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THEORETICAL AND ANALYTICAL ISSUES IN STUDYING ORGANIZATIONAL PROCESSES*

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Formulation of dynamic theories and process hypotheses is a crucial component in longitudinal research. This paper describes a framework for developing dynamic theory and hypotheses. The procedure requires the theorist to address six dimensions of process in each variable: continuity, magnitude of change, rate of change, trend, periodicity and duration. Further, theorists are encouraged to explore the dynamic relations between sets of variables, including rate of change, magnitude of change, lag, and permanence. Consideration is given to the problem of feedback loops. A typology of analytical alternatives for studying dynamic processes and longitudinal research data is provided.

(PROCESS, THEORY, DYNAMICS, LONGITUDINAL)

In a number of articles in the 1960s and 1970s, the eminent sociologist and methodologist H. M. Blalock argued that regression coefficients are the laws of social science (see, for example, Blalock 1972, p. 146). Blalock's assertion represented the vanguard of quantitative research methodology throughout much of the social sciences (economics and psychometrics excluded) at the beginning of the 1970s. Regression analysis was a well-understood statistical technique that was rapidly diffusing throughout sociology and the organizational sciences. It was the basis for the general linear model, which provided a comprehensive analytic framework for most univariate and multivariate techniques and which subsumed the classic ANOVA techniques as a special case. Further, regression was the basis for path analysis and structural equation modeling which were developing rapidly at this time (see Blalock 1972, Duncan 1966, Land 1969). Stemming largely from the early work of Simon (1957) and Blalock (1964) these developments were motivated by the desire to develop techniques that would generate valid causal inferences from correlational data acquired in cross-sectional designs. It had taken nearly two decades of work to develop the logic and analytic techniques of causal inference from correlational data. To many social scientists at the beginning of the 1970s, Blalock's assertion must have appeared to represent a stunning achievement, if it were true.

The past two decades have witnessed even further rapid development of structural equation techniques for causal inference from static data. Yet during this time an alternative perspective has slowly emerged which changes the emphasis on causal inferences to a focus on dynamic processes (Box and Jenkins 1976, Mohr 1982, Monge et al. 1984). Further, coincident with the emergent focus on process has been an increasing emphasis on longitudinal rather than cross-sectional research. As a consequence of these two developments, a variation of Blalock's assertion is now much more appropriate: various dynamic representations, such as time series coefficients, are slowly replacing static regression coefficients as the laws of social science.¹

*Accepted by George P. Huber; received March 5, 1990.

¹Regression techniques can be used to analyze longitudinal data. Hibbs (1974) describes these well, but they are rarely employed in organizational research. Further, there are clear advantages to using nonlinear techniques such as those developed by Box and Jenkins (1976) if the longitudinal data contain cyclicity.
This growing emphasis on dynamic processes is important because it has the potential to significantly alter and improve our fundamental knowledge about organizations. Organizational science has long been concerned with developing and empirically testing theories about organizations (Parsons, Shils, and Bales 1949). Most theorists state that they are interested in developing dynamic or process theories (see, e.g., Hannan and Freeman 1977, Markus and Robey 1988, Mohr 1982, Tushman and Romanelli 1985). Yet despite this widely held ideal, few theories have been developed that meet the requirements of dynamic or process theories. Similarly, much exhortation abounds urging researchers to conduct longitudinal research (Kimberly 1976). Yet the percentage of published research articles that report data collected at more than one point in time is miniscule.

There are two reasons for this state of affairs. The first is that the organizational and social sciences generally lack the conceptual tools with which to develop dynamic theories. As Weick (1987) argues, for the most part, theory in the organizational sciences is based upon verbal and linguistic analysis. Blalock (1989) puts it even more strongly with regard to sociology:

\[ \ldots \text{we seem to have the notion that "theory" involves the study of what dead sociologists (primarily European ones at that) have had to say about major historical processes, rather than, say what a theoretical physicist such as an Einstein or a Hawking actually does, namely thinking in terms of mathematical equations. In this respect we are much closer to historians than to economists. (p. 448)} \]

Weick’s and Blalock’s comments are not critical of verbal formulations. Process theories can and should be developed at the verbal level. However, as McPhee and Poole (1982) demonstrate, mathematical models provide an additional set of tools for thinking about process characteristics. Mathematics contains a reservoir of concepts and a framework for analysis that can increase the precision and rigor of conceptual and empirical work. These tools permit the scholar to examine the implications of different dynamic formulations and thereby explore the process ramifications of the theory in ways that are more difficult at the verbal level. As Blalock (1969) argues, moving from verbal to mathematical formulations provides considerable intellectual power for studying process characteristics.

The second reason for the paucity of process knowledge is that most of the empirical research has been conducted in single point in time, correlational designs. While it is possible to acquire parameters of processes from cross-sectional, correlational data, the required assumptions are so severe that they can rarely be met in social science data.

In one sense, the discipline suffers from a form of methodological determinism, a state of affairs where the methodological tools that are available determine the ways in which scholars think and develop their theories and research questions (Monge et al. 1984, see also Kaplan’s 1964 discussion of the “Law of the Hammer”). Without a history and tradition of thinking in terms of processes, and without expertise in designing and executing longitudinal research, it is difficult to make progress in this domain. (See Daft and Lewin’s 1990 arguments about the normal science mindset in organization science.)

Despite the limitations that methodological tools often place on theorizing, methodological developments can provide a framework for theoretical advancement. Polanyi (1958) points out that Einstein studied non-Euclidean geometry developed by Reimann at the turn of the century. Polanyi argues that it was Einstein’s familiarity with a geometry of infinite dimensions that enabled him to theorize about the world
as a four dimensional rather than three dimensional system. (See Hawking 1988, pp. 155–169, for a similar example in contemporary physics). Thus, innovations in methodology can often provide the impetus for developments in theory, just as theoretical advancements often require the development of new methodologies.

An interesting organizational example of this phenomenon is provided in a recent article by Williams and Podsakoff (1989). They document the change in knowledge that occurred in the field of leadership as a function of changes in methodological strategies. Beginning with the early correlational strategies of the 1950s they identify errors in inference that occurred as a result of the simple correlational techniques then in use. As researchers began to conduct panel studies, the earlier knowledge was replaced with a more accurate picture of leadership processes. However, because cross-lagged correlational analysis of panel data contain inherent flaws, this knowledge base has again been revised as researchers began to use structural equation modeling techniques such as LISREL.

The purpose of this paper is to present a framework for the development of dynamic theories of organizational processes. Additionally, the framework and issues raised should lead to improvements in the conduct of longitudinal research. The first section of the paper addresses several issues in theorizing about dynamic processes. The second section provides the framework for representing dynamic processes. This section is divided into three parts. The first part examines the dimensions of process characteristics that individual variables may display over time. These dimensions include: continuity, magnitude, rate of change, trend, and periodicity. The next part provides a typology for examining dynamic effects in process theories by exploring the possible relations between two or more variables over time. This typology focuses on the history of the variables, the time lag, the rate of change, the magnitude of change, and the permanence of change. The final part discusses the issues of feedback and stability in process theories. The third section of the paper presents a typology of alternatives for analyzing process data. The paper concludes with a discussion of important unresolved issues in process research.

Theorizing about Dynamic Processes

The choice to conduct longitudinal research should be governed by theoretical issues. If theory specifies that several variables constitute a process that unfolds over time, then there is good reason to design longitudinal research to study the process. If theory specifies that two or more phenomena covary within a population at any point in time, then it makes little sense to conduct longitudinal research; a static, cross-sectional research design is preferable. For example, a theory that specifies that organizations evolve through periods of convergence and reorientation (Tushman and Romanelli 1985) requires a longitudinal design of sufficient duration to cover the theorized punctuated equilibria. A static, cross-sectional design would not generate the data required to test the theory.

The easiest way to design longitudinal research is on the basis of a dynamic theory and process hypothesis. A good process theory describes, at least in broad outline, plausible time parameters associated with change within and between the phenomena of interest. Given general theoretical specification of changes over time, it is relatively easy to develop a research design to correspond to the theoretical specifications (see Monge 1982). Ideally, scholars should address the issue of time specification in the theoretical phase of their work before they address it in the research phase. Realistically, the current state of knowledge in organizational science rarely permits precise time specification. Nonetheless, even general time notions such as lag,
sequence, duration of change, etc., are important theoretical specifications. Vague and inexact specifications of process characteristics are preferable to no specifications at all.

Understanding the nature of process characteristics will sensitize both deductive and inductive scholars to focus on those characteristics in their research. The characteristics can be used to develop and test process theories, whether theorized in advance or discovered in the observational record. Each theoretical strategy has much to gain by focusing on process characteristics.

It is useful to ask the question, “What form would knowledge eventually take if organizational scholars were able to create valid scientific theories of dynamic processes in human organizations?” Irrespective of whether the theories were developed deductively or inductively, scholars would work toward the formulation of theories that correctly articulated the fundamental relations among variables over time. As with traditional theoretical work, attention would be given to the development of essential concepts. Similarly, the theories would stipulate the relations between the concepts, i.e., the hypotheses. However, in contrast to traditional theories, process hypotheses would describe the expected or observed behavior of each variable over time as well as the interrelations among the variables over time. These specifications would pay particularly close attention to the time lags of causal influence among variables and to the feedback loops specified or emerging in the theory, if any.

These theoretical specifications would be summarized in formal representations of the systems. One useful formalization is a set of dynamic equations. Data would be collected in longitudinal designs that fulfilled the requirements of the theory. Specifically, the theory would indicate the number of times data would be collected, the length of the interval between data collections, and consequently, the overall duration of the research. The set of relations contained in the longitudinal data would be tested against the system of equations which formally represents the theory, thereby determining the truth or falsity of the theory. If the data supported the theory, the system of equations could be used with the longitudinal data to forecast the behavior of the dynamic processes under investigation. In such systems, the dynamic coefficients represent knowledge about the interrelated processes among pairs of variables,\(^2\) in the same way that traditional regression coefficients represent knowledge about pairs of static relations in samples or populations at single points in time.

**A Framework for Representing Dynamic Processes**

*Dynamic Processes in Individual Variables*

Designing and executing a scenario like the above may seem like a formidable task, but it can be simplified by subdividing it into more manageable subtasks. One strategy is to think about the dynamic nature of each variable arrayed in time before attempting to deal with the interrelations among variables. This is important because the field of organizational science has almost no information about how variables behave over time. Further, knowledge about how variables behave independently over time provides a basis for better understanding how they relate to each other over time. In short, in most forms of dynamic analysis it is essential to know how variables depend upon their own past history, including trend and cycles (or previous develop-

\(^2\)Each dynamic coefficient represents the relation between the changes in the dependent variable over time and changes in one independent variable over time controlling for the over time influence of all other independent variables.
mental and evolutionary stages) as a basis for discovering how they relate to each other. This section provides a framework for representing dynamic processes in single variables. While extensive, it should be kept in mind that the current state of the framework is not yet exhaustive or comprehensive.

When theorizing about a dynamic variable in isolation, i.e., unrelated to any other variables, it is important for the theoretician to consider six dimensions of dynamic behavior. These are continuity, magnitude, rate of change, trend, periodicity and if the variable is discontinuous, duration.

Continuity, the first dimension, refers to whether the variable has a consistent nonzero value through time, where zero typically represents the nonexistence of the variable. A continuous-time variable, such as organizational climate, is typically viewed as one that always exists at some value (Joyce and Slocum 1984). A discontinuous-time variable, such as the payment of the monthly bonus in the Scanlon management process, is one that occurs, then doesn’t have a value until it occurs again at the next month (Monge and Cozzens 1987).

The second dimension, magnitude, refers to the amount of the variable at each point in time. Across time, magnitude may remain constant at any level or it can change considerably. The upper and lower bounds of magnitude are determined by the scale on which the variable is measured. Magnitude may be negative if the variable is measured on a scale with negative numbers.

Rate of change is the third dimension; it specifies how fast the magnitude increases or decreases per unit of time. Magnitudes, whether large or small, can change rapidly, even instantaneously, or they can increase or decrease slowly. For example, changes in organization climate are generally viewed as occurring quite slowly except in the case of organizational crisis. On the other hand, changes in the value of a firm’s stock often occur quite rapidly, especially when new products are announced and hostile takeovers are attempted.

Trend, the fourth dimension, refers to the long term increase or long term decrease in the magnitude of a variable. Since trend can either increase or decrease it can have a positive or negative value. Further, the trend can be large or small, indicating a large or small long term change in the magnitude. For example, salaries typically have a positive trend as a result of annual increases. Inflation that exceeds salary increases can give real income a negative trend. And, executives tend to have large salary trends while clerks have small trends. Variables that increase and decrease randomly fit the definition of trendless as do variables that are constant.

The fifth dimension is periodicity. It is the amount of time that transpires between the regular repeating of the values of a variable, controlling for trend. If a variable does not repeat on a regular basis, it has no period. The length of the period can vary from very short to very long. For example, the numbers of employees in a large firm changes daily with retirements, firings, layoffs, and hirings. Other business cycles occur on a quarterly or annual basis. And Kondratieff cycles are long term business cycles that are believed to have a period of approximately 50 years. Periods are usually measured from peaks to peaks (highest magnitude) or from valleys to valleys (lowest magnitude) in continuous-time variables, though any fixed interval referent works as well. For a discontinuous-time variable, periods are usually measured from the onset of the variable or from the point at which it reaches maximum magnitude.

The final dimension is duration. It relates primarily to discontinuous-time variables. Duration refers to the length of time that a variable exists at some nonzero value. For example, the major network evening television newscasts occur once per day (their periodicity) and last for 30 minutes. Some variables have a long duration while others have short durations. Further, the length of the duration may change over time. For
example, the length of time that an organization requires to manufacture a given product tends to decrease over time.

To explore these issues it is sometimes helpful to develop a time plot of the variable. Figure 1 presents an illustration of the six dimensions for representing the possible behavior of a single variable over time. The top half of Figure 1 is for discontinuous-time variables, the bottom half for continuous-time variables. In the discontinuous-time case, the rate of change is instantaneous, the magnitude for the first occurrence is eight units, the variable has a duration of two time units following which the magnitude drops instantaneously back to zero. Also, there is an upward trend of two units each time the variable recurs, and it recurs every six time units (onset to onset or termination to termination) indicating a periodicity of six.

The continuous-time variable illustration ranges in magnitude from a low of three units to a high of nine units. The rate of change is two units per time period. There is no trend since the magnitudes of the peaks and valleys are relatively constant. Finally,

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3This distinction is different from discrete and continuous measurement. Variables may be measured either discretely (categorically) or continuously (i.e., on a scale). This measurement is independent of whether the variables are viewed in a process as continuous-time (occurring at all points in time with nonzero values) or discontinuous-time (occurring with nonzero values at some points in time and having zero values at other points).
the periodicity of the variable is six units between peaks, valleys, or any other point on the graph.

It is informative to explore possible dynamic patterns that can occur in single variables as a function of different combinations of the six dimensions. Figure 2 presents eight possible scenarios for discontinuous-time variables and Figure 3 presents another eight for continuous-time variables.

The top four examples in Figure 2 show patterns for variables that occur for fixed durations; the bottom four show patterns of variable duration. The examples were further created by distinguishing between periodic and nonperiodic variables and between those that were of constant versus those that were of variable magnitude. It is important to recognize that in the case of discontinuous-time variables the focus is on variable versus constant magnitude rather than on rate of change. Finally, the distinction is made between those situations which display trends and those which are trendless. For example, Cell A shows a discontinuous-time variable of fixed duration that occurs at a regular period at a constant or fixed magnitude without trend. Cell H presents a discontinuous-time pattern of variable duration that is nonperiodic and of varying magnitudes with a trend. For comparison, Cell A shows a highly predictable pattern while Cell H shows a pattern that would be more difficult to predict.

Figure 3 provides eight possible examples for continuous-time variables. Duration is not an issue in continuous-time variables, so the dimensions illustrated in Figure 3 are trend, periodicity, rate of change, and magnitude. Cell A shows a continuous-time
Trend

Periodic

High Rate of Change Low Rate of Change

High Magnitude

Nonperiodic

High Rate of Change Low Rate of Change

High Magnitude Low Magnitude

Trendless

Periodic

High Rate of Change Low Rate of Change

High Magnitude Low Magnitude

Nonperiodic

High Rate of Change Low Rate of Change

High Magnitude Low Magnitude

Figure 3. Examples of Eight Dynamic Patterns That a Continuous-Time Variable May Display.

A variable that has a positive trend, is periodic, has a high rate of change and a high magnitude of change. Cell H illustrates a trendless continuous-time variable that is nonperiodic with a low rate of change and relatively low magnitude of change.

Dynamic Processes and Effects: A Typology

Dynamic theorizing requires an important change in the way hypotheses are stated. The traditional form, “an increase in \( X \) is related to an increase in \( Y \),” is appropriate for static, cross-sectional research, but it does not capture the dynamic aspects of process. Rather, it is essential to formulate hypotheses in such a way that they include the relevant aspects of time. This can be done by specifying one or more of the six dimensions of process analysis described in the previous section. One possibility is something like the following: “A change in the magnitude of \( X \) during the time interval between \( a \) and \( b \) leads to a change in the magnitude of \( Y \) during the time interval between \( c \) and \( d \).” Another hypothesis specifically addressing the lag dimension might take the following form: “Changes in variable \( A \) will precede changes in variable \( B \) by two to four weeks.” Yet another possibility which focuses on trend and period could be: “There will be a positive trend of one to two units per month together with a quarterly cycle in the magnitude covering six to eight units.” None of these hypothetical hypotheses is terribly precise, but each specifically addresses one
or more of the six essential process characteristics. It may not be possible to capture all of the relevant aspects of the process in a single verbal hypothesis. Rather, multiple hypotheses may be required.

Formulating process hypotheses such as these requires an understanding of various possible cause-effect relations. The analysis in the previous section produced six dimensions for theoretically specifying the time dependent behavior of individual variables. This knowledge is crucial for theorizing about the dynamic relations among two or more variables, specifically dynamic causes and effects. The present section describes a typology of dynamic effects to assist in theorizing about organizational phenomena. The typology consists of five components: the history of the variables, the lag (immediacy), rate of change, the magnitude of change, and the permanence of change. Some of these components are identical to the six dimensions of dynamic analysis presented in the previous section (e.g., rate of change); others are different (e.g., lag). Despite the overlap between the two schemes, all five components are useful in identifying cause-effect relations.

Consider the five components of the typology in the simplest case where there are two variables. First, each variable has an empirical history that approximates one of the behavioral patterns in Figures 2 and 3, at least theoretically. This history may be known or it may be hypothesized as part of the theory. As is well known, in order to determine a cause and effect, it is necessary to observe change in one variable that precedes change in the other and, of course, to rule out spurious causes. Thus, it is necessary to theoretically array the two variables such that changes in the cause precede changes in the outcome variable. The second component of the typology, lag, indicates the amount of time between the onset of change in the causal variable and the onset of change in the outcome variable. In other words, lag specifies the immediacy with which a change in one variable begins to effect the other variable.

The third component of the typology is rate of change, which refers to the rapidity of change in the causal variable and the rapidity with which the effect occurs, once it begins to take place. Rate of change can vary from very slow to virtually instantaneous.

The fourth component of the typology, magnitude, refers to the amount of change in each variable. Independent variables can change anywhere from a small amount of their possible variation over time to all of their possible variation. The same is true of dependent variables.

Permanence, the final component, refers to the degree to which a cause or effect continues throughout time. If an effect is permanent, then once the effect has occurred, the value of the variable remains unchanged until some other event causes it to change. If it is temporary, then the effect will terminate at some later point in time, if no intermediate events occur to sustain it.

Figure 4 shows the components of this typology of effects. Two vertical axes are provided in order to include a causal, independent variable, $X$, and an effects dependent variable, $Y$, that are measured on different scales (a five-point scale for $X$, a ten-point scale for $Y$). The horizontal axis represents time. The graph is divided into two parts. The history of the variables on the left side provides the context for interpreting the causal process. The right side is the causal process which displays how the cause and effect are theorized to occur. Each of the components of the typology, history, lag, rate of change, magnitude of change, and permanence is indicated on the graph. The example in this graph is a constant value for both variables throughout their relevant history. The rate of change in the independent variable ($X$) is theorized to be instantaneous; thus, it changes from a value of 1 to 2 at a specific point in time. The cause is viewed as lasting for one period of time and then returning to its prior value. Thus, the permanence of the independent variable is
one. Its magnitude of change is one unit or one fifth of its potential variation on a five-point scale.

The dependent variable, $Y$, is also theorized to have a constant history. There is a lag of three time periods before it begins to change relative to the onset of change in $X$. Rate of change is hypothesized to be two units of change in $Y$ over an interval of six time units, or a rate of change of $1/3$ (i.e., $1/3$ unit change in $Y$ per unit change in time). The graph shows that it requires six units of elapsed time before the effect is complete. The magnitude of change in $Y$ is two units over a ten-unit scale of variation, yielding a magnitude of $1/5$. This change is theorized to be permanent, at least until another change occurs in $X$ to produce further changes in $Y$.

Figure 4 can be summarized as a set of dynamic hypotheses something like the following: An increase in variable $X$ of at least 1 unit of magnitude for a period of one unit of time will cause a change in $Y$. The change in $Y$ will begin 3 time periods after the onset of $X$ and will require six periods of time to increase a maximum of 2 units. Thereafter, it will remain unchanged until another change occurs in $X$ (or another variable to which $Y$ is related). The focus of these hypotheses is on the change in the levels of the variables over time. Dynamic hypotheses can also be developed about the relations between levels and rates of changes and between just rates of change (see Tuma and Hannan 1984).

Imagine a scholar focusing attention on the components of cause-effect processes in a case study being conducted as a part of a larger effort to inductively develop organizational theory. Let us further imagine that what the scholar observes roughly corresponds to the general features shown in Figure 4. From knowledge of the variables, the researcher establishes a six-month observation plan in which measurements are made on the two variables on a weekly basis. What would the researcher
observe? For eight weeks the variables would remain constant at their respective X and Y values of 1 and 6. At the beginning of the ninth week the X variable would increase rapidly from a value of 1 to a value of 2. The researcher may have expected this change in X beforehand, though this is not necessary. Also, the researcher may or may not have participated in making X change. The X variable would remain at the value of 2 for one week and then return or be returned to its original value of 1. During this time the researcher would continue to measure Y, but Y would continue to remain constant at a value of 6 until three weeks after the beginning of change in X. Then, Y would change slowly for six weeks at the rate of 1/3 of a scale unit per week. During this time, X would remain constant at its prechange value of 1. At week eighteen, Y would stop changing and throughout the remainder of the research, Y would remain at a value of 8.

With this observational record in hand, the scholar could identify and plot the history, rate of change, lag, magnitude and permanence of the process. The history of

![Continuous Rapid Cause](image)

![Continuous Slow Cause](image)

![Discontinuous Rapid Repetitive Cause](image)

**Figure 5.** Five Possible Causal Scenarios. (Effects are not shown.)
the variables was a constant until \( X \) changed. The rate of change in \( X \) was virtually instantaneous; in \( Y \), \( 1/3 \). The lag was 3 weeks before change in \( X \) produced any observable change in \( Y \). The magnitude of change in \( Y \) was 2 units on its 10-point scale, while for \( X \) it was one unit of change on its five-point scale. And the change in \( Y \) was permanent even though \( X \) returned to its original value of 1 within a week after it changed to 2.

The distinctions made in the typology of causal effects provide a rich basis by which to explore possible causal patterns. For example, Figure 5 presents four causal scenarios that occur by different combinations of the two components of rate of change and permanence, specifically, contrasts between rapid and slow causes and between permanent and temporary causes. (For simplicity, the effects variable is not shown.) A fifth scenario shows a discontinuous, repetitive cause. Many other scenarios are possible.

It is also important to consider different plausible patterns of effects. Eight examples are provided in Figure 6. These effects scenarios assume that the history of each variable is constant prior to the onset of the causal process. For simplicity it also assumes that the causal variable occurs instantaneously and is temporary, returning quickly to its prechange value. This research design, where an event at a single point in time (or over a specific period of time) is viewed as causing a change in an ongoing process, is called intervention analysis (see Cook and Campbell 1979, Cook et al. 1980, and McCleary and Hay 1980). In this type of design, sorting out cause and effect is relatively straightforward. Since \( X \) does not vary over the history of the relation, then occurs briefly at a specific point in time and then not again, it is possible to determine its influence on \( Y \).

**Figure 6.** Examples of Cause-Effect Scenarios. These Are Derived from the Three Components of Lag, Rate of Change, and Permanence. The Causal Variable, \( X \), is a simple Intervention That Occurs Rapidly at One Point in Time with Minimal Duration.
A. X causes a change in the level but not the cyclicality of Y.

B. X is a discontinuous cause that occurs twice at different magnitudes. It affects the level but not the cyclicality of Y. The effect is delayed by 5 time units.

**Figure 7.** More Complex Causal Relations.

The examples in Figure 6 show contrasts between immediate and delayed effects, rapid and slow effects, and permanent and temporary effects for a simple intervention by a causal variable. For example, cell A shows an immediate effect (no lag), that is rapid and permanent. By contrast, Cell H shows a delayed effect which occurs slowly and is temporary.

It is worth exploring the implications of more complex causal relations. Figure 7 provides several. The first example (A) shows an X that causes an instantaneous change in the level of Y but does not affect the cyclicality of Y. Example B represents a discontinuous repeating cause that occurs twice at different magnitudes. It affects the level of Y twice, once for each occurrence of X, but it does not affect the cyclicality of Y. Further, there is a five-unit time lag before the effect takes place. Determining causality in these situations is analytically more complex, but the theorizing is relatively straightforward.

Dynamic theorizing frequently focuses on the relations between two or more variables that vary continuously over time. This case is known as concomitant variation. Three examples are provided in Figure 8. Example A shows two time series where X is historically the cause of Y in an inverse relation so that when X increases, Y decreases. During the causal effect period of interest, when X stops increasing, Y stops decreasing one unit in time later. A common example of this occurs in the housing market, where increases in the cost of funds leads to decreases
in mortgage applications until the increases in cost of funds level off leading to a stabilizing of mortgage applications at or near their obtained level.

Example B shows $X$ as a countercyclical cause of $Y$. Peaks of $X$ lead to valleys of $Y$, one time unit later. Similarly, valleys of $X$ cause peaks of $Y$ one unit later. An example of this kind of relation (though not the specific time lag) occurs in geographical regions that experience dry and wet seasons. In many western states, an increase in rain during the winter months leads to a decrease in forest and brush fires; a decrease in rain during the summer months leads to an increase in fires. Example C represents two processes whose cycles are aligned, with $X$ leading $Y$ by one time period. A peak in $X$ leads to a peak in $Y$, and $X$ valleys cause $Y$ valleys.

The issue of cause and effect is more complicated in the case of concomitant variation than in the case of intervention analysis. Whether changes in one variable lead changes in the second or the second leads the first is a matter of perspective. Since both variables vary together through time, it is difficult to determine which causes which. One solution to this problem was proposed by Granger (1966, 1980) and has become known as Granger causality. Granger was the first to point out the
necessity of controlling for the past history of a variable in order to determine causal effects on variables. Granger’s definition of causality was that one variable could be taken as a cause of another only after the influence of the past history of the second variable on itself has been controlled (Van de Ven and Poole 1990). The section prior to this one described several techniques for theorizing about the behavior of individual variables across time, including their histories; those techniques are directly relevant to the determination of Granger causality.

The identification of causes and effects is a fundamental aspect of organizational science. The notion of Granger causality described in this section identified procedures that can be used to determine causality in dynamic systems. Sometimes, however, the research goal is less on determining causal relations and more on specifying the overall dynamic process. Feedback loops are an important aspect of dynamic processes. The next section describes the role of feedback loops in dynamic theories and their place in the central issue of stability analysis.

*Dynamic Processes in Systems with Feedback Loops*

Many theories in the organizational sciences postulate one or more links which create feedback loops (See, e.g., Bagozzi 1980). A link is a relationship between two variables (or between the same variable at two points in time). Feedback loops are one or more links that eventually relate a variable to itself at a later point in time. By definition, feedback loops represent processes that occur over time. Analysis of the nature of the links and loops can provide important insights into the dynamics of the theory. This section provides an explication of the central features of feedback loops, primarily, stability analysis. It also relates the analysis of feedback loops to the forms of dynamic theorizing described above.

Feedback links represent positive (direct) or negative (inverse) relations (the sign of the link) that are typically viewed as causal (Kenny 1979). Further, feedback links are characterized by the magnitude of the relation, most often in the form of verbal descriptions or, quantitatively, in the form of standardized or unstandardized regression coefficients.

Feedback loops also have a positive or negative sign and are characterized as stable or unstable. The sign of the loop is determined as the algebraic product of the signs of each of the links in the loop (Kenny 1979). Stability is determined as the product of the magnitude of the coefficients of each of the links in the loop.

There are three well-known forms of feedback (Blalock 1969, Kenny 1979); they are presented in Figure 9. A self loop represents the influence of a variable on itself, i.e., the influence of its own history. A mutual causal loop represents the (nearly) simultaneous influence of two variables on each other. Finally, a standard loop represents the effect a variable has on itself through its influence on a chain of other variables.

Theorists who postulate the existence of feedback loops should be explicit about the time dependent nature of the feedback links and loops. Correct specification of a self loop is equivalent to explication of the historical behavior of a variable as illustrated in the previous sections. Theorists should specify whether the variable increases or decreases over each cycle of the loop and by what magnitude. (Most self loops are nonlinear, implying exponentially increasing or decreasing self influence over time.) Also, it is important to specify the frequency at which each cycle occurs. Similarly, theorists need to be specific about the sign, magnitude, and time dimension of mutually causal and traditional feedback loops. Drawing time graphs of concomitant variation like those in Figure 8 can provide useful precision.

Stability analysis is an important aspect of dynamic systems. Maruyama (1968) introduced to the social sciences the notions of deviation amplification and deviation
counteraction to represent the influence that a feedback loop has on the initial variable. Deviation counteraction is a negative feedback loop where a magnitude of change in one direction in the initial variable leads in time through the feedback loop to an eventual change in the initial variable in the opposite direction. Thus, an increase in the magnitude of X will lead eventually to a decrease in X through the subsequent influence of the other variables in the loop. Since X has changed a second time, it causes the process to repeat. However, since X decreased this time but the loop is still negative, this decrease in X leads eventually to an increase in X. Obviously, this is oscillatory behavior over time as X switches back and forth from increasing to decreasing with each cycle of the feedback loop. The same oscillatory pattern holds if X initially decreases rather than increases.

Deviation amplification represents a positive loop in which an initial change in a variable leads eventually to further changes in the variable in the same direction. Thus, an increase in the initial variable leads eventually to a further increase in the variable. Likewise, an initial decreases leads to a further decrease.

Obviously, variables cannot continue to increase or decrease indefinitely. At some point they will reach the limits of their capacity for change. Consequently, when theorists specify feedback loops, it is crucial that they identify whether the system is stable or unstable. As Blalock indicates (1969), stability is determined by the sign and magnitude of the product of the coefficients along the loop. Two general rules specify the type and stability of feedback. First, if the product of the coefficients is above zero, the feedback is positive; if below zero, the feedback is negative. Second, if the absolute value of the product is below one, the feedback is stable; if above one, the feedback is unstable. Figure 10 presents examples of the four possibilities: stable
and unstable deviation-amplifying (positive) and deviation-counteracting (negative) feedback loops. The figure also shows the two product rules governing each case.\(^4\)

Theorists who develop one or more feedback loops as a part of their theories should also specify the expected sign of the coefficient for each link and estimate the magnitude of the relation between each pair of variables. The rules above then make it possible to theorize whether the feedback is positive or negative and whether the model is stable or unstable.

**A Typology of Analytical Alternatives**

Theorizing about dynamic processes is essential for meaningful longitudinal research. Nonetheless, an important part of the research design is the selection of an appropriate statistical technique for analyzing the longitudinal data. The discipline’s collective experience in this domain is modest at best.

Table 1 presents a typology of statistical techniques for analyzing longitudinal designs. One axis of the typology represents the “Research Design” in terms of the

\(^4\)These criteria are for difference equations with lagged variables. Blalock also provides the criteria for linear differential equations as do Tuma and Hannan (1984), who also provide the criteria for nonlinear equations.
<table>
<thead>
<tr>
<th>TYPE OF MODEL</th>
<th>LONGITUDINAL</th>
<th>( t )-TEST</th>
<th>STRUCTURAL EQUATIONS</th>
<th>( x^2 )</th>
<th>( x^2 )</th>
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<td>Time Series</td>
<td>( t )-test</td>
<td>Structural equations(^a)</td>
<td>( x^2 )</td>
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<td>Event history analysis</td>
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<td>( t )-test</td>
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<td>Structural equations</td>
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<td>Structural equations(^b)</td>
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<td>MANOVA</td>
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TABLE 1 (continued)
A Typology of Analytical Alternatives for Longitudinal to Static Research Designs

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<tr>
<th>TYPE OF MODEL</th>
<th>Longitudinal</th>
<th>Static</th>
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<tr>
<td></td>
<td>Many Points in Time</td>
<td>Two or a Few Points in Time</td>
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<tr>
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<td></td>
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<tr>
<td>multiple</td>
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<td></td>
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<td>INTERDEPENDENCE MODELS:</td>
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<td>Multiple Continuous Variables</td>
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<td>Metric multidimensional scaling</td>
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<td>Confomatory factor analysis</td>
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<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>a. Also known as reliability and stability analysis</td>
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<td></td>
</tr>
<tr>
<td>b. Also known as path analysis</td>
<td></td>
<td></td>
</tr>
<tr>
<td>c. Logit and probit analysis</td>
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</table>
number of points in time at which data are gathered. This varies from static to
dynamic or, equivalently, from cross-sectional to longitudinal. This axis of the table is
divided into three sections: single point in time, two or a few points in time, and many
points in time.

The second dimension of the table pertains to the “Type of Model” being
analyzed. Of course, this model should correspond to the theory. There are four types
of models. Independence models examine single variables or single variable pro-
cesses. Dependence models look at relations between two or more variables. Interde-
pendence models focus on relations within a set of variables rather than relations
between variables. Finally, hybrid models constitute a residual category for tech-
niques that seem to fit into more than one category.

These four models are subdivided further by number of variables and levels of
measurement, where applicable. The number of variables is divided into single
variables and into multiple independent and multiple dependent variables. The levels
of measurement are split into categorical, which typically represents nominal or weak
ordinal level of measurement and continuous, which represents ratio, interval, and
strong ordinal measurement.

The cells of the typology represent statistical techniques that are appropriate for
the type of model and the research design chosen by the researcher. For example,
Glick, Huber, Miller, Doty, and Sutcliffe (1990) asked top executives to retrospec-
tively recall the occurrence of major organizational changes. Though each event is
different, at a higher level of abstraction each is an instance of the categorical
variable “organizational change.” Though the data were gathered at six month
intervals over a two-year period of time, the dates of change provided by these
informants permitted the approximate location in chronological time for each change,
thus producing a distribution of a single categorical variable across time. Figure 1
shows that an independence model with a longitudinal design can properly be
analyzed with Markov models in general and the sociological variant known as event
histories (Tuma and Hannan 1984, p. 91–115). The latter was the method they chose
for this part of their analysis.

An article by Monge, Cozzens and Contractor (1991) provides another example.
These researchers theorized that increases over time in two communication factors
and three motivational factors would lead over time to increases in the number of
innovations generated in a sample of firms. This dynamic theoretical framework
implies the “Longitudinal” category of the Research Design dimension of Table 1.
The specification of predictor variables and outcome variables implies a dependence
model in the Type of Model dimension of the table. There was one dependent
variable measured at the ratio level (number of innovations generated per week per
firm), so the first appropriate subdivision is single continuous dependent variable.
There were five predictor variables measured at the strong ordinal and interval levels.
Consequently, the appropriate subcategories are “Continuous Independent
Variable(s)” followed by “Multiple.” The cell representing this combination of
Research Design and Type of Model contains the entry “Multivariate Time Series.”
Since the researchers had collected weekly data on all six variables for 52 weeks,
multivariate time series was the analytic method of choice.

Conclusion

The central thesis of this article has been that the design and conduct of longitu-
dinal research should be a theoretical enterprise. This means that researchers must
specify the over time behavior of each variable in the design and should theorize
about the dynamic interrelations among the set of variables. The article has provided a framework to assist organizational researchers in this process.

Yet there are numerous issues that a primer such as this could not address within the confines of a journal length article. In this final section several of these will be briefly mentioned as an agenda for future investigations of dynamic process. Some of these issues are intellectual, others empirical. All provide a rich area in which to work.

Two broad classes of process theories exist in organization science: (1) those which conceptualize phenomena as recurring patterns of a cycle, and (2) those that conceptualize the processes as a sequence of events or stages. When viewing a process from this latter perspective, important considerations include the identification of the stages in the sequence and the specification of the conditions of movement from one stage to the next. Several stage theories exist in the organizational literature. For example, organizational life cycle theories (Kimberly and Miles 1980) propose that organizations proceed regularly through the stages of emergence, growth, maturity, decline, and death. Tushman and Romanelli’s (1985) metamorphosis model argues that organizations go through successive stages of convergence and reorientation. Van de Ven and Poole’s (1990) theory of innovation processes describes a sequence of stages as innovations emerge, develop, grow or terminate over time. They have developed a set of techniques to empirically determine the stages and transitions between stages of innovating. The current article has focused primarily on the cyclical form of theory. A similar explication of how to develop process stage theories, hypotheses, and research would enrich the organizational literature (see Abbott 1990, Mohr 1982, Tuma and Hannan 1984, Van de Ven and Poole 1989).

At the center of all dynamic analyses is the assessment of change over time (Kelly and McGrath 1988). There are several models of change that have been used in organizational and other social science theories. For example, Meyer, Brooks, and Goes (1989) present a typology of change models based on the distinction between continuous and discontinuous change and between firm and industry levels of analysis. The intersection between these two dimensions leads to four classes of change models: adaptation, metamorphosis, evolution and revolution. Further examination of the nature of various change models, the development of appropriate forms of hypotheses for each type of model, and the specification of relevant longitudinal research designs would substantially increase our understanding of dynamic processes.

Closely related to this issue is the one of linear and nonlinear systems or of order and chaos. Linear systems are generally viewed as orderly, steady state, equilibrium maintaining systems. Nonlinear systems may be orderly or they may be chaotic. Chaos generally refers to the fact that a small change in the initial parameters of a system can lead to radically large changes in the behavior of the system (Gleick, 1987). The framework described in this article assumes that change occurs rather orderly. Other frameworks need to be developed that focus on chaotic change (see Glass and Mackey 1988). For example, Fombrun (1986) argues that structural dynamics within and between organizations is a dialectic between convergence (equilibrium) and divergence (chaos), either of which may be dominant at any point in time. (See, also, Child and Keiser’s 1981 discussion of the nature of change in organizational development.)

Whatever the content, studying the dynamics of human systems places time at the center of all theory and research. Although time has been included in the analytic frameworks described above, nothing has been said about the nature of time. Jaques (1982) argues that the way we view time fundamentally affects the way in which we view phenomena. Much of the preceding analysis has been based on the notion of “clocktime” or “real time.” Yet Clark (1985) asserts that clocktime should be viewed
as only one of the several alternatives for determining time. He argues that organizational theorists should employ a plurality of time-reckoning systems. One example of analyzing an alternative to clocktime comes from Gersick’s (1989) recent research on group time reckoning during decision tasks with fixed deadlines. Her results show that most groups utilize the first half of their allotted time in relatively nonproductive activities, but at the half-way point they shift to highly focused, productive work. A thorough examination is needed between the nature of time in organizational theories and the role of time in hypotheses and research designs. (See, for example, Kelly and McGrath’s 1988 discussion of real time versus experimental time.)

There are a number of practical issues that must be addressed in the conduct of longitudinal research. One of these is the question of how often to gather data. In the case of cyclical processes, Arundale (1980) presents a theorem demonstrating that in order to reproduce the cycle, data must be gathered at least as often as one-half the periodicity of the phenomenon. Thus, for periodic phenomena, the issue of how often to gather data is directly related to the theoretical and/or empirical issue of how long it takes the phenomena in the theory to complete one cycle of change. Similar criteria would be helpful in stage theories and in chaotic phenomena.

Another practical issue related to sampling is who or what to observe. Almost by definition process research requires multiple observations on the same entity. Yet when the phenomena of interest are human processes, a host of problems arise pertaining to the effects this has on the people involved (see Cook and Campbell 1979). A number of solutions have been proposed, such as institutionalizing the data collection process as an inherent part of work (Monge et al. 1984) and taking unobtrusive measures, e.g., in studying electronic mail (Fulk, Schmitz, and Steinfield 1990). Another solution has been to draw random samples from organizations without replacement until everyone in the firm is sampled and then repeat the sampling frame as often as necessary. This strategy reduces the reactivity problem but produces a quasi-panel rather than a true panel design. Further research on this issue should help researchers make important choices in the conduct of longitudinal research.

Another practical issue is how to analyze process phenomenon in multiple cases. For example, most time series analyses focus on a few variables of a single entity measured at many points in time (e.g., several measures of the economy at quarterly intervals over several years). In essence, most time series analyses are case studies or what Kratochwill (1978) calls “single subject research.” Process techniques such as time series analyses have not yet been developed for analyzing many variables on many cases at many points in time. The work by Monge, Cozzens and Contractor (1991) described earlier in this article contained weekly measures on six variables over 52 weeks for five firms. Their analysis provided separate time series models for each firm, the results of which differed somewhat across companies. These researchers then conducted a meta analysis of the results from the five models. This strategy provided an estimate of the dynamic relations across all the firms in the study as well as an estimate of the stability of the coefficients across the firms. This is an indirect way to achieve what someday should be available for all process researchers: methods for directly analyzing dynamic processes across multiple cases.

Forecasting is an important but little known aspect of process research. It provides a unique way to test the adequacy of the process models, yet almost no organizational studies exist that utilize forecasting techniques. Forecasting is the dynamic equivalent of prediction in static research. By developing forecasting models on a part of the data, researchers can test their theories and models on later parts of the same data set. For example, Monge, Cozzens, and Contractor (1991) developed their models on the basis of 42 weeks of data. They used these models to forecast the accuracy of
their hypotheses over the remaining 10 weeks of data. In four out of the five model, the forecasting accuracy for all six variables ranged from 72 percent to 85 percent. The forecasts for the fifth model were less successful leading to an exploration of anomalies in this firm to explain the results.

There is little doubt that major contributions in empirical work in organizations will be made on the basis of longitudinal research (though see Blalock’s 1989 recent despair about methodological advances in sociology). As researchers acquire more experience in designing and conducting longitudinal research, they should also develop experience in thinking and theorizing dynamically. Eventually, new theories will be developed that are inherently dynamic. While that expertise is being developed, valuable progress can be made by translating existing static theories into dynamic form (see Contractor and Monge’s 1990 dynamic reformulation of equity theory).

Organization science is moving slowly in the direction of studying dynamic process. Someday, through a combination of inductive and deductive efforts, organization theories will be dynamic rather than static. Research will be based on longitudinal designs rather than single point in time designs. And data will be analyzed with inherently dynamic techniques such as time series and Markov models rather than with static correlational methods. This article provides a framework designed to assist in the development of that vision of organization science. Yet as this final section has amply demonstrated, much more needs to be known about the process of studying process.

Acknowledgements. This manuscript was prepared in part with support from the National Science Foundation, Grant No. ISL-8412761, Peter R. Monge and Richard V. Farace, co-principal investigators.

I would like to acknowledge the assistance of several individuals who commented on earlier drafts of this manuscript: Noshir Contractor, Janet Fulk, Bill Glick, George Huber, Arie Lewin, Bob McPhee, Scott Poole, Tom Reed, Andy Van de Ven and an anonymous reviewer for Organization Science. I would also like to acknowledge the contributions of the students in my research methods classes at the Annenberg School, who over the years have pressed me hard to clarify my ideas about process. Finally, I would like to thank Linnea Berg for her usual outstanding job of preparing the manuscript and graphics (with the assistance of Judy Chan).

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