandable, let us consider engineering. The probability of recruitment is .028. Examining the engineering column of the large matrix, we see that the probability of recruitment to engineering among those originally in vocational education is .060; among those originally in physical education, it is .008; and so on down to agriculture where the probability of recruitment to engineering is .012. The total probability of recruitment is, as indicated above, the weighted average of all these separate probabilities of recruitment from the various careers. The column entries of the large matrix thus show variations, by career, in the probability of recruitment to a given career. We shall make use of this fact in the subsequent analysis of patterns of movement among the careers.

The final cell of the simple 4-fold transition matrix is best found as 1.000 minus the probability of recruitment. It is the probability that a respondent not in the career at Time 1 is also not in it at Time 2. For engineering, this is:

$$1.000 - .028 = .972.$$

We have not presented the 4-fold transition matrices for each career because, as indicated above, they contain but one piece of information, the individual stability or turnover of the career. This piece of information is almost perfectly conveyed in the probability of loyalty to the career.

Stability and Career Predominance

As we have noted previously, variations in career stability are an important source of variation in career predominance. The correlation across careers between stability and career predominance is $r = +.75$ indicating that stability "explains" 56 per cent of the variance in career predominance. Those careers which are high in stability, for example, medicine, chemistry, and engineering, tend also to be high in career predominance.

The discussion of the previous section clarifies to some extent the relation between stability and career predominance. For those careers where loyalty is high and recruitment low, values have relatively less effect, while for those careers where loyalty is low and recruitment high, values have relatively more effect. We have noted previously that values generally have more effect upon recruitment than upon loyalty. This explains in part why values appear stronger for careers where recruitment is high.

In addition, for the more stable careers, loyalty to the career is high regardless of values, i.e., it is high among those with inconsistent values as well as among those with consistent values. This is not the case for careers which are low in loyalty. Consistent values thus appear to raise the probability of loyalty in careers where loyalty is generally low but do not raise the probability of loyalty in careers where loyalty is generally high. Medicine, for example, is so stable by college graduation that consistent values can do little to further increase the stability.

What we should like to know then is what factors apart from values produce career stability? While we cannot provide a complete answer to this question, we shall attempt a partial answer as we proceed.

Patterns of Movement among Careers

In addition to providing information on the stability of careers, the Time 1 to Time 2 career transition matrix, shown in Table 20, provides information on patterns of movement among the careers. As we shall see, these patterns of movement are strongly related to career predominance. More precisely, the clusters of careers within which movements are relatively frequent differ substantially in career predominance.

What we should like to know is whether certain careers are close together in the sense that movements occur relatively frequently between them. In other words, we want to determine the social distance between the various careers. In order to determine whether movements between two careers are relatively frequent or relatively infrequent, we need to define a model of random movement among careers. Then we will be in a position to say, for example, that movements from chemistry to physics are more frequent than would be expected by chance, or that movements from engineering to social work are less frequent than chance expectation.

Let us assume that at Time 2 each career has a certain number of vacancies to be filled by recruits. Assume further that the origin of the recruits is random, i.e., they are drawn by chance from among all those who were not originally in the career. It follows that recruitment is independent of career origin, or in other words, the probability of recruitment does not vary by Time 1 career. For example, of all those who were not in engineering at Time 1, 2.8 per cent have been recruited by Time 2. If recruitment occurs randomly, 2.8 per cent of each Time 1 career group will have been recruited to engineering. If recruitment is not random, some careers will contribute more than 2.8 per cent while others will contribute less than 2.8 per cent. The 2.8 per cent, in any case, is a weighted average of the percentage recruited from each Time 1 career other than engineering. Recruitment, in fact, is not random. While 8.9 per cent of the physical scientists change to engineering, virtually no social workers or historians change to engineering.

In Table 21, we have entered the difference between the observed percentage recruited to each career from every other career, and the percentage expected by chance. For example, the observed percentage recruited to engineering from physical sciences is 8.9 per cent, while the chance expectation is 2.8 per cent. The difference, or deviation score, is +6.1 indicating that physical sciences exceed chance expectation for recruitment to engineering by 6.1 percentage points.

It should be noted that these deviation scores are somewhat sensitive to the size of a career. For a large career, e.g., business, a relatively large proportion is recruited overall (6.5 per cent) and it is thus relatively easy to get variance in the deviation scores. For a small career, e.g., social work, a relatively small proportion is recruited overall (0.4 per cent) and it is relatively difficult to get variation in the deviation scores. While the deviation scores are somewhat sensitive to differences in career size, they are probably less sensitive than certain alternative measures. Notably they are less sensitive to size differences than the <u>ratio</u> of observed recruitment to recruitment expected by chance.

The deviation scores have been arranged, by inspection, into four empirical clusters. These clusters are set off by heavy lines in Table 21.

TABLE 21

CAREER MOVEMENT CLUSTERS

(Observed Minus Expected Percentage Recruited)

	Career--From:	To: Vocational Education	Physical Education	Educational Administration	Teaching	Religion	History	Humanities	Social Sciences	Social Work
Educational	Vocational education . .	-	+ 1.5	+ 9.9	+ .8	- .6	- .4	- 1.3	- 1.4	- .4
	Physical education	+ .4	-	+ 8.3	+ 5.3	- .6	- .4	- 1.3	- 1.4	- .1
	Educational administration	+ 4.5	+ 1.8	-	+24.5	+ .8	+ .5	- .6	- .2	+ .3
	Teaching	- .3	+ .5	+ 7.0	-	+ 1.2	+ 2.7	+ 3.0	+ .1	+ .3
Humanistic	Religion	- .4	- .3	- 1.7	+ 2.5	-	- .3	- .8	- .8	+ .6
	History	- .4	+ 1.8	+ 2.1	+14.3	+ 2.6	-	+ 4.4	+ 3.1	- .4
	Humanities	- .3	- .3	- 1.1	+ 9.2	+ 1.9	- .3	-	+ .2	- .1
	Social sciences	- .4	- .3	- .9	.0	+ 1.3	+ .6	+ .3	-	+ 1.0
	Social work	+ 3.8	+ 1.1	- 1.8	- 1.0	+ 1.5	- .4	- 1.3	+ 4.9	-
Pragmatic	Journalism	- .4	+ .1	- .4	+ 2.3	+ .1	- .4	+ 5.5	.0	- .4
	Law.	- .3	- .1	- 1.4	- 1.8	- .1	- .1	- .5	+ .3	- .3
	Business	+ .5	- .2	- .9	- 2.3	- .3	- .4	- .8	- .3	- .2
	Military	- .3	+ .1	- 1.8	- 1.3	- .6	.0	- .9	+ .4	- .4
Scientific	Engineering	- .4	- .2	- 1.7	- 2.8	- .6	- .4	- 1.1	- 1.3	- .4
	Physical sciences	- .3	- .3	- .7	+ .8	- .4	- .3	- 1.0	- .6	- .4
	Chemistry	- .4	- .3	- 1.8	- 1.9	- .4	- .2	- 1.0	- 1.4	- .4
	Dentistry	- .4	+ 2.8	- 1.8	.0	- .6	- .4	- 1.3	- 1.4	+ .1
	Medicine	- .4	- .3	- 1.8	- 2.2	- .6	- .3	- .7	- 1.1	- .4
	Biological sciences . . .	- .4	- .3	- 1.6	+ 2.8	- .6	- .4	- 1.1	+ .1	- .2
	Agriculture	- .4	- .3	- 1.6	- 1.7	- .6	- .4	- .13	- 1.0	- .4
	Not elsewhere classified	- .2	+ .1	- .8	+ .5	+ .3	.0	+ 1.8	- 1.0	+ .9

TABLE 21--Continued

To:												
Journalism	Law	Business	Military	Engineering	Physical Sciences	Chemistry	Dentistry	Medicine	Biological Sciences	Agriculture	Not Elsewhere Classified
- .1	- 1.1	+ 3.1	.0	+ 3.2	- 1.2	- .3	- .1	- .4	+ .1	- .4	+ 6.8
- .4	- 1.4	- 4.9	- .4	- 2.0	- .9	- .3	- .1	- .4	+ .3	+ .7	+ 3.6
- .4	- 1.2	- 3.9	- .2	- 1.9	+ .2	- .3	+ 1.3	- .4	+ 2.0	- .2	+ 2.8
- .1	- 1.0	- 2.7	- .5	- 2.3	+ 2.3	+ .2	.0	- .2	+ 1.2	- .2	+ 2.9
- .4	- .7	- 4.9	- .8	- 2.4	- 1.2	- .3	- .1	.0	- .8	- .4	- 2.3
+ .3	+ 1.8	- 1.2	- .2	- 2.8	- .5	- .3	- .1	+ .3	- .8	- .4	- 1.0
+ 3.1	- .6	- 3.4	- .4	- 2.4	- .7	- .3	- .1	- .1	- .8	+ .4	+ 1.4
+ .5	+ 2.2	+ 2.4	+ .2	- 2.4	- .3	- .3	- .1	- .4	- .4	.0	+11.8
- .4	- .7	+ 5.4	- .2	- 2.8	- 1.2	+ .4	- .1	- .4	- .8	+ 1.7	+ 6.3
-	+ 1.1	+ 5.3	- .9	- .3	- .5	- .3	- .1	.0	- .8	- .4	+ 1.2
- .2	-	+ 2.2	- .5	- 1.5	- .6	- .3	.0	- .1	- .8	- .3	- 2.5
+ .3	+ 1.0	-	+ .4	+ 1.0	- .7	- .2	- .1	- .3	- .8	- .1	- .6
.0	+ .4	+13.1	-	+ 2.3	- .5	+ .1	+ .3	- .4	- .8	.0	+ 3.6
- .4	- .9	- .9	- .2	-	+ .9	+ .2	- .1	.0	- .7	- .1	- 2.5
- .4	- 1.1	- 1.5	+ .1	+ 6.1	-	+ 1.8	.0	- .3	- .1	- .3	- .6
- .4	- 1.2	- 5.0	- .1	- .8	+ 3.0	-	- .1	+ .6	+ 4.2	- .4	- 2.3
+ 1.1	- 1.4	- 1.4	- .4	- 2.3	+ .3	+ 2.8	-	+ 2.7	- .3	- .4	- 2.3
- .4	+ .1	- 5.8	- .8	- 2.4	- 1.2	.0	+ .7	-	+ 1.7	- .4	- 3.0
- .4	- 1.4	- 4.8	+ .8	- 1.1	- .5	+ .7	- .1	+ 5.5	-	+ 2.6	+ .5
- .4	- .2	+ .6	- .6	- 1.6	- 1.0	- .3	- .1	- .4	+ 5.2	-	+ .3
.0	+ .9	+ 9.0	+ .7	+ 2.0	+ .2	.0	+ .1	+ .6	+ .3	+ .8	-

The interpretation of a career cluster is that movements between careers occur relatively frequently within the cluster, while they occur relatively infrequently between the clusters. The "educational" cluster consists of the four careers, vocational education, physical education, educational administration, and teaching. The "humanistic" cluster consists of the five careers, religion, history, humanities, social sciences, and social work. The "pragmatic" cluster consists of the four careers, journalism, law, business, and military service. Finally, the "scientific" cluster contains seven careers, engineering, physical sciences, chemistry, dentistry, medicine, biological sciences, and agriculture.

Inspection of Table 21 reveals first that the clustering procedure has not given exceptionally good results, i.e., there are many negative signs within clusters where one expects positive signs and there are many positive signs between clusters where one expects negative signs. Secondly, the results are uneven. The "educational" careers appear to cluster rather tightly while the "scientific" careers cluster quite loosely. The humanistic and pragmatic groups are intermediate in clusterability.

Table 22 provides a quantitative indication of how well the career clusters hang together. It reports the percentage of recruitment probabilities in excess of chance (i.e., the percentage of positive signs from Table 21) for movements from careers in the row clusters to careers in the column clusters. The upper left hand cell, for example, is derived as follows. There were twelve possible patterns of movement within the educational clusters (from vocational education to physical education, from vocational education to educational administration, and so on). Of these twelve possible moves, eleven or 92 per cent, occurred with recruitment probability greater than chance.

TABLE 22

CLUSTERABILITY OF CAREER CHANGES

(Per Cent of Recruitment Probabilities in Excess of Chance)

From Career in Cluster	To Career in Cluster			
	Educational	Humanistic	Pragmatic	Scientific
Educational	92 (12)	40 (20)	6 (16)	36 (28)
Humanistic	35 (20)	60 (20)	40 (20)	11 (35)
Pragmatic	25 (16)	20 (20)	67 (12)	14 (28)
Scientific.	11 (28)	6 (35)	18 (28)	36 (42)

The diagonal cells of Table 22 show that percentage of moves exceed chance <u>within</u> each of the four clusters. As we have said before, the figure is high (92 per cent) for the educational cluster, low (36 per cent) for the scientific cluster and intermediate (60 and 67 per cent) for the humanistic and pragmatic clusters.

Comparing the diagonal with the off diagonal cells, we see that movements within clusters generally exceed chance more often than movements between clusters. However, the "scientific" cluster makes a poor showing in this respect. Movements from the educational cluster to the scientific cluster exceed chance just as often as movements within the scientific cluster (36 per cent of the time). Most of this curious finding is accounted for by movements from the educational careers to biological sciences, all of which occur in excess of chance. We have no ready explanation for why this is the case.

Part of the reason for the poor clusterability of the scientific careers is that they are very stable. Other careers thus do not exert a very strong pull on the incumbents of scientific careers and movements from scientific careers do not exceed chance very often regardless of destination. In other words, while few movements exceed chance within the scientific cluster, still fewer movements exceed chance from the scientific cluster to other clusters.

It may be of some interest to examine Table 22 for between cluster movements which are especially unlikely to occur. Movements from educational to pragmatic careers occur rarely. Similarly movements from humanistic to scientific, from pragmatic to scientific, and from scientific to educational or humanistic careers are rare.

While the clusterability of career movements is far from perfect, movements generally, but, by no means always, tend to occur more often within clusters than between clusters.

To summarize the results of this analysis, movements between careers in the year following college graduation are not random. Rather, recruitment to a new career varies by career of origin. Patterns of movement among careers can be described, with some empirical justification as tending to occur within but not between four clusters of careers. These four clusters have been named educational, humanistic, pragmatic, and scientific.

Career Movement Clusters and Career Predominance

The four career movement clusters provide an empirical basis for classifying the careers into four groups. Table 23 gives the mean career predominance score for each of the clusters. It shows that the clusters vary considerably in the degree of career predominance. For the educational and humanistic careers, career choices and values appear about equally potent over time; for the pragmatic careers, career tends to be somewhat stronger than values and for the scientific careers, career tends to be considerably stronger than values.

TABLE 23

MEAN CAREER PREDOMINANCE BY CAREER MOVEMENT CLUSTER

		N
Educational. .	+.009	4
Humanistic . .	+.010	5
Pragmatic. . .	+.067	4
Scientific . .	+.133	7

In order to determine how much of the variance in career predominance is explained by the career movement classification, we have computed the correlation ratio, E^2, of career predominance on the career movement clusters.[1] The result, $E^2 = .625$, shows that career movement clusters explain 62 per cent of the variance in career predominance. This is slightly more than is explained by career stability.

Table 24 provides further clarification of this finding. It reports mean career effect and value effect scores separately for the four clusters. The educational careers tend to show modest effects of both careers and values with the net result of no career predominance. The humanistic careers tend to show strong effects of both types again with a net result of no career predominance. Pragmatic and scientific careers

[1]Walker and Lev, op. cit., pp. 276-278.

also tend to show strong career effects. However, pragmatic careers show modest value effects leading to a modest career predominance while scientific careers tend to show no value effects and thus strong career predominance.

TABLE 24

CAREER EFFECTS, VALUE EFFECTS, AND CAREER PREDOMINANCE BY CAREER MOVEMENT CLUSTER

(Mean Score for Cluster)

Career	Career Effect	Value Effect	Career Predominance
Educational	+.068	+.059	+.009
Humanistic.	+.139	+.140	+.010
Pragmatic	+.119	+.052	+.067
Scientific.	+.146	+.012	+.133

For humanistic, pragmatic, and scientific careers, the career effects remain uniformly strong and the only thing which varies is the value effect. The value effect is strongest for humanistic careers, modest for pragmatic careers and nonexistent for scientific careers. This generalization is weakened by the fact that educational careers tend to show weaker career effects than do the other clusters.

In sum, the career movement clusters explain much of the variation in career predominance. In general, this is because value effects are negligible for scientific careers, stronger for pragmatic careers and strongest for humanistic careers. We shall consider the reasons for this in more detail subsequently.

Graduate School Enrollment and Career Predominance

Our data refer to that segment of the career choice process which occurs in the first year following college graduation. Probably the most important aspect of the career choice or change process at this point in a young man's life is the decision either to attend graduate or professional school, or to enter the labor market directly. Careers, of course, differ in the extent and nature of post graduate training they require. Business careers, for example, can be entered directly while for medical careers, the educational preparation has just begun. In view of the importance of graduate school enrollment in implementing career decisions, we shall want to consider at this point what relation graduate school enrollment has to the relative strength of career and value effects.

Table 25 shows the relation, taking careers as the unit of analysis, between the proportion enrolled in graduate school and the measures of career effect, value effect, and career predominance. The twenty careers have been divided into three groups on the basis of the proportion who enrolled in graduate school one year after college graduation. The "high" enrollment careers are medicine, dentistry, religion, law, biological sciences, social sciences, and physical sciences. The average percentage enrolled for these seven careers is 73 per cent, ranging from 90 per cent for medicine to 62 per cent for physical sciences. The "medium" enrollment careers are chemistry, humanities, history, vocational education, educational administration, teaching, and engineering. The average percentage enrolled for these seven careers is 50 per cent, ranging from 60 per cent for chemistry to 36 per cent for engineering. Finally, the "low" enrollment careers are social work, physical education, journalism, agriculture, business, and military service. The average percentage enrolled for these six careers is 24 per cent, ranging from 36 per cent for social work to 9 per cent for military service.

TABLE 25

CAREER EFFECTS, VALUE EFFECTS, AND CAREER PREDOMINANCE BY GRADUATE SCHOOL ENROLLMENT

(Mean Score on Indicated Measure)

Enrollment	Mean Per Cent Enrolled	Career Effect	Value Effect	Career Predominance	N Careers
High.	73%	+.154	+.041	+.113	7
Medium.	50	+.113	+.066	+.047	7
Low	24	+.100	+.072	+.028	6

Table 25 shows a substantial relation between the proportion enrolled for graduate study and the measures of career effects, value effects, and career predominance. As enrollment declines, career effects decline while value effects increase. The net result is a strong decline in career predominance as enrollment decreases. It thus appears that for careers where the career decision is most often implemented by graduate training, career effects are relatively strong, and value effects are relatively weak; while for careers where the career decision is implemented by entry into the labor market after college, the career effects are not as strong, the value effects are relatively stronger, and the net result is roughly equal potency for career and value effects.

How important is graduate school enrollment to career predominance? The correlation across careers between the proportion enrolled and the career predominance measure is $r = +.45$ indicating that enrollment explains 21 per cent of the variance in career predominance. This is rather less variance than is explained by career movement clusters, or by career stability. In addition, the contribution to explained variance made by enrollment is not independent of the variance explained by career movement clusters and by career stability. The careers which are high in enrollment tend to be the scientific careers and also tend to be the more stable careers.

In order to further clarify the importance of graduate school enrollment, we divided our entire sample of young men into two groups, those who were enrolled in graduate school and those who were not enrolled in graduate school one year after college. We then computed, for each group separately, the career effect, value effect, and career predominance measures for each of the twenty careers. The results of these computations are summarized in Table 26. It reports the average across the twenty careers for the career effect, value effect, and career predominance measures and for those zero-order associations entering into their computation.[1]

The first five rows of Table 26 refer to the zero-order associations used in computing career effect and value effect measures. The sixth and seventh rows are the career and value effect measures and the eighth row, obtained by subtracting the value effect from the career effect, is the career predominance measure.

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[1]Expected values and partial cross-lagged associations were first computed for each career and the average then taken. The reader is cautioned that the average zero-order associations cannot be used to compute average partial associations since the product of means is not in general equal to the mean of products.

TABLE 26

RELATIVE STRENGTH OF CAREERS AND VALUES
BY GRADUATE SCHOOL ENROLLMENT

(Means for Twenty Careers)

Measure	(1) Total Sample	(2) Enrolled	(3) Not Enrolled	(4) (2)-(3)
Time 1 association	.277	.290	.248	+.042
Career stability	.682	.708	.580	+.128
Value stability	.343	.350	.330	+.020
Career ⟶ value cross-lag . . .	.222	.232	.194	+.038
Value ⟶ career cross-lag . . .	.245	.245	.257	-.012
Career effect	.123	.128	.112	+.016
Value effect	.059	.040	.113	-.073
Career predominance	.064	+.088	-.001	+.089
Name of careers where career effect is stronger	14	18	13	+5
Total careers	20	20	20	
Weighted N	22,057	9,354	12,703	

The first column gives the results for the total sample and is taken from Table 13. The second and third columns give the results for the enrolled and non-enrolled respectively. The fourth column gives the difference between the results for the enrolled group and the not enrolled group and shows the degree to which results are specified to one or the other group.

Table 26 shows that on the average career predominance is greater among those young men who are enrolled in graduate school. Among those who are enrolled, career effects exceed value effects, on the average, by 9 percentage points while for those who are not enrolled, career effects and value effects are, on the average, equally potent. Among the enrolled, career effects are predominant over value effects for eighteen of the twenty careers while among those not enrolled, career effects predominate for only thirteen of the twenty careers.

Table 26 further shows that the reason for greater career predominance among the enrolled is because of weaker value effects. While career effects are, on the average, about equally potent for the two groups, value effects on the average, are seven percentage points weaker among those who are in graduate school. Examination of the zero-order associations entering into the career and value effect measures shows that, mathematically, value effects are weaker among the enrolled primarily because career choices are more stable in graduate school than they are in the labor market.

Values then play a relatively greater role in the career changes of those who enter the labor market directly from college. This finding is either the effect or the cause of greater career choice stability among those who implement career plans through graduate training. One possible explanation is that graduate training creates a barrier to career change. For those who have enrolled in a particular graduate field, it is somewhat difficult to transfer to yet another field, particularly if the previous training is not appropriate to the new field. For those not in graduate school, the barriers to change will not be so great, assuming, of course, that the change does not require one to go to graduate school. Where barriers to change are greater, the effect of values upon change will be less. Conversely, where change is not constrained through graduate school enrollment, values are free to play a greater role.

Another way to put the matter might be that instead of being a <u>barrier</u> to career change, graduate school enrollment provides a <u>protection</u>

against change. The vicissitudes of the labor market might well produce unexpected abandonment of a planned career if, for example, no immediate job were available in that career. At that point, values might well play a part in the selection of an alternate career. In any case, to the extent that factors other than values act to increase the stability of career plans, the effects of values upon those plans will be lessened. Graduate training is one such factor.

Our analysis, at the individual level, of the effects of graduate enrollment supports the previous analysis at the career level. First, we found that in careers which required graduate training, value effects were relatively weak. We then found that for individuals who enroll in graduate school, value effects are also relatively weak. The additional analysis at the individual level not only reinforces the previous finding but also gives some insight into the mechanics of the relationship inasmuch as the career level finding is due, at least in part, to the individual level finding. We turn next to a consideration of academic ability in relation to career and value effects.

Academic Performance and Career Predominance

It has been empirically established that careers vary in the average level of general ability possessed by their incumbents. Medicine and the physical sciences, for example, tend to have more talented people while social work, business, and education have less talent. A rough indicator of talent employed by James A. Davis[1] in the primary analysis of the college senior study data is the "Academic Performance Index" (API). This index is based upon

[1] Davis, Great Aspirations.

college grade point averages corrected for school quality. Corrections are based upon the assumption that mediocre grades at top quality schools are the equivalent of top grades at mediocre schools.[1]

For the present analysis, we have dichotomized the index into "high" and "low" API groups. As expected, there is considerable variation across the twenty careers in proportion who score high in API. At one extreme, among those choosing medicine, 84 per cent are high in API while at the other extreme among those choosing physical education, only 25 per cent are high in API.

Table 27 shows the relation, taking careers as the unit of analysis, between the proportion high API and the measures of career effects, value effects, and career predominance. The twenty careers have been divided into three groups on the basis of the proportion of high API. The careers with most high API people are medicine, social sciences, humanities, history, physical sciences, law, and chemistry. The average percentage high API for these seven careers is 70 per cent. The range is from 84 per cent for medicine to 63 per cent for chemistry. The careers intermediate in proportion high API are engineering, biological sciences, religion, journalism, teaching, vocational education, and business. The average percentage high API for these seven careers is 50 per cent with a range from 56 per cent for engineering to 45 per cent for business. The lowest API career fields are educational administration, military service, agriculture, dentistry, social work, and physical education. The average percentage high in API for these six careers is 38 per cent, ranging from 42 per cent for educational administration to 25 per cent for physical education.

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[1]For details of the measurement of school quality and construction of this index, see _ibid._, pp. 256-268.

TABLE 27

CAREER EFFECTS, VALUE EFFECTS, AND CAREER PREDOMINANCE BY ACADEMIC PERFORMANCE LEVEL OF CAREERS

(Mean Score on Indicated Measure)

Percentage High API	Mean Per Cent High API	Career Effect	Value Effect	Career Predominance	N Careers
63-84	70	+.163	+.078	+.087	7
45-56	50	+.101	+.037	+.064	7
25-42	38	+.103	+.062	+.040	6

Referring to the career predominance column, there appears to be some relation, though not a large one, between the API composition of a career and the degree of career predominance. Those careers with many high API people tend also to be high in career predominance. The career and value effect columns of Table 27 show only that career effects are stronger for the highest API fields. The value effect measure does not vary monotonically with API. In general, API does not appear to have a strong or systematic relation to career and value effects. The correlation across careers between the percentage high API and the degree of career predominance is in fact only r = +.31. In other words, API composition explains only 9 per cent of the variance in career predominance, less than any of the other factors considered so far.

Despite the low correlation at the career level between API composition and career predominance, it is known that high API individuals make somewhat more stable career choices than low API individuals. Accordingly, we decided to examine the influence of API at the individual level as well. The total sample was divided into two groups of high and low API respectively, and the career effect, value effect, and career predominance measures were computed separately for each group and for each of the twenty careers. The average results across careers are summarized in Table 27.

Table 28 shows that the control for API at the individual level has no effect on our average measures of career effects, value effects, or degree of career predominance. The career effects, like the value effects, are equal in magnitude for high and low API groups and do not differ noticeably from the results for the total sample. For the total sample fourteen of the twenty careers showed stronger career effects than value effects. When high and low API individuals are considered separately, it is still the case that for each API group fourteen of the twenty careers show stronger career effects. This is another indication that the control for API has no effect on the results.

TABLE 28

RELATIVE STRENGTH OF CAREERS AND VALUES BY ACADEMIC PERFORMANCE INDEX

(Means for Twenty Careers)

Measure	(1) Total Sample	(2) High API	(3) Low API	(4) (2)-(3)
Time 1 association	.277	.284	.242	+.042
Career stability	.682	.706	.643	+.063
Value stability	.343	.360	.308	+.052
Career ⟶ value cross-lag	.222	.228	.194	+.034
Value ⟶ career cross-lag	.245	.264	.213	+.051
Career effect	.123	.124	.116	+.008
Value effect	.059	.068	.060	+.008
Career predominance	.064	.056	.056	.000
Number of careers where career is stronger	14	14	14	0
Total careers	20	20	20	
Weighted N	22,057	11,647	10,410	

Examination of the average zero-order associations used in computing career and value effects shows a slight specification. Namely, all the zero-order associations are slightly larger among high API individuals than among low API individuals. The net effect of this is nil. When all relevant associations are raised, the career and value effect measures do not change. Thus, while career choices are slightly more stable among the high API respondents, so are value patterns and all the other associations for that matter.

API has thus proved to be an unimportant factor so far as the relative strength of careers and values is concerned. API composition explains only 9 per cent of career variance in the relative strength of careers and values, and a control for it at the individual level does not modify our findings in any way.

Prestige and Career Predominance

The final factor we shall consider in our effort to understand career variations in career predominance is prestige. When one considers that we are dealing with the career plans of a college graduate population, the prestige of careers that are chosen will be high and fall within a narrow range as compared to the prestige of all occupations in society. In other words, virtually all our respondents are choosing high prestige careers and we cannot expect too much career variance in prestige.

In attempting to assign prestige ratings to the career choice categories, we were faced with a serious problem of poor matching between our categories and the occupational titles which have been used in empirical studies of occupational prestige. The most commonly used list of occupational prestige ratings is derived from the North-Hatt study of occupational prestige conducted by the National Opinion Research Center in 1947.[1] Although it is the most complete list extant, the North-Hatt study rates only ninety occupational titles.

Otis Dudley Duncan[2] has extended the NORC list by preparing regression estimates of NORC prestige scores for occupational titles in the census detailed list. Duncan used the education and income composition of occupations to estimate, by multiple regression, NORC prestige scores for titles common both to the NORC list and the census detailed list. He obtained a multiple correlation of R = .91, indicating very satisfactory estimates.

We attempted to find some sort of match to our career categories either from the NORC list or from the census detailed occupation list, whichever seemed closer. For those careers which more or less matched NORC titles, we used the NORC prestige score. For those careers which more or less matched census titles, we used Duncan's regression estimate of the NORC prestige score. The results of this procedure are given in Table 29. It will be noted that we were able to find matching titles for only fourteen of the twenty careers and that even among the fourteen, the matches are in some cases rather poor.

Prestige ratings for our careers range from 93 for medicine to 70 for agriculture, a range of 23 points, as compared to the range 96 to 33, or 63 points, for the NORC list as a whole. Thus, as we said, we have a restricted range of high status careers. Nonetheless, there is some variation in the

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[1] The results of this study can be found in Albert J. Reiss, Jr., Occupations and Social Status (Glencoe, Illinois: The Free Press, 1961).

[2] Ibid., pp. 109-161.

TABLE 29

PRESTIGE RATINGS FOR CAREER CHOICE CATEGORIES

Career	Matching Title(s)	Source*	NORC Prestige Score**
Medicine.	"Physician"	NORC	93
Physical sciences . .	Average of "Scientist," "Nuclear Physicist"	NORC	88
Chemistry	"Chemist"	NORC	86
Law	"Lawyer"	NORC	86
Dentistry	"Dentist"	NORC	86
Religion.	Average of "Minister," "Priest"	NORC	86
Engineering	Average of ten census "Engineers" specialities	Census	84
Social sciences . . .	"Social scientist"	Census	82
Biological sciences .	"Biologist"	NORC	81
Military service. . .	"Captain in the Army"	NORC	80
Teaching.	"Public-school teacher"	NORC	78
Social work	"Social and welfare workers"	Census	75
Journalism.	Average of "Radio announcer," Newspaper columnist," "Reporter on daily newspaper"	NORC	73
Agriculture	"Foresters and conservationists"	Census	70
Vocational education.	No matching title		
Physical education. .	No matching title		
Educational administration. . .	No matching title		
History	No matching title		
Humanities.	No matching title		
Business.	No matching title		

*NORC = North-Hatt occupational titles, census = Census detailed occupation titles.

**Where the source is "NORC" the NORC prestige scores are reported. Where the source is "Census" Duncan's <u>estimate</u> of the NORC prestige scores are reported.

prestige ratings and for the fourteen careers with ratings, we computed the correlation between prestige and career predominance. The correlation is substantial (r = +.74) indicating that for these fourteen careers, prestige explains 55 per cent of the variance in career predominance.

Table 30 illustrates this finding further. We have divided the fourteen careers for which there are prestige scores into two groups of high and low prestige respectively. The average prestige score for the high prestige careers is 87, ranging from 93 for medicine to 84 for engineering. The average prestige score for the low prestige careers is 77, ranging from 82 for social sciences to 70 for agriculture. For the high prestige careers, career effects are, on the average, strong while value effects are nil giving a high average career predominance score. For the low prestige careers both career and value effects are modest with the net result that careers and values appear about equally potent.

TABLE 30

CAREER EFFECTS, VALUE EFFECTS, AND CAREER PREDOMINANCE BY PRESTIGE OF CAREERS

(Mean Score on Indicated Measure)

Prestige	Mean Prestige Score	Career Effect	Value Effect	Career Predominance	N Careers
High.	87	+.175	+.024	+.152	7
Low	77	+.086	+.065	+.021	7

Prestige, then, appears to be an additional factor which is strongly related to career and value effects. Not only are value effects weaker for the high prestige careers but also, for high prestige careers, there seems to be a strong tendency for values to change in the direction of consistency with career choices.

Summary of Factors Related to Career Predominance

Before attempting a more substantive explanation of why career and value effects vary by career, let us summarize the foregoing analyses of sources of variance in career predominance. We have considered five factors, namely, career movement clusters, career stability, prestige, the graduate school enrollment composition of careers, and the academic performance composition of careers. The percentage of variance in career predominance explained by each factor has been computed and entered in Table 31. The career movement clusters explain 62 per cent of the variance; career stability, 56 per cent; prestige, 55 per cent; graduate enrollment composition, 21 per cent; and academic performance composition, 9 per cent.

TABLE 31

FACTORS RELATED TO CAREER PREDOMINANCE

Factor	Explained Variance (r^2)
Career movement clusters	62%
(Career stability)	(56)
Prestige	55
Graduate enrollment composition. . .	21
Academic performance composition . .	9

With respect to career stability, the fact that it is related is partly artifactual since it enters into the computation of career predominance. Stability is related to career predominance for a particular career by definition.

However, the fact that career stability is so strongly related to <u>variation by career</u> in career predominance is not artifactual. Career stability varies more by career than do any of the other associations entering into the computation of career predominance, i.e., career stability varies more than value stability, or either cross-lagged association between careers and values.

Of the other factors, the career movement clusters and prestige appear to be quite important, while graduate enrollment composition is less important and academic performance composition can be disregarded.

It is apparent that these factors do not contribute independently to the variance in career predominance. They are related, although not perfectly, to one another. Scientific careers, for example, tend to be stable, high in prestige, and high in graduate school enrollment, while educational and humanistic careers are unstable, low in prestige, and low in graduate school enrollment.

The precise computed percentages of variance explained should be taken with a large grain of salt. We have only twenty career choice categories and an N as small as twenty gives considerable unreliability in measures of correlation. Moreover, when prestige is considered, the number of careers is further reduced to fourteen. Because of this and because the career movement clusters involve the correlation ratio rather than the correlation coefficient, we do not feel that a precise estimate of the total amount of variance explained by the several factors in combination is warranted, nor do we feel that estimates of the independent or relative contributions of the factors would be warranted.

We do feel justified in asserting that career movement clusters, career stability, prestige and graduate school enrollment explain much of the variance in career predominance.

In addition to the factors discussed in the present chapter, we noted in the previous chapter that career predominance is related, in part, to what value patterns are involved. The careers which were classified as showing "mutual effects," i.e., exhibiting strong value effects as well as strong career effects, involve the value patterns of people orientation in combination with intellectualism or to a lesser extent people orientation alone. Career predominant careers, by contrast are more likely to involve intellectualism alone, or one of the enterprise patterns. One possible explanation is that values involving helping others are more potent in their effects than values involving helping oneself. The effect of value content is certainly not independent of career movement clusters and a control for career movement cluster would eliminate most of this effect. In other words the humanistic and educational career clusters tend to show relatively strong value effects and these clusters involve people orientation and intellectualism. The scientific cluster by contrast involves intellectualism alone or intellectualism with enterprise. The pragmatic careers tend to involve enterprise.

Since the career movement clusters differ in training requirements, expected income, and prestige, the relation of value content to career predominance may well be spurious.

What Produces Career Predominance?

At this point, it is time to begin a more substantive discussion of the implications of what has been found. We have found that the nature of the relationship between career choices and values varies by career and in the present chapter, we have identified a number of other characteristics of careers which appear to be related to that variation. We have so far largely deferred discussion of mechanisms explaining these relationships. Where careers are more stable, values have less effect. Why is this the case? Why do values have little effect for scientific careers and more effect for educational and humanistic careers? Why do values have relatively less effect for high prestige careers? Why do values have less effect for careers which require graduate training and for persons in graduate school? It may be the case that, more than anything else, it is the role of specialized preparation in the career choice process that explains most of our findings. For those careers and in those circumstances where a greater investment of time and energy in proportion is required, values appear to have less effect over time.

Rosenberg[1] noted a related phenomenon in his 1952 study of Cornell graduates. He found that careers that were more stable over time required on the whole more specialized undergraduate preparation. He argued that when a person makes a substantial "investment" of time and energy in preparing for a career such as medicine or engineering, he is motivated not to change his plans because the change would be too costly. The investment of time and energy would be, in a sense, wasted.

This argument bears not only on career variations in stability but also on variation in the nature of the relationship between career choices and values. The individual who has prepared himself for medical school through an undergraduate premedical course of study is unlikely to "waste" this preparation because of little desire to help people. The prospective social worker, on the other hand, who has little investment in specialized preparation is inclined to abandon social work for a field more congenial to his preferences when he recognizes that he has little desire to help people.

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[1]Rosenberg, op. cit., pp. 63-66.

In addition to reducing motivation to leave, specialized preparation also creates a barrier to entry into a field. A person's values may be perfectly consistent with a medical career, but if he lacks the requisite preparation, he cannot enter medical school regardless of personal preferences. Such a person would find it considerably easier, however, to enter fields such as social work or teaching if his values inclined him in that direction.

An important aspect of specialized preparation is the degree to which preparation can be transferred from one career to another. We know, for example, that when a person leaves medicine, his new career field is not chosen randomly. While it may be influenced by his values and interests, over and above the effects of value inclinations are the limitations imposed by the training. Defectors from medicine are especially likely to be recruited to biological sciences or to dentistry. The reason for this most probably is the fact that premedical training is also appropriate for biological sciences and dentistry. Training can be transferred to these fields without the same degree of waste that would be entailed if a defector from medicine were to enter, say, social work or teaching.

Let us consider how specialized preparation relates to patterns of movement among careers. There are two aspects to this. First similarity of preparation is probably what causes movements within career clusters to be more common than movements between clusters. Secondly, the career movement clusters vary in the amount of specialized preparation they require.

Regarding similarity of preparation within clusters, humanities and social science students, as an example, will have had many of the same courses in college. Physicists and engineers will also have had many of the same college courses. But the social scientists and humanists on the one hand will have had different courses than the physicists and engineers on the other. Because of such similarity in training, movements can occur relatively frequently between social sciences and humanities and between physics and engineering but movements from the humanistic careers to the scientific careers and vice versa occur only infrequently.

The principle by which we arranged the careers into the four clusters, educational, humanistic, pragmatic, and scientific, was the frequency of movement between careers. We arranged the clusters so that movements within clusters would be relatively frequent while movements between clusters would be relatively infrequent. We then considered what the careers within a cluster have in common that produces relatively frequent movement. The answer seems to be transferability of preparation activities from one career to another within the clusters.

How does this relate to the relative strength of career and value effects? The greater the variance in career choice that is explained by specialized preparation, the less variance remains to be explained by values. In other words, when a young man defects or is forced to defect from a career after graduating from college, his investment in specialized preparation while in college acts as a constraint on his freedom to choose a new career in accordance with his values or interests. He, in fact, is heavily constrained to choose a new career which does not require substantially different preparation than he has already had. Thus, defectors from physics move to engineering but not to the social sciences, and defectors from medicine move not to social work but to biological sciences.

Regarding variations from cluster to cluster in the amount of specialized preparation required, we suggest that scientific careers usually require the most specialized preparation while the other career clusters require less. Where specialized preparation is greater, as it is for the scientific careers, barriers are created both to exit and entry. With respect to exit from a scientific career, the cost in terms of wasted time and energy if a change were to be made acts as a barrier to leaving. With respect to entry, a person lacking the requisite preparation simply cannot get in. In the educational and humanistic careers, undergraduate specialization is not so great and less is lost if a person leaves one of these fields. Moreover, since the requisite training is less, entry is easier.

These considerations provide a plausible explanation for variations in value effects and hence in career predominance. Where the investment in preparation is greater, it is difficult for a person to leave even if his values are inconsistent with the career. Also where a person lacks the requisite preparation for entry, he cannot get in even if his values are perfectly consistent with the career. Thus, value effects will be less for those careers which require more specialized preparation.

Among the costs associated with exit from the scientific careers to the non-scientific careers is loss not only of time and energy, but of future expected earnings as well. The investment of time and energy in specialized preparation is important in relation to the future rewards it may be expected to bring. Thus, if a young man leaves physical sciences for teaching his preparation my be transferable to teaching, but he is nonetheless incurring a cost in terms of future income foregone. The prospect of such a loss reduces the tendency such a person might otherwise have to seek a career more consistent with his values.

Further evidence bearing on the importance of specialized preparation is provided by our findings on graduate school attendance. Attendance at graduate school is one indicator, although by no means the only indicator, of specialized career preparation. Graduate training represents a substantial investment of time and energy devoted to a particular field by those who enroll. At the same time, graduate training requirements act as a barrier against the entry of those not originally in the field. We found that for careers where graduate school enrollment was more common, value effects were less and career effects correspondingly greater. Similarly, value effects were less among individuals who enrolled in graduate school than among individuals who entered the labor market directly. The findings again suggest that specialized training, by acting as a barrier to career change, reduces the effect that values have upon that change.

Finally, we have to consider the relation of prestige to the relative strength of careers and values. This may also reflect the importance of specialized preparation. It will generally be conceded that higher prestige careers require more training for entry. Some theorists would even argue that the reason why some occupations are higher in prestige than others is that they require some training for entry.

Another possibility worthy of some consideration is that the desirability of a high prestige career is a value which, while not expressed, is somehow more universally accepted and important than other occupational values. If one asks a group of young children what they plan to do for their life's work,[1] the answers will be unrealistic in the sense that far more children choose high prestige professional occupations than will ever end up

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[1] See Roe, op. cit., for a review of studies on the occupational choices of children.

practicing in those occupations. By high school, the occupational choices will have become more realistic but high prestige professions will still be overchosen. College freshmen, while more realistic yet, still overchoose the professions and during college a net shift away from medicine, law, and the physical sciences into less prestigious fields is found.[1] Our own data suggest that by the end of college the distribution of career choices has finally become realistic in the sense that it has stabilized and is being realistically implemented.

If we view career choice as a continuous process occurring from the time of childhood on, it is apparent that the distribution of career plans continues to become more realistic because many who originally aspired to high prestige occupations are washed out somewhere along the line. Some are washed out because they failed to go to college, some change fields while in college, and some do not go to graduate school.

Although overchoosing of prestigious careers is a well known phenomenon, we have the anomalous finding that college students do not rank the desire for prestige very high among their expressed values. Rosenberg,[2] for example, found that prestige ranked ninth in expressed importance among ten occupational values. Moreover, those who do express an interest in prestige are not especially likely to enter the most prestigious careers, e.g., medicine or the physical sciences. Is, then, the desirability of high prestige occupations so basic that it need not be expressed?

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[1]Davis, Undergraduate Career Decisions.

[2]Rosenberg, op. cit.

If this is the case, then the desirability of high prestige occupations is another factor apart from specialized preparation which reduces the effects of values upon career plans for certain careers. There is relatively little recruitment to high prestige careers since they are originally overchosen and the net flow of movement is out rather than in. Hence on the recruitment side, there is relatively little for values to operate upon. Regarding loyalty, the loyalty to high prestige careers may well be so high in the first place that consistent values can do little to raise it. In any case, whether because of specialized preparation or because of intrinsic desirability, the high prestige fields are more stable and values thus are a less important determinant of career plans than they are for the low prestige fields.

In sum, many of our findings can be understood as due to the effects of special preparation upon the career choice process. Specialization introduces a realistic constraint on an individual's freedom to leave a career which is inconsistent with his values and acts as a barrier to his freedom to enter a field which is consistent with his values.

Conclusions

We should like to make two additional points which are rather speculative and carry us beyond the data which have been presented here. The first concerns freedom of occupational choice and the second concerns the ability of people to adjust to their occupational circumstances.

Many of our findings suggest that a person's value orientations affect his occupational choices when he is free to choose the occupation he pleases. To the extent that various external factors impose constraints upon a person's freedom to choose or change his career as he pleases, the effect of personal interests, values, or orientations upon the choice is lessened. Values, in short, affect career decisions when there is freedom of career choice.

It is interesting that when a student prepares himself through specialized training to pursue a particular career path, he tends to close off alternative career paths. In this sense, the investment of time and energy made in career preparation limits one's future freedom of action. A paradoxical aspect of the situation is that for the careers which are highest in prestige, those which are, presumably, the most universally desirable, the constraints upon people's freedom to act in accordance with their values appear greatest. The incumbent of a career like medicine is, in a sense, trapped by the very strenuous efforts he has made to put himself in that position. He can decide to leave only at great personal cost. Our data show that the tendency is not to pay the cost.

However, one would be wrong to infer on the basis of our findings that for people at the bottom of the occupational hierarchy values are a strong determinant of career choice. Efforts to construct tests of vocational interests which discriminate among blue collar occupations have generally failed, suggesting that interests are not particularly related to allocation among blue collar jobs. The crucial factor is not the occupational prestige itself but rather how prestige relates to freedom of occupational choice and hence to choice in accordance with values.

Studies of job choice among blue collar workers suggest that little freedom of choice in the sense of selection among alternatives is involved for those at the bottom of the occupational hierarchy.[1] Blue collar workers

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[1]See Seymour Lipset, R. Bendix, and F. T. Malm, "Job Choice and Entry into the Labor Market," in Sigmund Nosow and William H. Form (eds.), Man, Work and Society (New York: Basic Books, 1964), pp. 297-306.

generally take the first job they hear about without knowing of any other alternatives. Most often the job is heard about through friends or relatives. Thus values have little to do with the process of occupational choice for those at the bottom of the hierarchy.

As one moves up the occupational hierarchy to those careers which are chosen by college graduates, values do have an influence on career choice, but the influence is less at those times and for those careers where other constraints are imposed upon freedom of choice. Carrying this further, it would be reasonable to predict that for stages of the career choice process earlier than college graduation, the effects of values upon career plans would be greater than they appear in the present study. In high school, values might be a strong determinant of career plans, becoming progressively weaker through college as the individual accumulates a greater and greater investment in specialized preparation. Some years after college, values might have even less influence than they appear to have in this study being by that time strongly determined by the individual's actual involvement in occupational activity.

The final point we wish to make concerns people's adjustment to occupational circumstances. Our data show that for most careers, career effects are more potent than value effects. Career effects are particularly strong for the high prestige scientific cluster of careers where value effects are practically nil. This shows a strong tendency for people's values and interests to change in the direction of consistency with career plans. For the high prestige, or scientific, or "career predominant" careers, this tendency compensates for relatively weak value effects with the net result that a high correlation is maintained between career choices and values.

Thus, scientists are as likely to have consistent values as are humanists, or educationists. But the process or nature of the relationship is different. The scientists tend to change their values to fit career choices while the humanists are not so likely to change values and more likely to change careers.

In general, consistency is maintained between career choices and value dispositions. Under circumstances where career change is too costly a solution to inconsistency, people tend to adjust by changing their values. Where it is difficult for people to change careers, people tend to change themselves. People adjust.

Fron one theoretical perspective, it might be argued that if inconsistency between a person's career plans and his values were too great, he would experience "cognitive dissonance."[1] It is assumed that a person will act so as to avoid or reduce dissonance. Failure to perceive inconsistency is one solution. Another is to change career plans making them consistent with values. Still another solution is to change values making them consistent with the career choice. What we have is the rather mundane finding that where career change is difficult, values tend to change instead.

In closing, the reader is cautioned that the discussion in the latter part of this chapter has been speculative. The discussion hopefully puts the findings in some perspective and points in one or two directions where more research is needed.

Our major objective has been to clarify the empirical nature of the relationship between career choice and occupational values. The most important of our findings in this regard are, in summary:

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[1]Leon Festinger, A Theory of Cognitive Dissonance (Stanford, California: Stanford University Press, 1957).

1. In the year following college graduation, career choices are stronger than values for most careers.

2. There are, however, variations by career in the relative strength of career and value effects.

3. These variations are related to career stability, patterns of movement among careers, prestige of careers, and graduate training requirements.

4. The general explanation for these findings may be that where specialized career preparation is greater, values have less effect because specialized preparation acts as a barrier to career change.

APPENDIX A

DETAILED CAREER TITLES SUBSUMED UNDER EACH OF TWENTY-ONE CAREER CHOICE CATEGORIES

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DETAILED CAREER TITLES SUBSUMED UNDER EACH OF TWENTY-ONE CAREER CHOICE CATEGORIES

<u>Business</u>

Industrial and Personnel Psychology
Advertising, Public Relations
Accounting
All other Business and Commercial Fields (Business Administration, Marketing, Insurance, Finance, Industrial Relations, etc.)
Secretarial Science

<u>Engineering</u>

Aeronautical
Chemical
Civil
Electrical
Engineering Science
Industrial
Mechanical
Metallurgical
Mining
Other Engineering

<u>Teaching</u> (Junior College, College, and University Teaching are coded by field of specialization)

Elementary Education
Secondary English
Secondary Modern Foreign Languages
Secondary Latin, Greek
Secondary History, Social Studies
Secondary Natural Science
Secondary Mathematics
Music Education
Art Education
Other Education

Law

Law

Physical Sciences

Astronomy, Astrophysics
Physics
Geography
Geology, Geophysics
Oceanography
Metallurgy
Meteorology
Mathematics, Statistics
Other Physical Science

Medicine

Medicine

Humanities

Humanities
Fine and Applied Arts
English, Creative Writing
Classical Languages
Modern Languages
Philosophy

Social Sciences

Educational Psychology
Social Psychology
Experimental and General Psychology
Other Psychology
Anthropology, Archeology
Economics
Area and Regional Studies
Political Science, Government, International Relations
Sociology
Other Social Science

Religion

Theology, Religion

Chemistry

Chemistry

Agriculture

Agricultural Sciences
Forestry, Fish, and Wildlife Management
Farming

Biological Sciences

Anatomy
Biology
Biochemistry
Botany and Related Plant Sciences
Biophysics
Entomology
Genetics
Microbiology
Pathology
Pharmacology
Physiology
Zoology
Other Biological Science

Educational Administration

Educational Administration and Supervision

Physical Education

Physical Education, Health, Recreation

Vocational Education

Home Economics Education
Business Education
Trade and Industrial Education
Industrial Arts Education

History

History

Journalism, Communications

Journalism, Radio-Television, Communications

Military Service

Military Service, Military Science

Dentistry

Dentistry

Social Work

Social Work, Group Work

Not Elsewhere Classified

Other Health
Nursing
Optometry
Pharmacy
Physical Therapy
Occupational Therapy
Veterinary Medicine
Medical Technology, Dental Hygiene
Education of Exceptional Children
Agricultural Education
Counseling and Guidance
Clinical Psychology
Architecture, City Planning
Library Science, Archival Science
Public Administration
Foreign Service
Home Economics
Not Elsewhere Classified

APPENDIX B

SIXTEEN-FOLD TABLES FOR EACH OF TWENTY CAREERS

TABLE 32

SIXTEEN-FOLD TABLE FOR DENTISTRY

Career		Values				
		T_1: +	+	-	-	Total
T_1	T_2	T_2: +	-	+	-	
+	+	30	33	30	54	147
+	-	19	3	3	16	41
-	+	2	2	7	13	24
-	-	1,843	2,459	2,654	14,889	21,845
Total		1,894	2,497	2,694	14,972	22,057

TABLE 33

SIXTEEN-FOLD TABLE FOR CHEMISTRY

Career		Values				
		T_2: +	+	-	-	Total
T_1	T_2	T_2: +	-	+	-	
+	+	150	69	99	162	480
+	-	30	24	15	43	99
-	+	11	3	15	30	59
-	-	2,519	2,219	2,562	14,106	21,406
Total		2,710	2,315	2,691	14,341	22,057

TABLE 34

SIXTEEN-FOLD TABLE FOR MEDICINE

Career T_1	Career T_2	Values T_1 / T_2: + / +	+ / -	- / +	- / -	Total
+	+	533	49	219	130	931
+	-	32	25	15	31	103
-	+	23	2	42	18	85
-	-	4,895	1,479	4,687	9,877	20,938
Total		5,483	1,555	4,963	10,056	22,057

TABLE 35

SIXTEEN-FOLD TABLE FOR PHYSICAL SCIENCES

Career T_1	Career T_2	Values T_1 / T_2: + / +	+ / -	- / +	- / -	Total
+	+	352	105	149	210	816
+	-	93	41	62	141	337
-	+	62	22	64	111	259
-	-	2,203	2,147	2,416	18,879	20,645
Total		2,710	2,315	2,691	14,341	22,057

TABLE 36

SIXTEEN-FOLD TABLE FOR ENGINEERING

Career T_1	Career T_2	Values T_1 / T_2: + / +	+ / -	- / +	- / -	Total
+	+	700	340	536	1,240	2,816
+	-	79	70	71	203	423
-	+	91	47	104	279	521
-	-	1,840	1,858	1,908	12,619	18,297
Total		2,710	2,315	2,691	14,341	22,057

TABLE 37

SIXTEEN-FOLD TABLE FOR LAW

Career T_1	Career T_2	Values T_1 / T_2: + / +	+ / -	- / +	- / -	Total
+	+	249	90	275	452	1,066
+	-	41	25	68	143	277
-	+	37	28	59	162	286
-	-	1,786	1,463	3,574	13,605	22,428
Total		2,113	1,606	3,976	14,362	22,057

TABLE 38

SIXTEEN-FOLD TABLE FOR RELIGION

Career T_1	Career T_2	Values T_1 + / T_2 +	T_1 + / T_2 -	T_1 - / T_2 +	T_1 - / T_2 -	Total
+	+	403	36	102	32	573
+	-	47	19	26	14	106
-	+	80	5	27	18	130
-	-	4,953	1,495	4,808	9,992	21,248
Total		5,483	1,555	4,963	10,056	22,057

TABLE 39

SIXTEEN-FOLD TABLE FOR BUSINESS

Career T_1	Career T_2	Values T_1 + / T_2 +	T_1 + / T_2 -	T_1 - / T_2 +	T_1 - / T_2 -	Total
+	+	604	939	535	2,253	4,331
+	-	87	211	74	605	977
-	+	88	178	135	692	1,093
-	-	505	1,477	859	12,815	15,656
Total		1,284	2,805	1,603	16,365	22,057

TABLE 40

SIXTEEN-FOLD TABLE FOR AGRICULTURE

Career T_1	Career T_2	Values T_1: + / T_2: +	T_1: + / T_2: -	T_1: - / T_2: +	T_1: - / T_2: -	Total
+	+	84	100	30	167	381
+	-	21	33	1	59	114
-	+	17	13	14	41	85
-	-	1,715	3,922	1,441	14,399	21,477
Total		1,837	4,068	1,489	14,666	22,057

TABLE 41

SIXTEEN-FOLD TABLE FOR TEACHING

Career T_1	Career T_2	Values T_1: + / T_2: +	T_1: + / T_2: -	T_1: - / T_2: +	T_1: - / T_2: -	Total
+	+	236	174	229	511	1,150
+	-	101	89	145	441	776
-	+	89	60	171	308	628
-	-	1,222	1,348	2,164	14,769	19,503
Total		1,648	1,671	2,709	16,029	22,057

TABLE 42

SIXTEEN-FOLD TABLE FOR BIOLOGICAL SCIENCES

Career T_1	Career T_2	Values T_1 / T_2: + / +	+ / -	- / +	- / -	Total
+	+	114	77	20	71	282
+	-	27	45	4	39	115
-	+	46	27	27	82	182
-	-	3,833	4,564	1,930	11,151	21,478
Total		4,020	4,713	1,981	11,343	22,057

TABLE 43

SIXTEEN-FOLD TABLE FOR JOURNALISM, COMMUNICATIONS

Career T_1	Career T_2	Values T_1 / T_2: + / +	+ / -	- / +	- / -	Total
+	+	68	21	43	34	166
+	-	44	20	13	34	111
-	+	42	2	35	15	94
-	-	4,303	2,073	4,573	10,737	21,686
Total		4,457	2,116	4,664	10,820	22,057

TABLE 44

SIXTEEN-FOLD TABLE FOR MILITARY

Career T_1	Career T_2	Values T_1 / T_2: + / +	+ / -	- / +	- / -	Total
+	+	54	39	22	45	160
+	-	21	23	15	49	108
-	+	37	34	37	81	189
-	-	2,602	3,450	2,468	13,080	21,600
Total		2,714	3,546	2,542	13,255	22,057

TABLE 45

SIXTEEN-FOLD TABLE FOR HUMANITIES

Career T_1	Career T_2	Values T_1 / T_2: + / +	+ / -	- / +	- / -	Total
+	+	292	57	84	71	504
+	-	109	28	64	53	254
-	+	142	18	75	37	272
-	-	3,206	1,623	4,564	11,634	21,027
Total		3,749	1,726	4,787	11,795	22,057

TABLE 46

SIXTEEN-FOLD TABLE FOR PHYSICAL EDUCATION

Career T_1	Career T_2	Values T_1 / T_2	+ / +	+ / -	- / +	- / -	Total
+	+		120	82	11	27	240
+	-		66	23	12	20	121
-	+		45	14	4	6	69
-	-		5,198	4,748	2,455	9,226	21,627
Total			5,429	4,867	2,482	9,279	22,057

TABLE 47

SIXTEEN-FOLD TABLE FOR EDUCATIONAL ADMINISTRATION

Career T_1	Career T_2	Values T_1 / T_2	+ / +	+ / -	- / +	- / -	Total
+	+		48	50	27	52	177
+	-		48	73	26	97	244
-	+		48	57	79	211	395
-	-		1,750	2,317	2,562	14,612	21,241
Total			1,894	2,497	2,694	14,972	22,057

TABLE 48

SIXTEEN-FOLD TABLE FOR SOCIAL SCIENCES

Career T_1	Career T_2	Values T_1 + / T_2 +	T_1 + / T_2 -	T_1 - / T_2 +	T_1 - / T_2 -	Total
+	+	177	74	73	69	393
+	-	86	34	82	97	299
-	+	85	25	64	132	306
-	-	3,401	1,593	4,568	11,497	21,059
Total		3,749	1,726	4,787	11,795	22,057

TABLE 49

SIXTEEN-FOLD TABLE FOR VOCATIONAL EDUCATION

Career T_1	Career T_2	Values T_1 + / T_2 +	T_1 + / T_2 -	T_1 - / T_2 +	T_1 - / T_2 -	Total
+	+	25	53	21	75	174
+	-	28	57	10	56	151
-	+	16	18	9	47	90
-	-	2,643	4,164	2,709	12,126	21,642
Total		2,712	4,292	2,749	12,304	22,057

TABLE 50

SIXTEEN-FOLD TABLE FOR SOCIAL WORK

Career T_1	Career T_2	Values T_1 + / T_2 +	+ / -	- / +	- / -	Total
+	+	56	10	11	3	80
+	-	30	8	9	15	62
-	+	35	2	40	5	82
-	-	5,362	1,535	4,903	10,033	21,833
Total		5,483	1,555	4,963	10,056	22,057

TABLE 51

SIXTEEN-FOLD TABLE FOR HISTORY

Career T_1	Career T_2	Values T_1 + / T_2 +	+ / -	- / +	- / -	Total
+	+	91	7	16	16	130
+	-	44	15	21	58	138
-	+	27	11	35	19	92
-	-	3,587	1,693	4,715	11,702	21,697
Total		3,749	1,726	4,787	11,795	22,057