CAMBRIDGE

Cambridge University Press
978-0-521-11524-7 - Structural Modeling by Example: Applications in Educational, Sociological, and Behavioral Research
Edited by Peter Cuttance and Russell Ecob
Excerpt
More information

1

Introduction

PETER CUTTANCE AND RUSSELL ECOB

Structural modeling can be thought of as the marriage of two lines of methodological and statistical development in the social and behavioral sciences. These developments have their seminal roots in early attempts to apply statistical methods to economics and psychology, although similar developments can be observed in other disciplines also. The development of methods for the interpretation of data from widespread mental testing of adult populations in North America and Britain went hand in hand with the development of theories of mental ability. In order to test the efficacy of the various theories of mental ability put forward, the statistical model known today as factor analysis was developed. Since it was evident that a single test item could not tap the full extent of a person's ability in any given area, several items were employed jointly to measure ability. The variation that was common or shared among the items was interpreted as a measure of the underlying ability. Different sets of items were designed as measures of each of the mental abilities hypothesized by the alternative theories. The covariation among these underlying abilities (which were called factors or constructs) was then interpreted in terms of the evidence it provided for the alternative hierarchical and relational models of human abilities put forward in the research.

One aspect of these early models that has been carried over to structural modeling is the idea that a latent construct or factor can be *measured* by the responses to a set of items on a test. In later work this idea was carried forward as the concept of observable indicators for an unobservable construct or, in another context, as multiple measures of a *true score* in test score theory.

A second idea that has been carried forward into structural modeling is that of the correlation between unobservable constructs. This gives rise to the model of covariance structures among latent constructs in structural modeling. The essential feature of covariance structure models is that they deal not with the causal or predictive relationships between the substantive constructs of a theory, but rather with the covariation among latent constructs.

© Cambridge University Press www.cambridge.org

CAMBRIDGE

Cambridge University Press
978-0-521-11524-7 - Structural Modeling by Example: Applications in Educational, Sociological, and Behavioral Research
Edited by Peter Cuttance and Russell Ecob
Excerpt
More information

In contrast, developments in economics focused on the analysis of causal and predictive relationships between one set of variables (the dependent variables) and another set of variables (the independent variables). Economists were initially interested in simple single-equation models, but before long their attention turned to the modeling of systems of equations, representing several processes that theoretical models argued were interlinked and operating simultaneously.

The birth of the methodology known today as structural modeling was brought about by the recognition that many social and behavioral processes could be thought of as causal processes operating among unobserved constructs. This suggested the merging of the latent construct model from psychology with the causal models found in economics. Although the recognition of this model in the form of the path analysis model was useful, it was soon realized that this solution was inadequate, for two reasons. First, it did not allow the researcher to test how well the model explained the covariation in the data, and second, the parameter estimates for the model were apt to vary with the restrictions employed in identifying the model. In general, the substantive models that path models represented were often overidentified, because they posited that several of the causal relationships were zero, and this meant that the remaining relationships in the model could be estimated from different combinations of the correlations among the observed variables. These different combinations do not necessarily yield identical estimates of the parameters in the model. Hence, some method of obtaining estimates of parameters that in combination gave the best fit to the covariation among the observed variables was required, given the causal relationship specified by the model. This led to the development of maximum likelihood estimation methods for estimating and testing the fit of structural likelihood estimation methods for estimating and testing the fit of structural models. Other methods that make less restrictive distributional assumptions about the data have also been developed.

The major advance of structural modeling, then, has been that it has provided a means of testing the capacity of alternative substantive models to account for the pattern of covariation among the observed variables in the data and to do this in terms of latent constructs that parallel the underlying constructs of the substantive model.

Although this advance is in line with recent arguments about the nature of the relationship between theory and the measurement of social and behavioral phenomena, it obviously does not deal with the more radical critiques of the relationship between theory and observation/meaning emanating from phenomenological perspectives of the social world. It is useful for the researcher who uses structural modeling methods to keep in

© Cambridge University Press www.cambridge.org

CAMBRIDGE

Cambridge University Press
978-0-521-11524-7 - Structural Modeling by Example: Applications in Educational, Sociological, and Behavioral Research
Edited by Peter Cuttance and Russell Ecob
Excerpt
More information

mind that there are alternative views of the appropriate methodology for studying social and behavioral phenomena, because it is unlikely that any one perspective or methodology for investigating and understanding the behavior under study will yield the *true* understanding of the behavior.

Chapter 2 provides an overview of structural modeling and presents the formal mathematical and statistical model employed to represent the substantive model the researcher wishes to investigate. Unless readers are already familiar with the basic statistical framework for the LISREL model, they are advised to acquaint themselves with the material in that chapter before going on to the other chapters. Chapter 2 is not intended, however, to be a detailed introduction to the model, for which the reader is referred to the text by Saris and Stronkhorst (1984) or the other material listed in the Reference section of Chapter 2.

Chapters 3–5 illustrate the application of structural modeling to situations that conform to psychologists' models of covariation among the latent constructs of a substantive model. In Chapter 3 Katharine Parkes examines the relationship between constructs represented in two widely used self-report inventories for measuring different aspects of neurotic disorders. The analysis compares the structure of disorders between two groups of subjects. The data had been analyzed previously by conventional correlational methods, and the structure of the relationships among the disorders found to differ between the two groups; however, the present simultaneous analysis of the data suggests that this earlier conclusion was unwarranted. The two main reasons for revising the conclusions are to be found in the fact that the structural modeling approach takes account of the fallibility of the measurement of the individual items in the model and formally tests the hypothesis that the structures differ in the two groups. The model that posits identical structures in the two groups can explain the pattern of covariation among the variables observed in the data just as well as the alternative model, which posits that the structure is different in the two groups. Thus, structural modeling analysis leads to a conclusion about the nature of neurotic disorders with respect to these groups that is substantially different from that arrived at by the earlier naïve analysis of the data.

Chapter 4 by Lee Wolfle illustrates a model of the structure of responses by high school seniors to a questionnaire inquiry about the level of education and the occupation of their parents. These responses are contrasted with those of the parents themselves. The social science survey literature indicates different subgroups in the population may respond with different degrees of accuracy and reliability on questionnaire items relating to parental background characteristics. In this study Wolfle models the responses of black and white children and their parents.

© Cambridge University Press www.cambridge.org

CAMBRIDGE

Cambridge University Press
978-0-521-11524-7 - Structural Modeling by Example: Applications in Educational, Sociological, and Behavioral Research
Edited by Peter Cuttance and Russell Ecob
Excerpt
More information

Measures of covariation and of the strength of causal relationships are attenuated by error introduced in the measurement of such characteristics, and differential attenuation across subgroups in the data could lead one astray when interpreting intergroup differences in such relationships. This chapter again illustrates the interplay between the substantive, methodological, and statistical aspects of the specification and fitting of structural models. The actual model presented is relatively simple, three factors among six observed variables, but because of the clarity of the methodology it yields significant information about the response reliability of the subgroups studied.

In Chapter 5 Peter Hill presents a structural model to test Bloom et al.'s (1956) taxonomy of cognitive learning structures. This taxonomy posits a hierarchical relationship among various learning behaviors and is modeled as an extension of Guttman's (1954) simplex design. This design specifies a hierarchical structure through an ordered multiplicative relationship among the constructs. Since the model takes into account the errors of measurement in each of the observed variables, the appropriate version of the design is that known as a quasi simplex. The analysis provides tests of certain specific substantive hypotheses that allow the researcher to refine issues of uncertainty sequentially in this field of empirical inquiry.

Chapters 6–8 illustrate how structural modeling can be applied in a causal framework. Here the factor and construct methodology of the psychologist is linked to the causal framework derived from that developed in economics. In Chapter 6 Leslie Hendrickson and Barnie Jones specify and estimate a model of the relationships between pupil achievement in the third and fourth grades. They contrast the modeling of this process in a causal framework with that of the usual gain score framework and show that the latter model is likely to yield misleading results in the presence of measurement error, because it omits relevant intervening variables from the model. They illustrate the use of sensitivity analysis to investigate key aspects of the specification of the model.

In Chapter 7 Robert Hauser and Peter Mossel model the relationship between educational attainment and occupational status attainment among siblings within families and among families. This allows them to estimate the variance components associated with families and hence to investigate the dynastic influences of families on the occupational careers of their offspring. They work with a relatively simple model containing only four observed variables, which again illustrates the point that one does not necessarily require highly complex models containing a large number of variables in order to make progress. Indeed, one of the lessons to be learned from successful applications of structural modeling methods

© Cambridge University Press www.cambridge.org

CAMBRIDGE

Cambridge University Press
978-0-521-11524-7 - Structural Modeling by Example: Applications in Educational, Sociological, and Behavioral Research
Edited by Peter Cuttance and Russell Ecob
Excerpt
More information

is that models that are poorly thought out in terms of the substantive theory on which they are based rarely yield interpretable findings.

In Chapter 8 Russell Ecob employs a structural model to estimate and fit a longitudinal model of the relationship between learning difficulties and progress in learning to read. The model can be viewed as an extension of the conventional cross-lagged correlation model, but by incorporating it into a structural modeling framework he is able to take account of the fallibility of the observed measures and to control for aspects of pupils' social backgrounds that influence the process of learning. He shows that a model that fails to take account of these two dimensions of the research question is likely to provide a misleading account of the relationship between learning difficulties and progress in learning to read.

Chapters 9 and 10 report two studies of the robustness of structural modeling against the assumptions made in estimating and fitting the model. In Chapter 9 Anne Boomsma presents findings from a large-scale Monte Carlo study of the maximum likelihood method for estimating model parameters and tests of the fit of a model. She investigates the behavior of the method for a range of distributional features of data found in the social and behavioral sciences. This study is the most extensive investigation of the robustness of structural modeling conducted thus far and provides several benchmarks for the use of the method in various applied situations. In general, it suggests that the maximum likelihood estimator is relatively robust against modest departures from the skewness and kurtosis of the normal distribution for parameter estimates, but that the standard errors, confidence intervals, and likelihood ratio test of fit are somewhat more sensitive to such departures from the characteristics of the normal distribution. Joan Gallini and Jim Casteel investigate the structural modeling analogue of the issue of influential observations in the regression analysis model in Chapter 10. They compare estimates for a model based on a data set trimmed of outliers with those for the full data set. As in the regression analysis case, the influence of outliers is greatest in models estimated from small samples. They authors suggest that the effects of outlier observations on parameter estimates and standard errors are minor in moderately large samples.

In Chapter 11 Willem Saris, J. den Ronden, and Alberto Satorra present the statistical issues the researcher faces in assessing the fit of models through the use of the likelihood ratio test statistc. They demonstrate that many of the path models published in the literature do not fit the data and that the failure to test the fit of a model has often led to conclusions that are not warranted by the data. They argue that it is not sufficient to assess the fit of a model solely on the basis of the likelihood ratio test statistic, that the power of the test must also be taken into

© Cambridge University Press www.cambridge.org

CAMBRIDGE

Cambridge University Press
978-0-521-11524-7 - Structural Modeling by Example: Applications in Educational, Sociological, and Behavioral Research
Edited by Peter Cuttance and Russell Ecob
Excerpt
More information

account before any conclusions about the adequacy of the model can be drawn. They show that tests of hypotheses associated with the parameters in a model are dependent both on sample size and on the structure and magnitude of parameters in the model. Some models can yield a relatively powerful test even if the samples are small, but others require much larger samples if the hypothesis tests are to yield informative results. The authors propose a formal testing procedure that also indicates the degree of power of the test. This procedure is to be incorporated into the LISREL program (version VII and later versions) so that it can be employed routinely in structural modeling applications.

In Chapter 12 Henk Kelderman shows how constraints on the relationships among the parameters in LISREL models can be incorporated into more advanced applications of structural modeling. Other parametrizations of structural models such as EQS in BMDP (Bentler 1984) and COSAN (McDonald 1985) deal with such constraints more directly because they employ a different basic parametrization of the model. A specific case of interest in many situations is the parametrization that can be used in LISREL to ensure that all estimates of error variances are positive, that is the avoidance of Heywood cases.

In the final chapter Peter Cuttance discusses a range of issues and problems that bear on the robustness and validity of the estimates from the various methods of estimation now available in structural modeling programs. He argues that the confirmatory aspect of structural modeling in conjunction with the replication of findings are at least as important in assessing the evidence about the robustness and validity of findings as are issues about the statistical robustness of the estimators and tests of model fit.

The chapter examines the role of replication in social and behavioral research before considering the methodological issues that influence the statistical robustness of parameter estimates, hypothesis tests, and tests of model fit. Given the imperfections of data collection, sample design, and sample administration in most social and behavioral research, we must evaluate the extent to which we emphasize the statistical robustness of the testing procedures and parameter estimates and the extent to which we focus on the replicability of the research findings. Structural modeling is, after all, only an intermediary between the observations of real social and behavioral processes and the theories or models through which we interpret and understand those processes. Hence, considerations of validity and interpretability require referents that are ultimately external to the model testing and estimation procedures themselves. It is these referents to which the methodology of replication and confirmation

© Cambridge University Press www.cambridge.org

CAMBRIDGE

Cambridge University Press
978-0-521-11524-7 - Structural Modeling by Example: Applications in Educational, Sociological, and Behavioral Research
Edited by Peter Cuttance and Russell Ecob
Excerpt
More information

appeals for its veracity. The statistical robustness of models reduces the opportunity for disagreement among models that are true representations of the underlying processes when they are replicated using data collected from independent studies.

The characteristics of measurement in social and behavioral science underlie the basic concerns about the distributional properties of observed variables, which directly influence the choice of and characteristics of the measures employed to summarize the covariation in the data. The robustness of alternative estimators is discussed in terms of their susceptibility to departures from the distributional properties of the normal distribution. The class of estimators based on the maximum likelihood and generalized least squares estimation procedures are robust to moderate departures from normality. The findings from the chapter by Boomsma and from related studies provide a guide as to when more sophisticated distribution-free estimators should be employed. The distribution-free estimators are now more widely available, but they are still too computationally expensive to be employed as front line estimators to replace the maximum likelihood and generalized least squares procedures in the routine estimation of models.

The Appendix lists the LISREL model specifications required to estimate the main models in each of the chapters. It also illustrates the relationship between the mathematical model in its equation and matrix format, as well as the relationship between the latter and the LISREL matrix formulation of the model. The details of the model specification process shown in the Appendix should allow readers to check their own formulation of the models presented in the chapters and to run the models in order to check whether their estimates correspond to those presented in the text. The data for the analyses are also listed in the Appendix, and we suggest that readers make use of the material there to verify their understanding of the methodology and models presented in the book.

References

Bentler, P. M. (1984). *Theory and Implementation of EQS: A Structural Equations Program*. Los Angeles: BMDP Statistical Software.

Bloom, B. S., Englehart, M. D., Furst, E. J., Hill, W. H., & Krathwohl, D. R. (1956). *Taxonomy of Educational Objectives, Handbook 1: Cognitive Domain*. New York: McKay.

Guttman, L. (1954). A new approach to factor analysis: The radex. In P. Lazarsfeld (Ed.), *Mathematical Thinking in the Social Sciences*. Glencoe, IL: Free Press.

© Cambridge University Press www.cambridge.org

CAMBRIDGE

Cambridge University Press
978-0-521-11524-7 - Structural Modeling by Example: Applications in Educational, Sociological, and Behavioral Research
Edited by Peter Cuttance and Russell Ecob
Excerpt
More information

McDonald, R. P. (1985). *Factor Analysis and Related Methods*. Hillsdale, NJ: Erlbaum.

Saris, W. E., & Stronkhorst, L. H. (1984). *Introduction to Causal Modeling in Non Experimental Research*. Amsterdam: Sociometric Research Foundation.

© Cambridge University Press www.cambridge.org

CAMBRIDGE

Cambridge University Press
978-0-521-11524-7 - Structural Modeling by Example: Applications in Educational, Sociological, and Behavioral Research
Edited by Peter Cuttance and Russell Ecob
Excerpt
More information

2

An overview of structural equation modeling

RUSSELL ECOB AND PETER CUTTANCE

Introduction

As indicated in Chapter 1, *structural equation modeling* can be conveniently viewed as a product of the merging of two approaches to model fitting: *multiple regression* and *factor analysis*. The multiple regression approach expresses the relationship of a dependent variable to a number of *regressor* variables, the partial relationship with each variable being expressed by the regression coefficient corresponding to that variable. In contrast, the factor analysis approach finds a number of underlying or latent variables (or factors) that account for the common relationship among a number of observed variables.

In this chapter we examine characteristics of the two approaches and illustrate the differences between them. We then show how the method of structural equation modeling arises from a merging of the two approaches. Finally, we list and explain the general conditions, or framework assumptions, of the models examined and the statistical assumptions required to make the estimation of the models tractable.

The regression (or structural) model

The regression model has four basic characteristics. First, it comprises one equation. Second, this equation specifies a directional relationship between two sets of variables, the dependent variable and a set of *regressor* variables. The variation in the dependent variable is explained by a weighted combination of the values of the regressor variables, the weights being the regression coefficients.[1] Third, the regressor variables are assumed to be measured without error. Fourth, each regressor variable is assumed to be linearly related to the dependent variable.

Of these four basic characteristics, only the second is fundamental to the regression model. All the others can be relaxed within the so-called general linear model. By considering more than one equation simultaneously, a variable that is a regressor variable in one equation can be

© Cambridge University Press www.cambridge.org

CAMBRIDGE

Cambridge University Press
978-0-521-11524-7 - Structural Modeling by Example: Applications in Educational, Sociological, and Behavioral Research
Edited by Peter Cuttance and Russell Ecob
Excerpt
More information

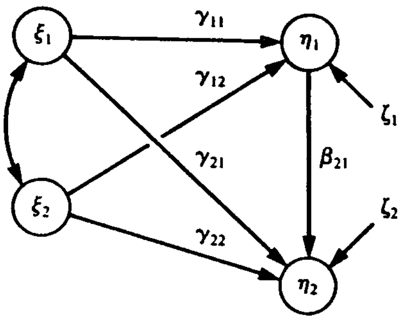

Figure 2.1. Structural model.

specified as a dependent variable in another. This system of equations is known to sociologists as *path analysis* and will be seen to represent the structural aspect of some of the applications in this volume. It also represents the basic form that many econometric models take.[2]

Unreliability, or measurement error, in the regressor variables, either when known by independent means or when estimated from the sample, can be dealt with in the regression approach. This is done by specifying the proportion of variance in the observed variable that is attributable to measurement error (Fuller & Hidiroglou 1978; Goldstein 1979).

Within the structural equation framework the regression model is specified in the *structural* model, and the factor analysis model is specified in the *measurement* model. Figure 2.1 shows a simplified version of the model employed in Chapter 6, which we use to illustrate the LISREL formulation of a structural model. We can think of the two latent constructs denoted by ξ_1 and ξ_2 as the regressor variables in the model and the two latent constructs denoted by η_1 and η_2 as the dependent variables in the model. The relationships between the dependent and regressor variables are then described by the following two equations:

$$\begin{aligned}\eta_1 &= \gamma_{11}\xi_1 + \gamma_{12}\xi_2 + \zeta_1 \\ \eta_2 &= \beta_{21}\eta_1 + \gamma_{21}\xi_1 + \gamma_{22}\xi_2 + \zeta_2\end{aligned}$$

How is this system related to the characteristics of the regression model introduced earlier?

There are now two equations, each involving a dependent variable. The regressor variable set is different in the two equations. The first equation includes the two constructs ξ_1 and ξ_2. The second equation includes, in addition, η_1. It is clear that a variable can serve in two roles, as a regressor variable in one equation and as a dependent variable in another.

In order to accommodate this, variables that function only as regressor

© Cambridge University Press www.cambridge.org