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THE BLENDING OF THEORETICAL AND EMPIRICAL KNOWLEDGE IN STRUCTURAL EQUATIONS WITH UNOBSERVABLES

by

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Introduction

Not until recently has the practicing researcher had access to tools of statistical analysis equipped to deal with multidimensional phenomena in systems of relationships incorporating both observable and nonobservable terms that allow for an effective interplay between theory and data. Earlier statistical techniques forced the analyst, willingly or not, to either (1) conform to the doctrine of operationalism--a philosophical position essentially abandoned many years ago in philosophy of science, and/or (2) to follow an early positivistic dictation about the independence of theory and data. For example, traditional econometric modeling almost always requires operational definitions of its variables; the theoretical concepts must be synonymous with a corresponding set of measurement operations. Psychometric modeling, on the other hand, while emphasizing the theoretical desirability of specifying underlying unobservable variables that account for some observed phenomenon (usually a response to a stimulus), also typically requires that data are independent of the context in which they occur. This is the case in classical test theory and its implementation in factor analysis. It is assumed that (1) "true scores" do exist and (2) that they are invariant across different theoretical networks.

As noted by Suppe (1974), "it seems to be characteristic, but unfortunate, of science to continue holding philosophical positions long after they are discredited" (p. 19). The problem is not necessarily that practicing researchers may be unfamiliar with the developments in philosophy of science, but that methodology has lagged in development relative to the logical and epistemological advances in philosophy of science.

Recently, however, significant progress has been made in statistical methodology. A new generation of methods enable researchers to rid themselves of (at least some) the untenable facets of operationalism and logical empiricism. Specifically, it is no longer necessary to insist that theoretical concepts be synonymous with measured variables or to assume that observation is independent of theory.

As practicing researchers begin to apply these methods, however, they are confronted with issues that remain largely unanalyzed in the methods literature and faced with numerical results that challenge some firmly held convictions about theory evaluation. This paper, in the context of the methods of covariance structure analysis (Joreskog, 1973) and Partial Least Squares (Wold, 1975, 1982), discusses the implementation of the theory/data interaction and its implications in terms of theory testing. Let us begin by briefly reviewing the status of abstract variables and their interaction with empirical data in contemporary philosophy of science. Subsequently, we present a discussion of abstract and empirical meaning and how the two are combined in analysis.

Theory and Data Interaction

Measurement in economic science is viewed as an attempt to tie a concept to the empirical world. In doing this, two contradictory forces become immediately apparent: on the one hand, there is the desire to faithfully reproduce the "economic world" as it is known by its actors; yet there is also the ambition to discover the underlying and, thus abstract, properties of "economic order." Faithfulness is always forfeited when abstraction is achieved. Yet, without abstraction there is no theory.

Abstraction can be accomplished in various ways and through various stages. For example, distinctions are sometimes made between observational terms (which can be directly observed), indirect observables (which require some sort of inference) and constructs (which have no direct linkage to the empirical world). Thus, in linking the abstract to the empirical, observational terms imply operational definitions; that is, the concept is synonymous with some corresponding set of operations. While operationalism might have value in terms of "faithfulness to reality" (although this is debatable), it is not a satisfactory substitute for abstraction and for theoretical work. The reason is two-fold according to Suppe (1974): (1) theoretical terms are not explicitly definable if the theory is to be axiomatized in first-order predicate calculus with equality and (2) alternative experimental procedures for measuring the same theoretical property make it unreasonable to identify the theoretical property with any one experimental procedure or even any specified set of alternative procedures.

The recognition of the difficulties in equating the theoretical and the empirical has led to a variety of suggestions concerning the linkages (correspondence rules) between them. As a consequence, operationalism has long been abandoned in the philosophy of science literature. More recent interpretations of theoretical terms are found in the realist approach and in the instrumentalist approach to theory. The former lets theoretical terms refer to real but nonobservable phenomena. The latter, considers theoretical terms to be more or less expendable; they are not explicitly defined and their sole purpose is to define the class of theoretical laws for the theory. Nevertheless, whatever the role of theoretical terms is supposed to be, there is basic agreement about their abstract or nonobservable status. This is true for logical empiricism as well.

Examples of observational terms might be such things as volume, cell nucleus, or market share. Among the theoretical terms would be things like atoms, genes, virus, attitude, and demand elasticity. However, as suggested by Achinstein (1968) a distinction between the observational vs. the theoretical is not possible because "observation" involves attending to something and how many aspects of that something and which aspects one must attend to before it can be said that observation has taken place, will depend upon prior concerns and knowledge. That is,

(1) Observation if it is to be relevant, must be interpreted.

(2) That in terms of which interpretation is made is always theory.

(3) The theory not only serves as a basis of interpretation, but also determines what is to be counted as an observation, problem, method, solution, and so forth.

In other words, all the information collected by a researcher is conditioned by the context into which the research is placed.

Abstract Meaning[1]

Figure 1 presents a diagram that can be used to illustrate the idea of abstract or theoretical meaning. Here, for simplicity, the discussion is

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1) This section draws heavily from Bagozzi and Fornell, 1982.

restricted to the interpretation of a single focal concept, F. In general, the meaning of F is obtained through a specification of three criteria: (1) the definition of F, (2) the antecedents, determinants, or causes of F, and (3) the consequences, implications or results of F. Though a complete meaning of F is achieved only when all three criteria are addressed, it is possible that any particular study, depending on its purposes, may emphasize a subset. Generally, a minimal interpretation of F at the conceptual level requires a definition of F plus either an antecedent, A, or a consequence, C, and its relationship to F.

The definition of a concept can take a number of forms. Perhaps the most common is one that specifies the attributes, characteristics, or properties of F (termed an attributional definition). A concept will have a set of descriptors which can nominally be considered as definitionally equivalent to the concept. Typically this set consists of attributes whose content and number evolve over time, conditioned on intersubjective agreement among scientists.

INSERT FIGURE 1 HERE

We may further note two subtypes of attributional definitions: namely, the atomistic-analytical and the holistic-contextual. An atomistic-analytical attributional definition consists of a set of properties such that each property is a subdimension of the idea represented in the concept. For example, a definition of a market might include the following properties: two or more actors are involved; the actors are in communication with each other; each has something of value desired by the other; one is termed a buyer and the other a seller; the transaction is characterized by offers and counter-offers; and so on. A holistic-contextual attributional definition, in contrast, comprises a number of elements and relationships among the elements. The definition of a concept requires specification of the entire network, and the elements and relations are exhaustive. This contrasts with the atomistic-analytical attributional definition, where some properties are essential or necessary to a definition while others are non-essential to the essence of the concept but serve to elaborate a particular manifestation or subtype of idea implied by the concept. An example of a holistic-contextual attributional definition of a market might be: a meeting of minds where actors construct a shared reality concerning the allocation and distribution of goods and services.

Another basic form a definition might take is as a description of capacities, tendencies, or dispositions of a concept (termed a dispositional definition). Unlike the attributional definition, which is limited to a description of the properties of a concept (for example, the individual physical, psychological, or social characteristics implied by a concept, or a system of these characteristics), the dispositional definition refers to the intrinsic nature of a concept. Typically, this will encompass specification of the internal structure of a concept and its potential for either influencing another concept or being influenced by it in some way. For example, one might use a dispositional definition of an attitude to specify a structure of cognitions and evaluations having certain capabilities and linked in such a way that the introduction of a stimulus communication would lead to attitude change and this, in turn, would influence choice behavior. An attributional definition of attitude would be limited to a description of the elements of attitude (for example, a set of beliefs and evaluations) and perhaps a rule for combining the elements. A dispositional definition contains a representation of the ability or power of the concept to undergo change and to produce change in other concepts, in addition to specification of the elements of the concept and interrelations among elements. Although such capabilities might be implicit in the attributional definition, they are formally delineated in the dispositional definition.

The abstract meaning of a focal concept, F, is also determined by its antecedents (see Figure 1). Whereas a definition specifies what a concept is and perhaps what is is capable of being and doing, its antecedents supply information as to where it has been (that is, its history or development) and/or how it is formed or influenced. However, if one is to reveal the meaning provided by an antecedent, it is not sufficient to merely indicate what the antecedent is. Rather, as represented in Figure 1, one must also specify the content of the hypothesis linking antecedent to the focal concept (that is, H_{af}) and the rationale for the hypothesis (that is, R_{af}). The content of a hypothesis consists of a statement of the nature of the relationship of antecedent to focal concept and is expressed in proposition form. This might entail a relatively nonspecific statement such as "the greater the magnitude or level of A, the less the magnitude or level of F," or it might entail a more specific statement as to the functional form of the relationship or even the amount of change expected in F as a function of A. The rationale for the hypothesis is needed to complete the meaning of F provided by A. In general, a rationale for a hypothesis can be obtained through specification of the mechanisms by which A influences F and/or the laws under which A and F are regularly conjoined.

In a parallel fashion, the meaning of F is also determined through its relations to consequences (see Figure 1). The implications of a focal concept, F, supply information as to where a phenomenon is going, what it can lead to, and/or what influence it has. Again, it is not sufficient to identify what the consequences are. Rather, one must also describe the nature of the hypothesis connecting focal concept to consequence (that is, H_{fc}) and the rationale for the hypothesis (that is, R_{fc}).

The depth of abstract meaning achieved through specification of antecedents and/or consequences depends on the extent of the description of the relationships and their rationale. Further, we may ascertain the adequacy of the meaning so provided through examination of the internal consistency of the propositions, analysis of alternative hypotheses, asking "what if" questions, performing thought experiments with regard to the system of propositions, and conceptually integrating and comparing the hypotheses to the existing body of knowledge related to the focal concept. Thus, it can be seen that, while much of the abstract meaning of concepts depends on logical (semantic and syntactic) criteria residing in definitions and in the relations of antecedents and consequences to a focal concept, empirical criteria also enter the picture. They do this through the normative of conventional standards imposed by a community of scientists as well as through the inductive generalizations of past research that guide the selection and formation of concepts and the hypothesized relations to other concepts in a theory. This infusion of empirical content has often been implicit and nonformal, however.

Empirical Meaning

The primary and formal route to the empirical meaning of concepts is through correspondence rules. As shown in Figure 2, a correspondence rule (cr) is a relational concept linking a nonobservational focal concept, F, to empirical measurements, $f_1, f_2, \ldots, f_n$.

With the exception of operationalism, perhaps the most common way that empirical meaning is achieved is shown in Figure 2 where the focal concept is specified as a unidimensional theoretical variable and each of n measurements represents either (1) alternative or redundant indicators of the concept or (2) conceptually independent subdimensions of the concept. In the first case, the n measures will covary as a consequence of their common content. We might think of the measures as correlates of the concept or as being caused or implied by the concept. In the second case, each measurement is an empirical manifestation of only an explicitly defined portion of the object or event implied by the focal concept. The n measures need not necessarily covary at a high or uniform level.

INSERT FIGURE 2 HERE

The abstract-empirical relationships, as depicted in Figure 2, while more common in psychology than in economics, are a manifestation of the early logical positivist's assertion that data are neutral with respect to theory. In order to arrive at a more realistic representation, we can combine Figure 1 (depicting a process by which abstract meaning is formulated) and Figure 2 (depicting relationships between the abstract and the empirical) into a system that encompasses both abstract and empirical meaning. Figure 3 shows the result in this case. Here again we have the focal concept, F, determined by its antecedents, A, and determining its consequences, C. We also have linkages for each abstract concept to corresponding observations (i.e., a's, f's, c's). The empirical linkage need not be as simple and direct as suggested in Figure 3, but let us maintain this simplicity for now and focus on two important questions:

1. What is the directionality of the abstract-empirical linkage? That is, what comes first, theory or observation?
2. How can theoretical and empirical knowledge be balanced in the analysis? What type of knowledge should be given more weight and how can the weighting be implemented in analysis?

INSERT FIGURE 3 HERE

The Directionality of The Relationship Between Theory and Data

While the discussion of observables-unobservables and the difficulty in making a general distinction between the two has a long history in philosophy of science, it pales compared to the longevity of the debate regarding directionality: do our observations lead us to theory or do our theories lead to certain observations? In 1620, Francis Bacon wrote:

> "There are and can only be two ways of searching into and discovering truth. The one flies from senses and particulars to the most general axiom, and from these principles, the truth of which its takes for settled and immovable, proceeds to judgment and to discovery of middle axioms. And this way is now in fashion. The other derives from the senses and particulars, rising by gradual and unbroken ascent, so that it arrives at the most general axiom last of all."

The first approach is deductive with its starting point in the abstract with propositions, that if true, imply specific observable events. The second approach is inductive and begins with observation and observational patterns that are formalized into theory. Our schematic for abstract and empirical meaning (Figure 3) can be augmented to include both inductive and deductive modes. Figure 4 illustrates a relationship between observables and unobservables as implied by a deductive approach.

INSERT FIGURE 4 HERE

In this model, the theoretical system represented by A, F, C and their relationships, imply the observations a_i, b_i, c_i, $i = 1 \ldots 3$. In other words, the observations are reflective of the theoretical model.

INSERT FIGURE 5 HERE

In Figure 5, the observations a_i, b_i, c_i, $i = 1 \ldots 3$ "make up" the theoretical variables A, F, C. Thus, the observations are formative (of the theoretical model).

Simply speaking, in the deductive case we take the observations as dependent upon the abstract theoretical model, whereas in induction the theoretical variables are taken as dependent upon the observed variables. As might have been surmised from our earlier discussion of the lack of a clear distinction between what is observable and what is not, it is equally problematic to make a distinction with respect to directionality. Certainly, knowledge is produced by a continuing dialogue between theory and data. The context of a specific situation must determine what should be regarded as unobserved or observed and what the linkage should look like. Similarly, the context determines the bearing of a priori theoretical knowledge in the analysis. And this is the question of how theoretical knowledge and empirical data should be balanced. Let us now turn to the implementation of these notions.

Implementation: Covariance Structure

The objective of covariance structure models is to construct a network of abstract theoretical variables that account for the correlations between observed variables. Thus, in this respect, it conforms to deductive reasoning as illustrated in Figure 4. For sake of illustration, consider a very simple model.

INSERT FIGURE 6 HERE

In terms of product moment correlations, the above covariance structure model can be written:

$$\mathrm{Cor}_{x_1x_2} = (\mathrm{Cor}_{Xx_2})\ (\mathrm{Cor}_{Xx_1}) \tag{1}$$

$$\mathrm{Cor}_{y_1y_2} = (\mathrm{Cor}_{Yy_2})\ (\mathrm{Cor}_{Yy_1}) \tag{2}$$

$$\mathrm{Cor}_{x_1y_1} = (\mathrm{Cor}_{Xx_1})\ (\mathrm{Cor}_{XY})\ (\mathrm{Cor}_{Yy_1}) \tag{3}$$

$$\mathrm{Cor}_{x_1y_2} = (\mathrm{Cor}_{Xx_1})\ (\mathrm{Cor}_{XY})\ (\mathrm{Cor}_{Yy_2}) \tag{4}$$

$$\mathrm{Cor}_{x_2y_1} = (\mathrm{Cor}_{Xx_2})\ (\mathrm{Cor}_{XY})\ (\mathrm{Cor}_{Yy_1}) \tag{5}$$

$$\mathrm{Cor}_{x_2y_2} = (\mathrm{Cor}_{Xx_2})\ (\mathrm{Cor}_{XY})\ (\mathrm{Cor}_{Yy_2}) \tag{6}$$

From estimating the correlations between the observed variables, we use equations 1-6 to solve for correlations involving the unobserved theoretical variables. For example, some simple algebraic manipulation gives:

$$\mathrm{Cor}_{XY} = \pm\ [(\mathrm{Cor}_{x_1y_1})\ (\mathrm{Cor}_{x_2y_2})/(\mathrm{Cor}_{x_1x_2})\ (\mathrm{Cor}_{y_1y_2})]^{1/2} \tag{7}$$

and

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$$Cor_{XY} = \pm\,[(Cor_{x_1y_2})\,(Cor_{x_2y_1})/(Cor_{x_1x_2})\,(Cor_{y_1y_2})]^{1/2} \tag{8}$$

In statistical estimation (using, say, Jöreskog's maximum likelihood program) a weighted average of the two algebraic solutions of Cor_{XY} is produced.

Consistent with the specification of reflective indicators, the abstract model specification plays a large role in determining the results; almost to the point that it "overrides" the data. For example, with noisy and unreliable data, we would expect low correlations between the indicators $x_1 - x_2$ and $y_1 - y_2$. Since the product of these correlations appear in the denominator, the lower the correlations between observed measures, the higher the resulting correlation between the abstract variables (relative to the x-y correlations). Thus, it is here that the researcher must make a decision about the relative weight that should be given to data vs. theory. If the indicator correlations are low, the only justification for this type of model is that much of the observed data can be "explained away" as random noise and that the theory is plausible enough to give it a dominating role in the analysis. As the indicator correlations increase, the observed data have greater impact. In the limit, with correlations at one, the theoretical variables become synonymous with the observed variables and we have a form of operationalism.

An Example

Consider the following correlation matrix:

x_1	1			
x_2	-.109	1		
y_1	-.126	.114	1	
y_2	.190	-.171	-.260	1

All correlations in this matrix are fairly low. Ignoring signs, the correlations between x- and y-variables range from .114 to .190. If we construct theoretical variables as in Figure 6 using equations (7) and (8), what is the correlation between X and Y? Using the correlations in the matrix above, we find that the equations (7) and (8) give the same estimate of .873. Clearly, this correlation is very different from the correlations between the observed x- and y-variables. Is this reasonable? That depends on how much the analyst is willing to discredit the observations (in terms of random noise) and stand by the theory.

Fortunately, alternatives to covariance structure analysis are available when the analyst is unwilling to depart too far from the data and wants to obtain a different balance between theory and observation. One such alternative is Partial Least Squares (PLS) developed by Herman Wold.

Implementation: Variance Structure

The objective of variance structure models, such as PLS, is to construct a network of abstract theoretical variables that account for the variances of theoretical and/or empirical variables. Note the critical difference between the covariance structure and the variance structure implementation. Covariance structure models always attempt to recover the full correlation matrix of observed variables; in variance structure models, the analyst specifies what variable variances he wants to account for. For example, in the model of Figure 4, it is implied that the model is designed to account for the variation of F, C, a_i, f_i, c_i, i = 1 ... 3. The model of Figure 5 is designed to account for the variation in F and C only.

In order to limit the distance from the data in analysis, the theoretical variables are required to be composed of nothing but a combination of the empirical variables. This assures that the analysis cannot go "beyond the data" as was the case in the covariance structure implementation. On the other hand, it is a restriction on theory in the sense that more weight is given to the data.

Several weighting schemes have been developed for the minimization of residual variances within the PLS algorithm (Lohmöller, 1983). Wold's (1966) original algorithm treats each residual separately by determining a set of local minimization criteria. For example, the minimization criteria of the model in Figure 6 apply to the residuals associated with Y, x_1, x_2, y_1 and y_2. Without going into the details of the algorithm used to accomplish a joint minimization of the local residuals, suffice to say that a part of the minimization criteria is satisfied while some other part is considered to be known and, therefore, fixed. In the iterative estimation procedure, the local criteria treated as fixed in one cycle are relaxed in the next cycle and vice versa until convergence.

Example 1

Let us again use the same data as before (the 4 x 4 correlation matrix) and the model in Figure 6. Recall that the observed x-y correlations were low (range .114-.190) but that the estimate of the theoretical correlations between X and Y were quite high (.873). What is the result from the PLS estimation? As expected, the coefficient turns out to be significantly lower at .262. While this is still higher than what the correlations between observed variables indicate, the data now play a larger role in determining the results.

Since variance structure models limit their focus to variances, the covariance of observed variables is not of primary interest. For the example here, where the covariance structure model recovers the correlation of observed variables perfectly, the PLS model does not.

The two models illustrated, covariance structure and variance structure with reflective indicators, represent very different types of combining the abstract with the empirical. Theory is given a much stronger voice in the covariance structure model. There are, however, other possible combinations of theory and data within similar types of models. If we change the specification from reflective to formative indicators, we obtain yet another data/theory mix.

Because the covariance structure model does not readily accept formative indicators, we limit our discussion to the PLS approach.

Example 2

The illustration of the difference between formative (mode B in Wold's terminology) and reflective (mode A in Wold's terminology) indicators is taken from a theory developed by Albert O. Hirschman (1970). The theory deals with consumer response to decline in quality. Basically, the dissatisfied consumer faces a choice between two options: exit or voice. The exiting consumer makes use of the market by switching brands, terminating usage, or by shifting patronage--all economic actions. Voice, on the other hand, is a political action: a verbal protest to the seller. The theory suggests that when the exit option is unavailable (as it might be in a monopoly), or when consumers are reluctant to change (as might be the case when cross-elasticities are low), voice will increase. By this reasoning, exit should dominate in highly competitive markets, whereas the more a market resembles the monopoly situation, the more voice would be expected.

A much discussed measure of monopoly power are industry concentration ratios. These ratios measure the market shares held by the largest four firms, eight firms, twenty firms, and fifty firms. If the ratios are high, the interpretation has been that this is an indication of monopoly power. More recently, however, it is generally recognized that concentration ratios are very fallible measures of monopoly power. Spence (1981) for example, shows that three or four firms may be sufficient for acceptable consumer welfare (if there is price competition). He warns against using measures of market share, such as concentration ratios, in public policy in order to enforce competition. A problem for public policy, however, is that there are not many comprehensive measures of competition or monopoly power within easy access. And, even though concentration ratios are fallible indicators of monopoly power, they probably contain <u>some</u> information about such power. The task is then to separate valid information (variance) from that which is not relevant.

Let us now consider how this could be done. If we create an unobserved variable from the four concentration ratios, should we use reflective or formative indicators? The answer to this question depends primarily on how one conceptualizes the theoretical variable and what the objective of the model is supposed to be. Let us present the results first and then return to these issues.

The theory predicts a negative relationship between monopoly power and exit and a positive relationship between monopoly power and voice. If we think of concentration ratios as reflecting the theoretical variable, monopoly power, two measures of consumer voice (aided and unaided respondent recall) as reflective of a theoretical consumer voice variable, and finally consider consumer exit to be synonymous with its measure, the following results are obtained:

INSERT FIGURE 7 HERE

Reformulating to formative indicators, we obtain these results:

INSERT FIGURE 8 HERE

In both cases, the direction of the relationships is as predicted by Hirschman's theory, but the magnitude of some of the relationships vary markedly between the two models. First, consider the theoretical variable, monopoly power. If we consider monopoly power to be an underlying construct that is reflected in measures of industry concentration, we note that there is a close correspondence between the construct and its measures as indicated by loadings (here correlations of .94 to .99). Is this evidence in support of using concentration ratios as measures of monopoly power? In principle, the answer is yes, but only in the context of the particular exit-voice model. Thus, before one can draw any meaningful conclusions about the role of concentration ratios in the study of monopoly power, one has to examine the context in which the conclusions are supposed to hold. In this case, it is apparent that there is only very weak support for the theoretical model. The explanatory power as measured by R^2 is very low. Consequently, any practical use of this model to predict exit or voice from monopoly power (as measured here) is extremely limited.

The most striking difference between the results in Figure 7 (reflective indicators) and Figure 8 (formative indicators) is in the correspondence between concentration ratios and monopoly power and in the relationship between monopoly power and exit. On the average, only 22 percent of the variance in the concentration ratios $[(.40^2 + .50^2 + .58^2 + .42^2)/4 = .22]$ is included in the monopoly power construct when indicators are formative. As a result, the theoretical variable is now very different and explanatory power for exit has increased over 7 times ($R^2 = .22$).

Comparing the two models, the first shows strong "support" for concentration ratios as indicators of monopoly power but only in the context of very weak theoretical model results. Hence, given our earlier discussion about the interdependence between theory and data, one would be hard pressed to find any real support here for concentration ratios as measures of monopoly power. Only if we ignore the theoretical context, would it be possible to make a claim of support. Indeed, in our second model almost 78% of the variance in the concentration ratios is discarded (not extracted in forming the monopoly power construct). Given the (at least moderate) support for the substantive theory in this model, the implications about the quality of concentration ratios as indicators of monopoly power would be (1) that there is not a close correspondence between indicators and construct but (2) there is a minor portion of information that is valid. Again, however, there is no justification for generalizing beyond the theoretical context in which the modeling was done.

Instead, we have now illustrated, via simple examples, the specification of meaning; that it has both a theoretical and an empirical aspect. This is nothing new to the "abstract methodologist" or to the philosopher of science, but this is certainly not the case for most practicing researchers, particularly in economics.

As Kaplan (1946) wrote on the definition and specification of meaning:

> "The situation is like that of the delicately balanced constructions by Calder, in which the artist is free to add or remove weights wherever he pleases, but must make compensating changes to maintain the balance and thus the specification at any stage is a provisional one, both as to the indicators included, and the weights associated with them." (Kaplan, 1946, p. 286)

Kaplan further notes:

> "As the context of application grows, the specified meaning grows--and changes--with it. The stipulation of new indicators affects the weights of the old ones, while they in turn limit the range of choice in the stipulation. The adequacy of a particular indicator is not judged by its accordance with a pre-determined concept: the new and old indicators are appraised conjointly." (Kaplan, 1946, p. 287).

Had the quote above been of more recent vintage and read by someone interested in the statistical modeling of unobservables, Kaplan's statements might have been interpreted as directly concerned with some method of structural equations with unobservables. And, despite the fact that such methods were not developed until about thirty years after the publication of Kaplan's article, such an interpretation appears to be far from distorted. Whenever we add or delete indicators or change their status between formative and reflective, we also change their weights and the meaning of the unobservables.

Implications

The application of covariance or variance structure analysis implies fundamental changes in current research methodology, particularly in economics. What has been shown in philosophy of science (e.g., Swinburne, 1971) --that empirical confirmation or verification is full of paradoxes and cannot serve as a meaningful criterion of science--becomes apparent in using these methods. Perhaps more critical, the popular alternative to verification--Popper's (1962) program of falsification is equally elusive. The reason, of course, is found in the impossibility to obtain "theory-free" data. In order to be able to falsify a theory empirically, it must be assumed that the interpretation of data is independent of the theory being tested and other theories as well. This assumption has more or less been declared obsolete in philosophy of science, but is at least implicitly maintained in traditional methodology of economics and other social sciences.

As was illustrated in the examples of this paper, the interaction between theory and data can have a substantial impact upon results. Research conclusions are highly dependent on how we specify the theoretical model as well as the relationships between model and data. Accordingly, it makes little sense to follow the common practice of assuring quality of measurement (via various reliability and validity tests) in <u>isolation</u> of the theory to which the measures relate and <u>before</u> they are used in a substantive context. The measurement model and the theoretical model should be analyzed simultaneously. Only after such an examination would it be possible to draw conclusions about the quality of measurements and theory, although one is always interpreted in the context of the other. If one is changed (e.g., theory), chances are that the way we interpret the other (e.g., data) changes too. For example, if the theory relations are changed in, say, a PLS or covariance structure analysis, the measurement relationships (i.e., the loadings) may change as well. Of course, this does not suggest that one's measurement model always changes as a result of a respecification of the theoretical model. It seems entirely possible that certain variables are indifferent to certain differences in theory. The point is that it would be better to test for the extent of data-theory dependence than to assume it away as would be necessary if one first subjects measurements to validity testing via, say, confirmatory factor analysis, and subsequently employs the measures found "valid" in a substantive context.

Towards a Unification of The Sciences?

In view of the many substantial advances in natural science, it is perhaps understandable that many social scientists look to the methodology of natural science as a role model. Yet, much of the criticism leveled at logical empiricism charge that it is modeled on an early understanding of certain pieces of 19th century physics and that the natural sciences may not be an appropriate role model for the social sciences. The typical argument is that the subject matter of the natural sciences is so different from the subject matter of the social sciences that the methodology must also be different. Freedman (in press) speculates on what would have happened if Kepler had known multivariate statistics and suggests that the application of statistics would have led him to the best-fitting circular planetary orbits and the elliptical orbits would have been ignored.

While it is true that traditional multivariate statistics were almost never employed in physics and relatively seldom in chemistry, it appears that methods such as covariance and variance structure analysis may be relevant to all sciences. For example, modern physics (e.g., quantum theory) involves statistical relationships, unobservable variables, system behavior, and theory-laden observations. This is, of course, exactly the type of phenomena that these methods are designed to analyze. Thus, it may well be that the new statistics will not only have a profound impact upon methodology in the social sciences but will also perhaps unify some methodological aspects of natural and social sciences.

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FIGURE 1

A Schematic for Ascertaining the Meaning
of a Single Concept, F

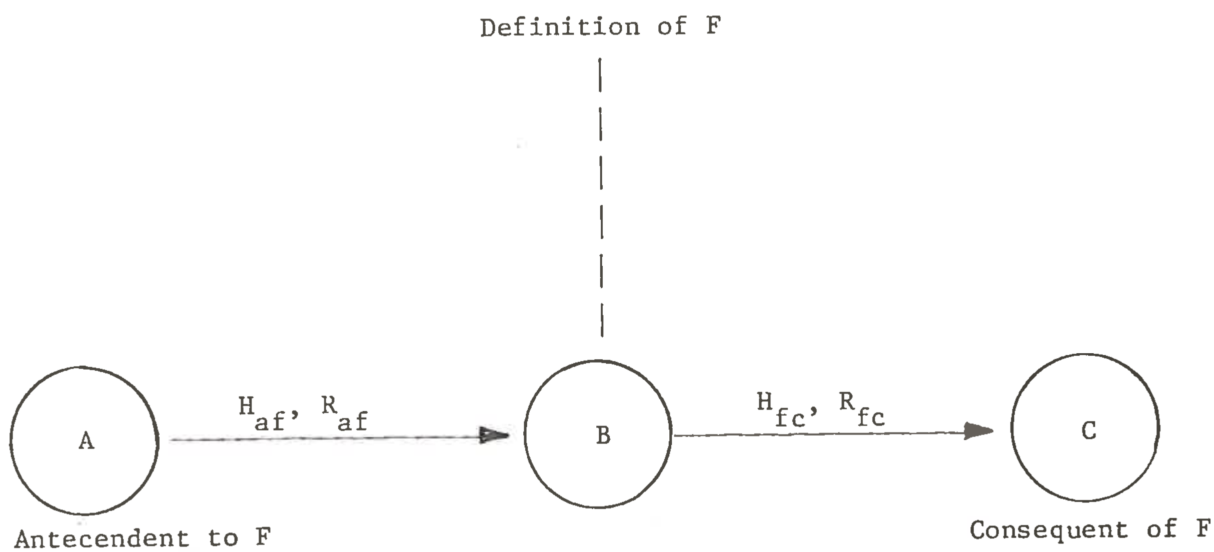

FIGURE 2

A Schematic for Ascertaining the Empirical Meaning of a Single Unidimensional Concept, F

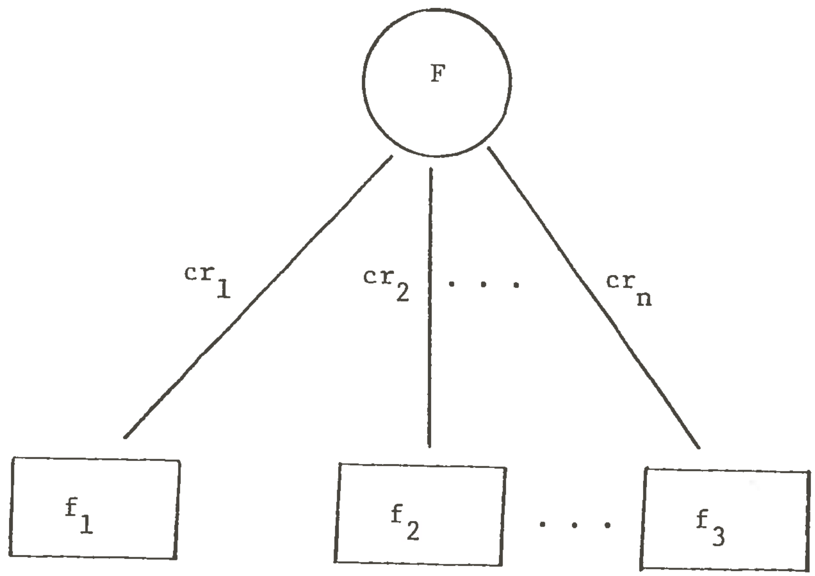

FIGURE 3

A Schematic for Both Abstract and Empirical Meaning

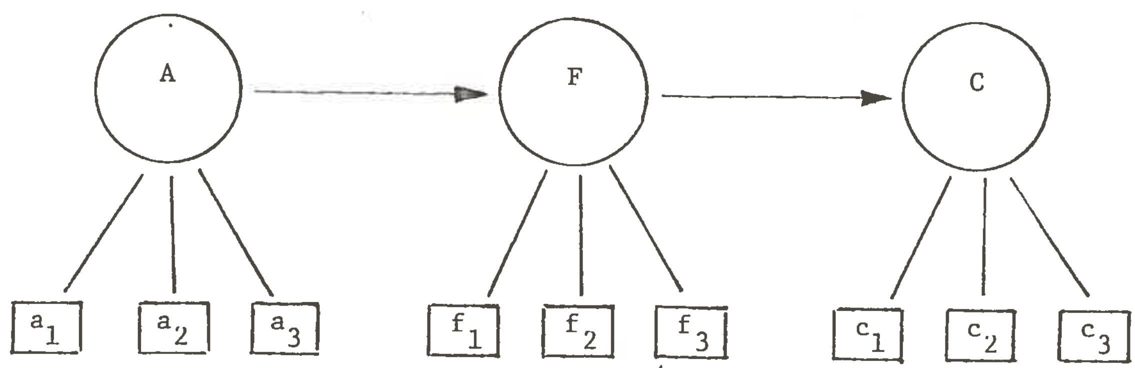

FIGURE 4

Deductive Modeling

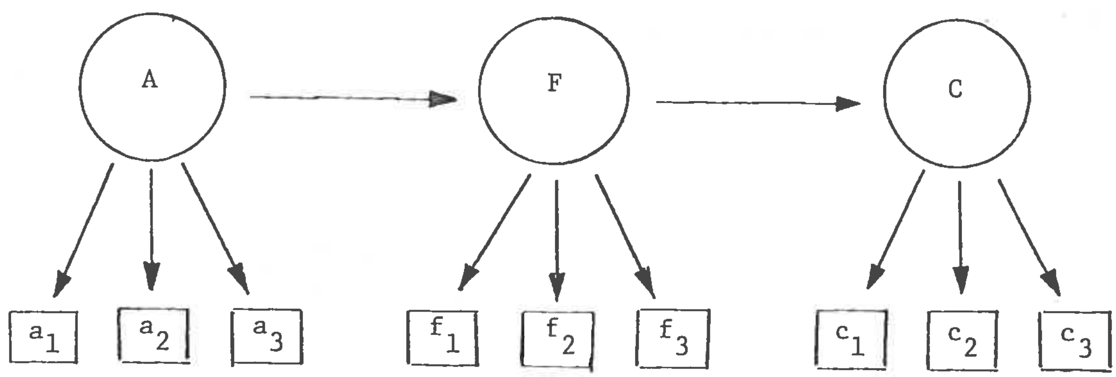

FIGURE 5

Inductive Modeling

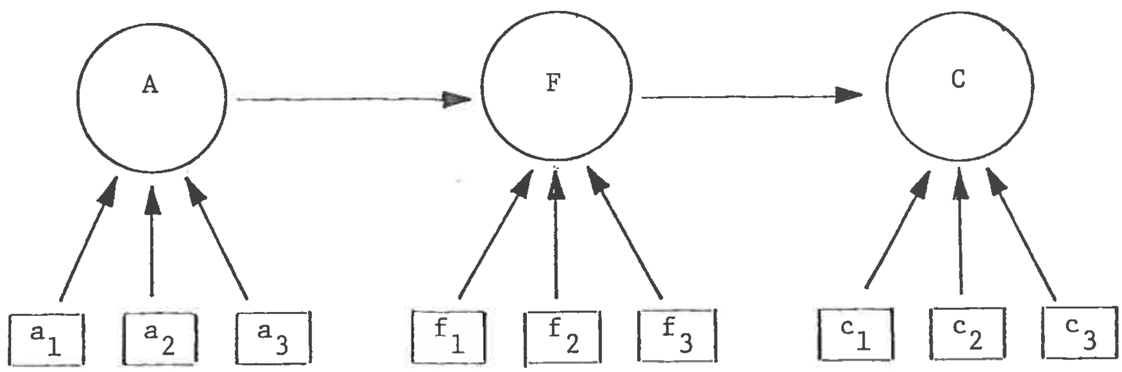

FIGURE 6

A Simple Model

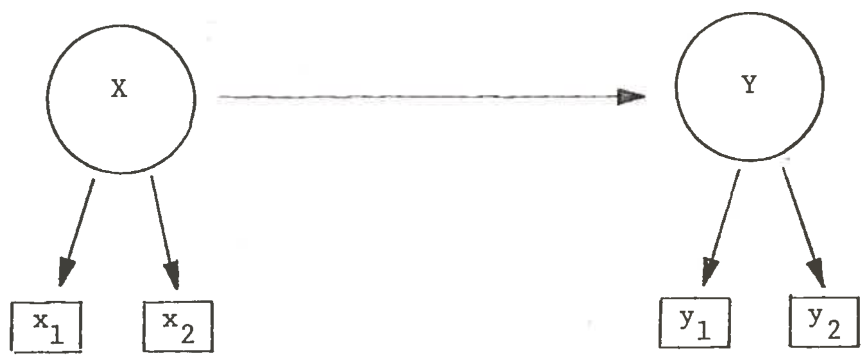

FIGURE 7

Exit-Voice with Reflective Indicators

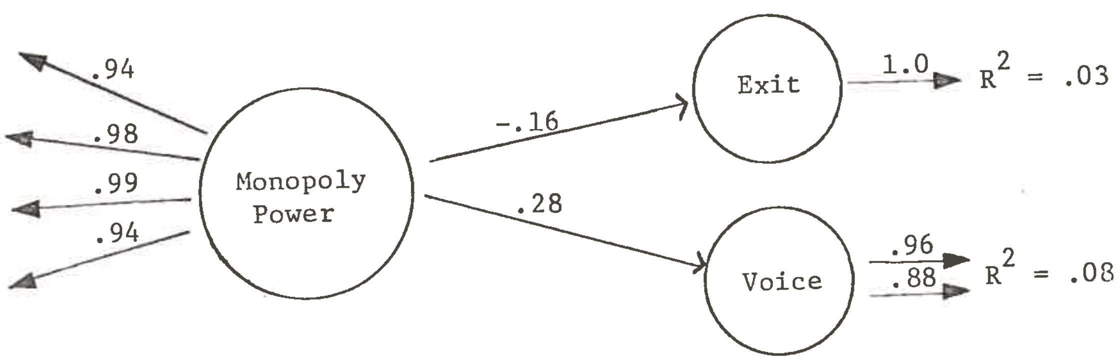

FIGURE 8

Exit-Voice with Formative Indicators