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CAUSAL ANALYSIS OF CROSS-SECTIONAL AND OVER-TIME DATA: WITH SPECIAL REFERENCE TO THE STUDY OF THE OCCUPATIONAL ACHIEVEMENT PROCESS

Aage B. Sørensen

UNIVERSITY OF WISCONSIN - MADISON

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ABSTRACT

This paper discusses what inferences may be drawn on the effect of a set of independent variables on a dependent variable that undergoes change over time, when the analysis is based on cross-sectional data. When a linear model for change describes the process it is shown that the use of cross-sectional data invites caution when drawing conclusions regarding the absolute magnitude of effect and the amount of variance explained, even when the process has reached a stable level for the sample studied. Furthermore, in an age-related process the effect parameters may be strongly dependent on age and hence vary with the age-distribution of the sample. The occupational achievement process is used to exemplify the arguments presented.

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1. Introduction

Causal analysis of data collected at one point in time is often accompanied by a plea for replication of the analysis on longitudinal data. There are two reasons for such a plea. First, causal analysis on cross-sectional data demands assumptions about the temporal ordering of the variables. Second, the effects of independent variables are usually interpreted as meaning that change in a dependent variable is brought about by the independent variables focused upon in the analysis. Only the analysis of over-time data can directly establish these effects.

The collection of over-time data in order to establish the temporal ordering of variables needs no elaborate justification. It should be noted though that over-time data of course does not alleviate the need to impose a causal structure. Observations at several points in time on a set of variables does not free the investigator from making decisions regarding which variables are to be considered exogenous and which are to be considered endogenous. The virtues of collecting over-time data in order to establish the magnitudes of causal effects are less obvious. This paper attempts to point out some of these virtues. It is useful to see our purpose in the framework of causal analysis in recent sociological research, and a brief overview seems therefore appropriate.

Causal analysis in sociology has been greatly advanced over the last decade by the use of path-analysis introduced into sociology by Duncan (1966) and Boudon (1964) and inspired primarily by earlier work by Wright (e.g. 1934), Simon (1957) and Blalock (1964). Path analysis, in sociological applications, is most often used to test a set of causal hypotheses about the interrelationships among a set of variables, hypotheses that may account for the observed correlations among the variables. The outcome of the analysis is a set of path coefficients that measure the effect of independent variables (exogenous and endogenous) on the dependent variables, nearly always in a linear recursive system.

Path coefficients are estimated as standardized regression coefficients in identified systems. They measure the amount of variation in the dependent variables associated with a unit (standard deviation) variation in the independent variable. Thus, they measure the effect of independent variables relative to the actual amount of variation found in the population studied. Tukey (1954) and Blalock (1967) have pointed out that this property of standardized measures of effect hinders the comparison of causal effects from one population to another (or for the same population over time) since the variation in variables cannot ordinarily be assumed to be identical in the different populations. Unstandardized regression coefficients are argued to be appropriate for such comparisons. In path analysis these coefficients are sometimes referred to as concrete path coefficients (Wright 1960).

Unstandardized measures of effect are not population specific, and they represent the formulation of a causal law (Blalock 1967), that is a statement regarding the amount of change produced in the dependent variable if the independent variable changes one unit. Not only can such measures be the most appropriate for causal analysis, they often also will be the most useful measure of effect as a guideline for policy. If the independent variable is a policy instrument with a variation that may be manipulated, then a standardized measure of effect that is given relative to the actual variation in the population can be seriously misleading since such a measure contains little information on what would happen if a change in the independent variable is carried out.

This paper will argue that for some phenomena even unstandardized measures of effect may be inappropriate, that is, if they are based on cross-sectional data. The phenomena in question are variables that show change over time in such a way that the amount of change is dependent on the level already achieved. Such a pattern of change may be seen as the result of the operation of a feedback that influences the rate of change in the variable of interest in such a way that the magnitude of change is dependent on the value of the variable itself. We shall demonstrate that on cross-sectional data, this feedback cannot be identified. Measures of effect based on cross-sectional data therefore can be misleading, for they will give the effect relative to the magnitude of the feedback, when a dependent variable shows change over time, and not the absolute magnitude of effect of independent variables. But the magnitude of the feedback may vary from one population to another, and comparison of effect across different populations may be hindered. Furthermore, within the same population, a measure of effect relative to the feedback may be dependent on time and if established on cross-sectional data reflect the age-distribution of the population. Direct study of change does make it possible to identify the feedback, hence measures of effect derived from the direct study of change will be shown to be important both for our theoretical understanding of the phenomenon under investigation, and for policy purposes.

A number of phenomena could provide examples for our argument. Especially important are those phenomena that undergo some growth process for such processes often stabilize at a certain level--a pattern that may be seen as produced by the operation of a negative feedback. We shall use as our example the occupational achievement process, the process through which persons obtain a certain level of occupational status or prestige. Considerable methodological sophistication has been applied in the analysis of this process, but the best known studies have been cross-sectional (Blau and Duncan 1967) or have utilized a method of analysis that treated over-time data much as though they were cross-sectional.[1] Because recently there has been quite a controversy about the absolute magnitude of the effects of independent variables, especially the effect of education (Jencks, et. al. 1972), this research provides a useful substantive exemplification of the points we would like to make in this paper.

A substantive exemplification is useful also because the main arguments of this paper may appear rather technical. We shall use a mathematical model for change to reach our conclusions: the linear model for change described by Coleman (1968);[2] but the study of change remains a complicated matter and easily becomes a technical tour de force.

Our strategy is to compare the information obtained from cross-sectional data on a process, with the information that would be obtained had the process been analyzed on over-time data using the linear model for change. This necessitates a brief summary of the properties of the linear model of change.

2. The Linear Model for Change

The models for change described by Coleman (1968) are all models where change in a variable X_1 is a function of X_1 itself and a set of exogenous variables. Both linear and non-linear models are reviewed by Coleman and among the linear models we find models where the exogenous variables are assumed to change over time, and models where this is not the case. We shall use the simplest model here, that is the linear model for change with exogenous variables assumed to remain constant over time. More complicated models would not change our basic argument which concerns the impact of the feedback on measures of effect of independent variables obtained from cross-sectional data. Also this simple model suffices for the purposes of this paper as a first approximation to describe the occupational achievement process, our substantive example. The number of exogenous variables does not affect the following discussion so we shall only deal with the case of one exogenous variable, denoted X_2. The model can then be written as:

$$\frac{dX_1(t)}{dt} = b_0 + b_1X_1(t) + b_2X_2 \ . \qquad (1)$$

The quantity $dX_1(t)/dt$ is the rate of change in $X_1(t)$ at time t. This quantity is a conceptual abstraction that enables us to characterize the system by its rate of change at a particular point in time so that we may take change as an attribute of the system at a point in time, just as we treat other attributes of the system. We cannot observe $dX_1(t)/dt$ directly, however, but need to integrate the differential equation (1) in order to estimate the quantities b_0, b_1, and b_2, and in order to study the behavior of the system over time.

The parameter b_0 measures the amount of change in $X_1(t)$ produced by exogenous variables whose contribution to the rate of change is constant over time and across individuals. The quantity b_2 measures the amount of change produced by the variable X_2 in $X_1(t)$. As mentioned above, we shall assume X_2 constant over time, but varying across individuals. The quantity b_2

is a direct measure of the effect of X_2 for it measures the amount of change in $X_1(t)$ associated with a unit difference in X_2. The model (1) is a deterministic one. The introduction of a disturbance term, necessary in empirical applications, creates special problems of estimation. These problems do not affect the argument presented in this paper. They are briefly outlined in the Appendix.

The quantity b_1 is the effect of the level of $X_1(t)$ at time t on the change in $X_1(t)$. This effect is a feedback of the variable $X_1(t)$ on itself, and as pointed out by Coleman (1968) represents our ignorance about the process since this feedback reflects the operation of unmeasured variables that act from $X_1(t)$ back to $X_1(t)$, that is a causal loop such that: $X_1 \longrightarrow Z_1 \longrightarrow ..Z_i \longrightarrow X_1$, where the Z_i's are the unmeasured variables that enter into the causal loop. These variables could be specified in a system of simultaneous equations. Some sociological examples of how this may be done, are presented by Blalock (1969).

Integration of (1) enables us to relate this model of change to observable quantities, and also to study the behavior of the system. If we assume that b_0, b_1 and b_2 are constant over time and across individuals, and X_2 is constant over time, we obtain as the solution to (1)

$$X_1(t) = \frac{b_0}{b_1}(e^{b_1\Delta t}-1) + e^{b_1\Delta t}X_1(t_1) + \frac{b_2}{b_1}(e^{b_1\Delta t}-1)X_2 \qquad (2)$$

where $X_1(t)$ is the value of X_1 observed at time t, $X_1(t_1)$ is the value at time t_1, and $\Delta t = t - t_1$ is the length of the time interval between observations. Equation (2) is of the form

$$X_1(t) = b_0^* + b_1^*X_1(t_1) + b_2^*X_2. \qquad (3)$$

Ordinary least squares may be used to estimate b_0^*, b_1^*, and b_2^*. From these estimates we may derive b_0, b_1, and b_2 using the relations:

$$b_0 = \frac{b_0^* \ln b_1^*}{\Delta t(b_1^*-1)} \tag{4}$$

$$b_1 = \frac{\ln b_1^*}{\Delta t} \tag{5}$$

$$b_2 = \frac{b_2^* \ln b_1^*}{\Delta t(b_1^*-1)} . \tag{6}$$

If we let $t_1 = 0$ in equation (2), that is the start of the process, we obtain a formulation that may be used to study the behavior of the system. It is easily seen that the value of b_1 is crucial for the behavior over time. Since $\Delta t = t$ if $t_1 = 0$ we obtain first for $b_1 = 0$,

$$X_1(t) = X_1(0) + t(b_0 + b_2X_2) \tag{7}$$

with a slope equal to $b_0 + b_2X_2$, that is the same for all values of t.

When $b_1 \neq 0$, we obtain the same form as (2) with t_1 replaced by 0 and $\Delta t = t$. If $b_1 > 0$, $X_1(t)$ will increase with an ever increasing slope; the process will explode. This is not a common situation;[3] more frequent is the situation where the change in $X_1(t)$ gradually decreases. This occurs when $b_1 < 0$ since in that case the term $e^{b_1 t}$ will approach 0 as t increases. The result will be the eventual attainment of a constant level of $X_1(t)$. This constant value of $X_1(t)$ we shall call the <u>equilibrium</u> <u>level</u> of X_1. It can be found by solving for X_1 in (1) when $dX_1(t)/dt = 0$. The equilibrium value of $X_1(t)$ denoted $X_1(e)$ is

$$X_1(e) = -\frac{b_0}{b_1} - \frac{b_2}{b_1} X_2 \quad . \tag{8}$$

The model is easily generalized to more than one exogenous variable. In the general case, with n exogenous variables, the fundamental equation will be:

$$\frac{dX_1(t)}{dt} = b_0 + b_1X_1(t) + b_2X_2 + b_3X_3 \ldots b_nX_n \tag{9}$$

with a solution of the same form as (2).

A process that gradually reaches an equilibrium is the most important application of the model. It is rare that a variable increases linearly in time forever, which would be the case if $b_1 = 0$, or grows at an ever increasing rate, if $b_1 > 0$.

After this brief review of the linear model for change we can now undertake the major task of the paper which is to compare measures of effect obtained from studying a process that is governed by the model (9) on cross-sectional data to the measures obtained from using change data. A number of problems in connection with the model (1) have not been discussed here because they are not crucial for our argument. Especially important are the estimation problems the use of the linear model for change presents. A treatment of the estimation problems raised by models of the forms given by (3) is presented for example by Griliches (1967) and Johnston (1972).

3. Analysis of Cross-sectional Data on a Process in Change

Cross-sectional data are ordinarily obtained from some population at a point in time. In survey research the population is often defined as the total population in some political unit above a certain age and a sampling scheme is devised so that all elements of that population have an equal probability of being represented in the sample. The distribution of the sample will, except for sampling error, equal the distribution of the population. In particular, the age-distribution will be one where there is considerable variation. If the phenomenon under investigation is age-related, (as is occupational achievement) this means that for some parts of the sample change will still occur, whereas for others--the older respondents--the process may have reached an equilibrium.

There are two problems to consider when comparing the inferences that may be obtained from cross-sectional data to the inferences that may be made from change data on the same process. One is the extent to which the possibility of change still occurring for part of our sample affects our inferences. The second problem is what kind of inferences can be made for those for which the process has reached equilibrium. We shall consider the latter problem in detail first.

Suppose, to simplify matters, that we have obtained data for a cohort at a point in time when the process has in fact reached equilibrium. On these data we estimate the equation:

$$X_1(e) = c_0 + c_2X_2 + c_3X_3 \ldots + c_nX_n \quad . \tag{10}$$

The quantities c_0, $c_2 \ldots c_n$ will be the measures of effect of the variables X_2, $X_3 \ldots X_n$ that we obtain. How do these quantities relate to the fundamental parameters b_0, b_1, $b_2 \ldots b_n$?

If the process is described by the linear model for change with n exogenous variables, we can write $X_1(e)$, a function of the exogenous variables and the feedback of $X_1(t)$ on itself as [cf. equation (7)]:

$$X_1(e) = -\frac{b_0}{b_1} - \frac{b_2}{b_1}X_2 - \frac{b_3}{b_1}X_3 \ldots - \frac{b_n}{b_1}X_n \quad . \tag{11}$$

Had we studied the process while change was still going on we could have estimated all the parameters b_0, b_1, $b_2 \ldots b_n$ using the linear model for change. But on cross-sectional data from the process in equilibrium we can only estimate c_0, $c_2 \ldots c_n$. In terms of the fundamental parameters the c_i's will be

$$\begin{aligned} c_0 &= -\frac{b_0}{b_1} \\ c_2 &= -\frac{b_2}{b_1} \\ &\vdots \\ c_n &= -\frac{b_n}{b_1} \end{aligned} \qquad (12)$$

Since b_1 in equation (11) is negative (otherwise the process would not be at equilibrium), the signs of the coefficients c_0, $c_2 \ldots c_n$ will correspond to the signs b_0, b_2, $b_3 \ldots b_n$. Also the relative magnitude of the coefficients c_0, $c_2 \ldots c_n$ will correspond to the relative magnitude of the fundamental parameters, b_0, $b_2 \ldots b_n$.

Thus, if we are only interested in the signs and relative magnitudes of parameters, cross-sectional data on a process in equilibrium will provide sufficient information. But we cannot identify b_1 from cross-sectional data. This does affect statements on the absolute magnitudes of effect, for the absolute value of c_0, $c_2 \ldots c_n$ will vary with the magnitude of b_1. This has two important implications. The first and most obvious implication has to do with the magnitude of effect. It is clear from equation (11) that even if all variables are perfectly reliable, and even if all important exogenous variables are in the equation, the coefficients c_0, $c_2 \ldots c_n$ may all be low, if there is a large negative feedback of $X_1(t)$ on itself. The specification of this feedback is not done by adding additional variables to equation (11) or by improving the reliability, but is done by adding equations that mirror the negative effect of X_1 on itself. But such extensions of the model demand over-time data because variables that are engaged in the feedback are endogenous to $X_1(t)$ and usually cannot be identified with cross-sectional data. If we have over-time data we do not need to specify the feedback in order to estimate the parameters b_2, $b_3 \ldots b_n$.

The second implication has to do with comparisons of measures of effect based on cross-sectional data among populations separated by time or by place. Unstandardized measures have, as mentioned, been argued to be appropriate for this purpose as they are measures of effect that do not depend on the actual amount of variance in the variables. But it is clear that any comparison of the effect of exogenous variables obtained from cross-sectional data will be a comparison of the effect relative to the feedback term, if the dependent variable is one that undergoes change. The magnitude of the feedback in turn is likely to differ among different populations or in the same population over time. This means that a difference observed between two coefficients c_i' and c_i'' for the same variable may be due solely to a difference in the b_1's of equation (11) and not to a difference in the direct effect, the b_i's. The effect of education on occupational status may thus be found to differ between two populations, not because education is less valuable in one society for obtaining gains in status than in the other, but because less gain in status occurs due to a stronger negative feedback, and therefore less remains for education to act on. Unambiguous inferences on the sources of differences in the c_i coefficients can only be made if one is willing to assume an identical feedback in the process in the populations compared. This is a strong assumption and we shall later show that for example in the comparison of the occupational achievement process for Blacks and Whites it appears to be wrong.

Intuitively, the reason for these properties of estimates of effect obtained from cross-sectional data is that b_1 governs the overall amount of change in $X_1(t)$. As b_1 increases in absolute value there will be less change in $X_1(t)$ and the exogenous variables will have less to act on. As b_1 gets closer to zero, more and more change in $X_1(t)$ is available for the exogenous variables to act on. Therefore, the absolute magnitudes of effect of exogenous variables estimated from cross-sectional data will be determined by the strength of the feedback of $X_1(t)$ on itself, and this feedback cannot be identified from data collected at one point in time. The presence of a negative feedback in turn is the likely explanation for a stable value of a variable that in earlier periods underwent change.

It is, of course, rare that we have direct evidence from a cross-sectional sample on whether a process is in equilibrium or not. But often we may suspect that at least for some age groups, the phenomenon of interest is still undergoing change. This is certainly the case in the study of occupational achievement where the younger respondents in a sample cannot be assumed to have reached their equilibrium level of achievement. How do parameters that we estimate from observations taken when the process is still undergoing change differ from those that would be obtained from the process in equilibrium or from the direct study of change?

To simplify matters we shall again assume that we have obtained data on a cohort, now at a point in time when the process is still undergoing change. From our observations we again estimate:

$$X_1(t) = c_0 + c_2X_2 + c_3X_3 \ldots c_nX_n \quad . \tag{13}$$

If the process had been in equilibrium we could have written the quantities c_0, $c_2 \ldots c_n$ in terms of the fundamental parameters of the change model as shown above. In this instance, where change is still going on, the coefficients c_0, $c_2 \ldots c_n$ will also be a function of time. This is easily seen in the case where b_1 of equation (9) is equal to zero, because then

$$X_1(t) = X_1(0) + t(b_0 + b_2X_2 + b_3X_3 \ldots b_nX_n) \tag{14}$$

which means that the coefficients c_0, $c_2 \ldots c_n$ will be proportional to the amount of time for which the process has gone over; that is $c_2 = b_2t$, $c_3 = b_3t \ldots c_n = b_nt$, while $c_0 = X_1(0) + b_0t$.

In the case where $b_1 \neq 0$ the relationship between c_i and time is a bit more complicated. Integration of the fundamental differential equation with n exogenous variables from time 0 to t gives:

$$X_1(t) = \frac{b_0}{b_1}(e^{b_1t}-1) + e^{b_1t}X_1(0) + \frac{b_2}{b_1}(e^{b_1t}-1)X_2 + \frac{b_3}{b_1}(e^{b_1t}-1)X_3$$

$$\ldots \frac{b_n}{b_1}(e^{b_1t}-1)X_n \quad . \tag{15}$$

Now in this expression the coefficients to the exogenous variables are all a product of the direct measures of effect, the b_i's, and a quantity $\frac{1}{b_1}(e^{b_1 t}-1)$. This quantity, call it $v(t)$,[4] is a function of time and the size of the feedback term b_1, and both quantities, that is the amount of time passed since the process started and the magnitude of the feedback, govern the change we will observe in the estimated coefficients $c_0, c_2 \ldots c_n$. More specifically the coefficients c_0, $c_2 \ldots c_n$ will be functions of the fundamental parameters b_0, $b_2 \ldots b_n$ and time, such that

$$
\begin{aligned}
c_0 &= X_1(0) + \frac{1}{b_1}(e^{b_1 t}-1)[b_0 + b_1 X_1(0)] \\
c_2 &= \frac{1}{b_1}(e^{b_1 t}-1) b_2 \\
&\vdots \\
c_n &= \frac{1}{b_1}(e^{b_1 t}-1) b_n \quad .
\end{aligned}
\tag{16}
$$

Now $v(t) \to -\frac{1}{b_1}$ as $t \to \infty$. Hence at equilibrium c_0, $c_2 \ldots c_n$ will be $-b_0/b_1$, $-b_2/b_1 \ldots -b_n/b_1$ as should be the case. At any time before equilibrium c_i will be less than $-b_i/b_1$ and the difference will be greater the closer t is to zero. Hence the c_i's will increase over time until they reach a stable level, and they will reach the stable level sooner the larger b_1 is in absolute value. The exception is the constant term c_0. This term will increase in time if $b_0 > b_1 X_1(0)$ or decrease if $b_0 < b_1 X_1(0)$.

Intuitively, the reason for the dependency of the c_i's on time is that the amount of time passed since the start of the process governs how much change there has been for the exogenous variables to act on. At the same time the amount of change is also governed by the magnitude of the feedback. This means that for an age related process studied with cross-sectional data the measures of effect will not only reflect the magnitude of the feedback, they will also reflect the age distribution of the population from which the data are obtained.

In an age related process the age change in the measures of effect of course can be detected if we stratify our cross-sectional sample according to age and estimate the c_i coefficients in each age group. However, it can be misleading to draw inferences on the age dependency of the process from the observed variation in the c_i's with age, for the age groups may differ with respect to the magnitude of the feedback that governs their process, a point we shall discuss further in relation to the occupational achievement process.

It is clear from the form of the expressions for the c_i's that the problem of time dependency in the measures of effect is not handled by introducing time as an independent variable alongside the exogenous variables. The relationship between time and the c_i's is clearly non-linear and the interaction furthermore seems impossible to specify a priori unless the value of b_1 is known, which it is not in cross-sectional data.

In conclusion, measures of effect based on cross=sectional data may be appropriate for comparisons of relative effects when the dependent variable undergoes change. They are clearly inappropriate for statements on the absolute magnitudes of effects unless one is indifferent with respect to how much the size of the effect parameter is influenced by the magnitude of a feedback in the process[5] and by the age distribution of the sample. We hope to demonstrate in the example of the occupational achievement process, to be discussed next, that such an indifference may lead to quite misleading, or at least ambiguous, inferences about the causal effect of variables on the phenomenon of interest even if unstandardized measures of effect are used.

Unstandardized measures of effect based on cross-sectional data have the virtue of being independent of the actual amount of variation in the independent variables. But for a dependent variable that undergoes change, these measures are not independent of the distribution of the dependent variable, for this distribution as a result of the feedback will determine the rate of change in the dependent variable that will result from a unit change in the independent variable. In an age dependent process, the distribution of the dependent variable depends on the age distribution of the sample. Over and above that, the dependency of the rate of change on the values obtained of the dependent variable, that is the feedback, is likely to differ from one population to another.

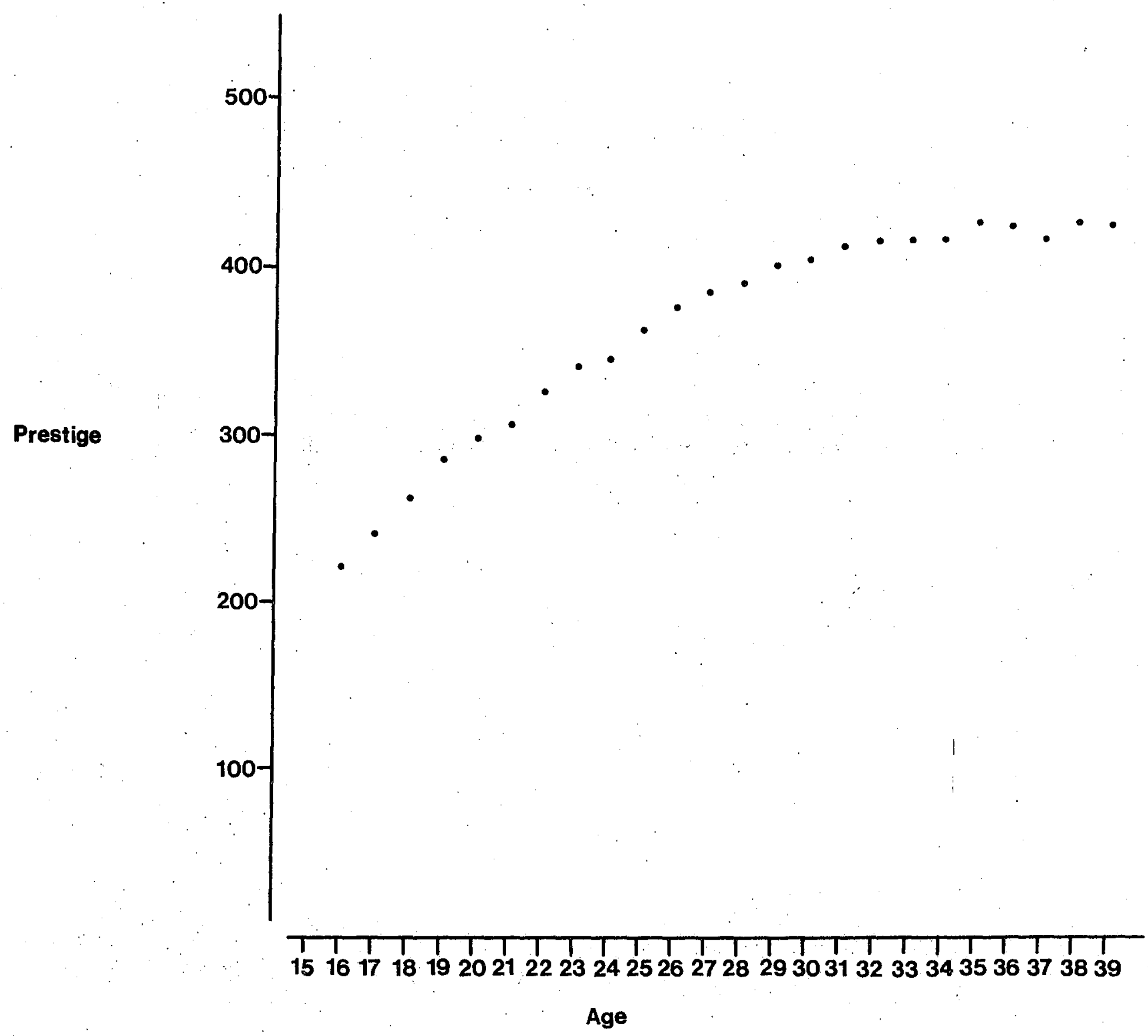
4. An Example: Growth in Occupational Status

The conclusions arrived at above shall now be illustrated on a concrete example of an age-related process: growth in occupational status or prestige. Equation (9) can be taken as a model of this process. The variable $X_1(t)$ would then denote the status of a person at age t, the exogenous variables X_2, $X_3 \ldots X_n$ will be measures of individual attributes that affect occupational status. In the research on occupational achievement mentioned in the Introduction, these variables would be the education and family background of the respondents, where the family background is measured by such characteristics as the education of parents and the occupational status of the father.

The process defined by equation (9) seems a reasonable model for the growth over age in occupational status. In Figure 1 we have plotted the occupational prestige of a cohort of 30- to 39-year-old white males at

Occupational Prestige By Age — Whites

Figure 1a.



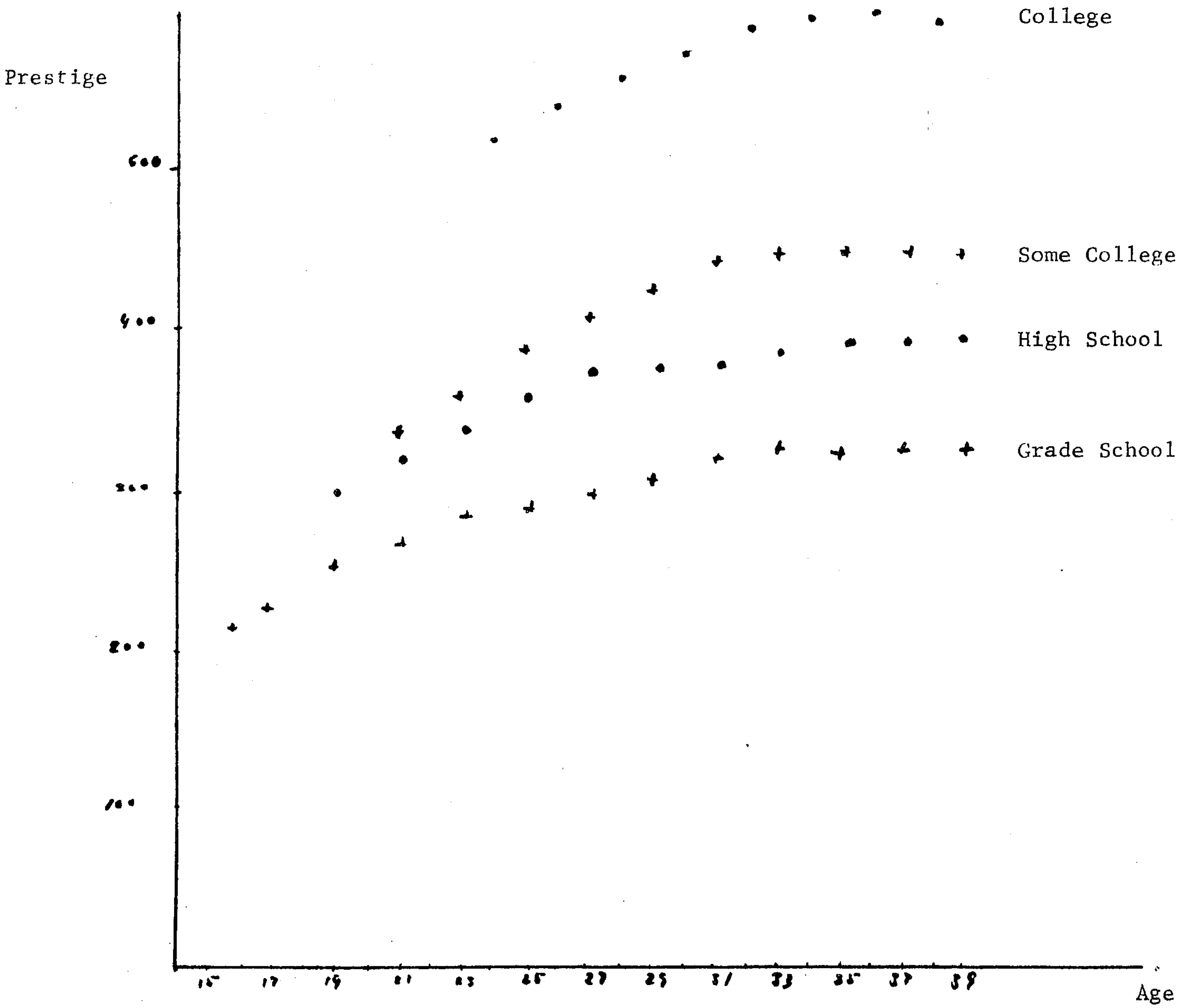

Prestige
College
Some College
High School
Grade School
Age

Figure 1 b.

various ages. These data were obtained from the Hopkins Life-History study.[6] It will be noticed that the growth in status shows the pattern to be expected from the model if b_1 is negative, and $b_0 + b_1X_1(t) + b_2X_2 \ldots b_nX_n > 0$. The prestige changes rapidly in the younger ages and gradually levels off.

However, Fig. 1a. is deceiving when used to support the use of equation 9 as a model for status growth. The increase in mean occupational status with age partly reflects that persons with higher education enter the labor force later and with higher status jobs. Figure 1 b. therefore gives the age variation in prestige for groups of persons with identical educational attainments. These graphs show that holding education constant over time and across individuals we obtain the age variation predicted from equation 9. Furthermore, it can be shown that the educational attainments do not change much after entry into the labor force. The mean attainment at entry is 3.93 (on a scale 0-8) and the mean total increase for everyone over the following 10 years is .26. The use of equation 9 as a model for status growth thus seems justified for the growth pattern has the expected form, and the assumption of constant exogenous variables seems reasonably approximated for the variables education and family background.

The process of status growth can be conceptualized as one in which individuals utilize opportunities for increases in status over time. Given their education and family background, the higher the status already achieved the fewer opportunities for advancement will be available. This would account for the negative feedback of status $[X_1(t)]$ on itself, and seems a reasonable interpretation of this feedback. The quantity b_1 then measures the level of opportunities and the closer b_1 is to zero the more opportunities there are in society and the more growth can take place. Given the level of opportunities the occupational resources measured by the variables X_2 , $X_3 \ldots X_n$ determine the status that an individual will eventually attain [cf. equation (1)]. The parameters b_2, $b_3 \ldots b_n$ measure the effect of these variables on growth in status and therefore also on the status an individual will eventually attain.

The model for status growth defined through (9) sees status as a result of the interaction between structural opportunities for advancement and personal attributes such as education and background. It thus mirrors a traditional conceptualization of mobility as a result of the interplay between structural characteristics and individual characteristics.

An objection to this use of the model may be that the variables $X_2 \ldots X_n$ are only background variables, and the model will exclude variables such as training and experience acquired after the entry into the labor force. This is true, and the use of (9) as a model for status growth may be too much of a simplification of the process as a consequence. However, the existence of such unmeasured variables that change over time, and also the possibility of change in the measured exogenous variables, will not invalidate the principles arrived at in the preceding section that we shall now illustrate.

The problems encountered when attempting to compare measures of effect obtained from cross-sectional data can be illustrated on the occupational achievement process. Much attention has been given here to the comparison of the achievement of Blacks and Whites (Duncan 1969, Siegel 1965; Coleman et. al. 1972), and to comparisons over time (Hauser and Featherman 1972). A well known result of Black/White comparisons is that the effect of education on occupational achievement is lower for Blacks than for Whites (for example, Duncan 1969). But from the argument presented in the preceding section, it follows that such a difference may be at least partly produced by a difference in the magnitude of the feedback, that is the size of b_1, for the two groups. This would reflect more unfavorable occupational opportunities for Blacks permitting less status growth, and hence less growth for education to act on.

That the difference in the effect of education between Blacks and Whites partly may be explained by differences in the strength of the negative feedback in the occupational achievement process for the two groups can be illustrated on the life-history data already used to give Figure 1.

In Table 1 we present estimates of the fundamental parameters of change for Blacks and Whites using the linear model for change as a model of the occupational achievement process. The exogenous variables are education, and father's status. The estimates are obtained by using equation (10) for the two groups with occupational prestige at age 30 as the dependent variable $[X_1(t)]$ and prestige at age 26 as the lagged independent variable $[X_1(t-1)]$.[7] From the estimates of b_0^*, b_1^*, b_2^* etc., the fundamental parameters are obtained by using equations (4), (5), and (6).

Table 1

Estimates of Fundamental Parameters of Change in Occupational Prestige

Independent Variable	Blacks	Whites
Prestige (b_1)	-.236	-.192
Education (b_2)	8.773	9.659
Father's Prestige (b_3)	.026	.024
Unmeasured Variables (b_0)	37.381	33.887

Note: Computed from growth in prestige between aged 26 and 30.

There is clearly a difference in the value of b_1 for Blacks and Whites, a difference that can be interpreted to reflect the different occupational opportunities for Blacks and Whites. The various background variables and education also show some differences between Blacks and Whites, a difference that points to a double handicap for Blacks: they have fewer opportunities for growth and even if they had the same opportunities, their occupational return on education is lower. This lower return may reflect a lower quality of education for Blacks, but could also be due to employer discrimination in favor of whites with the same educational credentials as Blacks.

The handicap of Blacks is in fact a triple one, for Blacks tend to have lower levels of education than whites. This, in combination with the results illustrated in Table 1 has considerable practical importance for they identify the magnitude of the various form for discrimination and handicaps that Blacks encounter. Such knowledge is obviously important for the formulation of policies intended to equalize the occupational achievement of Blacks and Whites. The level and quality of education for Blacks may be equalized to that of Whites and still not equalize occupational achievement unless Blacks also are given the same occupational opportunities for growth in status as Whites. The latter would demand intervention in the labor market. The pay-off of such alternative policies can only be assessed however if the achievement process is studied with the model for change, for only such studies permit the identification of the feedback term that reflects the differences in occupational opportunities.

In the preceding section we also demonstrated that the coefficients of effect obtained from cross-sectional data would increase with age until the equilibrium level is achieved. That this is indeed the pattern that the coefficients show if the cross-sectional model (14) is applied to a variable that changes over time is shown in Table 2.

Table 2

Summary of Regression of Occupational Prestige on Education and Father's Prestige at Various Ages for Whites

		Raw Regression Coefficients			
Age	N	Education	Father's Prestige	Constant	R^2
22	483	25.809	.047^{ns}	193.174	.151
26	736	37.934	.040^{ns}	200.937	.278
30	795	42.724	.082	184.656	.353
34	512	43.219	.070	199.718	.393
38	175	44.687	.155	175.171	.445

ns: Not statistically significant.

In Table 2 we have regressed the occupational status at the ages shown on the measures of education and father's prestige using the life-history data. There is a marked increase especially in the effect of education as expected from (16). Also the R^2's go up markedly. The behavior of the constant is not as we would predict. The constant term should show a monotonic increase or decrease with age. The irregular pattern observed in Table 2 probably is due to a different composition with respect to starting points of the samples included in the regressions at the various ages. However the pattern of change for the remainder coefficients follows our predictions.

The implication is clear. When studying an age-related phenomenon such as occupational achievement, the estimates of effect we obtain from a cross-sectional sample will depend on the age distribution of that sample. This result and the result obtained in the preceding section will now be discussed further in terms of some recent controversies and results in the study of occupational achievement.

5. Discussion

The obvious solution to the problem of the age-dependency of the coefficients c_i is to carry out separate estimations in different age groups. This will at least permit us to obtain coefficients for the oldest age groups that are at their maximum, provided the process has reached an equilibrium at these ages. The coefficients will still only measure the effect of exogenous variables relative to the feedback of the dependent variable on itself, but they will not be biased due to change still taking place.

Blau and Duncan (1967) carried out estimation in four age groups after they had estimated the parameters of their basic model. Their results may seem somewhat contradictory to what should be expected from the above argument. They find that the correlation between respondents' education and status in 1962 shows a slight monotonic decrease with age--just the opposite of what we would expect.

There may be technical reasons for the discrepancy in the results of Blau and Duncan (1967) and our prediction. Correlation coefficients are not well suited for comparisons of effects for different populations. The age groups used by Blau and Duncan are wide, the first covers the ages 25 to 34. The occupational achievement process may already have reached an equilibrium for that age. Our model is based on the assumption of a constant effect of exogenous variables throughout the process, and does not allow for the changing effect of on-the-job training and experience. Such forces might produce a growth in status over and above the equilibrium level predicted by the education of the respondent and in this way reduce the effect of education.[8] Finally, the famous random events may have a cumulative impact that produces the result shown.

All these explanations are plausible but untestable on the cross-sectional data used, because the age groups are different populations that have experienced growth in status in different historical periods and different occupational structures. Blau and Duncan's interpretation is that the results reflect an increased importance of education for occupational status for the youngest cohort due to a change in the labor market, and present some indirect evidence for this interpretation.

From our results we would predict that the effect of education would be smallest in the youngest age group and increase or remain stable for the older groups, that is if b_1 is the same for all age groups. Blau and Duncan's result could be interpreted within this framework to reflect either (1) that there is a secular trend toward a greater effect of education on change in status that in fact is so strong that it reverses the predicted pattern, or (2) that the b_1 for the different cohorts differs in such a way that the observed pattern emerges. The second interpretation would mean that b_1 is largest for the older age cohort, a phenomenon that according to our previous interpretation of b_1 indicates that there has been a trend toward increased occupational opportunities. The two interpretations are quite different. According to the first interpretation, employers rely more heavily on educational credentials today than earlier. According to the second interpretation, the result reflects changes in occupational structure that have increased the occupational opportunities for the younger cohorts and thus permits more growth in occupational status for education to act on, even though the reliance on educational credentials has remained unchanged.

These various interpretations of the results obtained from cross-sectional data are all left inconclusive. Even if we analyze the process separately by age groups to eliminate the age variation in parameters, the fact that the different age groups are from different historical periods makes it impossible to compare the coefficients of effect even for the age groups where the process is in equilibrium, unless one is willing to make the assumptions that the occupational structure acts the same, that is, produces identical b_1's, for the whole period covered by the sample. Despite the ingenuity shown by Blau and Duncan in their analysis of synthetic cohorts the lack of information about the process in cross-sectional data prohibits very conclusive evidence for any statement of trend. Life-history or similar change data are clearly more appropriate, and preferably life-history data on several cohorts so that cohort, period and age effects can be separated.

Blau and Duncan do caution explicitly about the limitations of cross-sectional data. Since their main preoccupation is to establish the relative effect of variables for occupational achievement their main results are unaffected by the limitations of cross-sectional data pointed out here. The use of such data to argue for definite policy implications of the absolute effect of variables is, however, quite dubious, it seems. The main argument of Jencks et. al. (1972), that reducing inequality of educational opportunity will not reduce inequality, may seem compelling. But the fact that most of the evidence marshalled for this argument is derived from cross-sectional data on the occupational achievement process is a serious shortcoming.

First of all, as pointed out by Coleman (1973), the main argument should have been evaluated from evidence on the effect of a change in the distribution of education on the distribution of status and income. The occupational achievement process is the process through which persons come to occupy unequal positions. It would run counter to most stratification theory to assert that this process explains why positions are unequal to begin with. It is possible that there is some co-variation between the distribution of education and the distribution of income and status, although for income there is evidence that while the distribution of education changed markedly since the Second World War, the distribution of income did not (Thurow and Lucas 1972). But the research on the occupational achievement process used by Jencks gives no information on such a co-variation.

However, we might still assign policy significance to the effect of education for occupational achievement, for this effect would tell us how important education would be for changing the achievement of a sub-population, for example Blacks, relative to other groups. But the amount of variance explained by education in status and income, a quantity Jencks relies heavily on, does not indicate how much change in the inequality between population groups could be brought about by changing educational attainments. The amount of variance merely describes the existing state of affairs with respect to the relation between a person's education and the position he occupies in society, and since Jencks lumps age groups together, it doesn't even describe the existing state of affairs very well.

If the variance in education is low because few have any education, the amount of variance explained by education will be low too. This need not indicate that education could not be important for changing the status of a person. Part of the problem then is the use of standardized measures of effects. However unstandardized measures would not be appropriate either, for they would give the effect of education relative to the existing occupational opportunities when obtained on cross-sectional data. A low effect of education therefore again need not indicate that education is unimportant for changing the status of a person, if the opportunity structure were changed. Only direct measures of the effect of education obtained from the study of change in occupational achievement would tell unambiguously how important education is for the occupational achievement process.

It is possible to conceive of a society where education or some other personal attribute would completely determine inequality, although it be a highly imaginary one. This would be a society where there is no negative feedback on the change in status over time, that is where occupational opportunities are infinite, for in such society the status of a person at a point in time would be completely determined by his education, and other personal attributes, cf. equation (14). The distribution of education would then indeed determine the distribution of status. But no known society is like that, instead we have a distribution of opportunities reflecting the structure of inequality that constrains the variation in status so that the higher the level of status already achieved the fewer opportunities there are for additional gain. The resulting negative feedback determines both how much variation is to be explained by education and other personal characteristics and the magnitudes of effect parameters, when cross-sectional data are used. To use the amount of variation not explained as a measure of the importance of luck, as Jencks does, is therefore clearly misleading, and unduly depressing for those who want to design policies to alter inequality.

6. Conclusion

The limitations of cross-sectional data argued in this paper should apply whenever a variable that shows growth over time is investigated. For individuals this would be age-related phenomena such as income and status, education and life-cycle components such as marriage, childbirth and the like. The same ideas are applicable to other units of analysis such as organizations and communities. Here the tradition has been to focus on a few or only one unit and the specific development and structure of that organization or community has often been very much in focus. However, recently (Blau and Schoenherr 1971) there has been a quest for larger samples in order to study sources of variations in structures or output and for such analyses our considerations apply, because samples of communities and organizations are usually samples of units in different stages of growth.

As a concrete example of the use of the model for change on phenomena other than occupational achievement, we can mention its use on growth in academic achievement. The author has attempted to use the model for change on over-time data on the academic achievement of students. The feedback term here was argued to reflect opportunities for learning created by the school and class-room environment the student is exposed to. School effects are thus not conceived of as additive effects parallel to individual variables such as family background, I.Q., etc., as is customary. Rather it is argued that schools, through the creation of opportunities for learning, influence how much the rate of change in achievement is dependent on the level of achievement already obtained. Bad schools would produce a large negative feedback by creating few opportunities for learning.[9] Good schools would create a small negative or maybe even positive feedback.

The attempt to validate these ideas has run into a technical but serious problem. The amount of change in academic achievement was, on the data utilized in the analysis, constrained by the simple fact that the achievement test used had an upper bound that a sizable number of students were close to or had reached at the second point in time at which achievement was measured. This "metric constraint" of course creates a trivial source of "feedback" that unfortunately produced ambiguous results of the analysis.

This experience illustrates one of the many difficulties that analysis of change data presents. The appendix will outline some of the serious estimation problems that may be encountered. Analysis of change data thus is likely to present considerable costs. The gathering of such data in itself usually is costly. This paper has illustrated some of the considerable benefits that the analysis of such data may bring.

Footnotes

[1]We are referring to the studies carried out by Sewell and associates (see, for example, Sewell, Haller and Ohlendorf 1970) on a cohort of Wisconsin youth. The studies apply the same methodology to these data as has been applied to cross-sectional data, focusing on level of achievement.

[2]The linear model for change is of course only one of many approaches to the analysis of change data. Often in the statistical literature a dependent variable is seen as a function of time itself. The fitting of a function (often polynomial) of time to a time series usually does not represent a causal model, however. Dynamic causal models are extensively treated in the econometric literature (e.g., Christ 1967; Johnston 1972), but nearly always with the fundamental equation being a difference rather than a differential equation, as in the linear model for change. A main preoccupation in econometrics has been the estimation problems dynamic causal models present. The problems are relevant for applications of the model discussed here, but not for the argument presented in this paper. They are briefly reviewed in the Appendix.

[3]Dempster (1960) presents an example of a system where a positive feedback does not lead to instability. However his defining equation is a difference, rather than a differential equation. Stability conditions are different if feedback is defined in a difference equation, so his conclusion does not necessarily contradict the one argued here.

[4]The quantity $v(t)$ may be seen as a transformation of time so that the solution (15) is linearly dependent on $v(t)$.

[5]Blalock (personal communication) has come to a similar conclusion from working with simultaneous equations where intervening variables (that cause feedback) are omitted.

[6]The Life-History Study dealt with the occupational, educational, familial and residential experiences from age 14 to time of interview. The universe is the total population of males 30-39 years of age, in 1968, residing in households in the United States. Two samples were drawn: (a) a national sample and (b) a supplementary sample of Blacks. The total number of interviews obtained was 1589: 738 Blacks and 851 Whites. The completion rates were 76.1 percent for sample (a) and 78.2 percent for sample (b). The Life-History Study was initiated by James S. Coleman and Peter H. Rossi of the Department of Social Relations, the Johns Hopkins University.

[7]The two years were chosen so that a large fraction of the samples would have jobs in both years.

[8]It is, however, argued by Human Capital theorists that training should be correlated with education which would produce the opposite result (Becker 1964).

[9]That feedback is interpreted to reflect opportunity level in both this example and the main one should not be interpreted as meaning that b_1 always has to be interpreted this way. Obviously the phenomenon under investigation will determine which interpretation is the appropriate one.

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