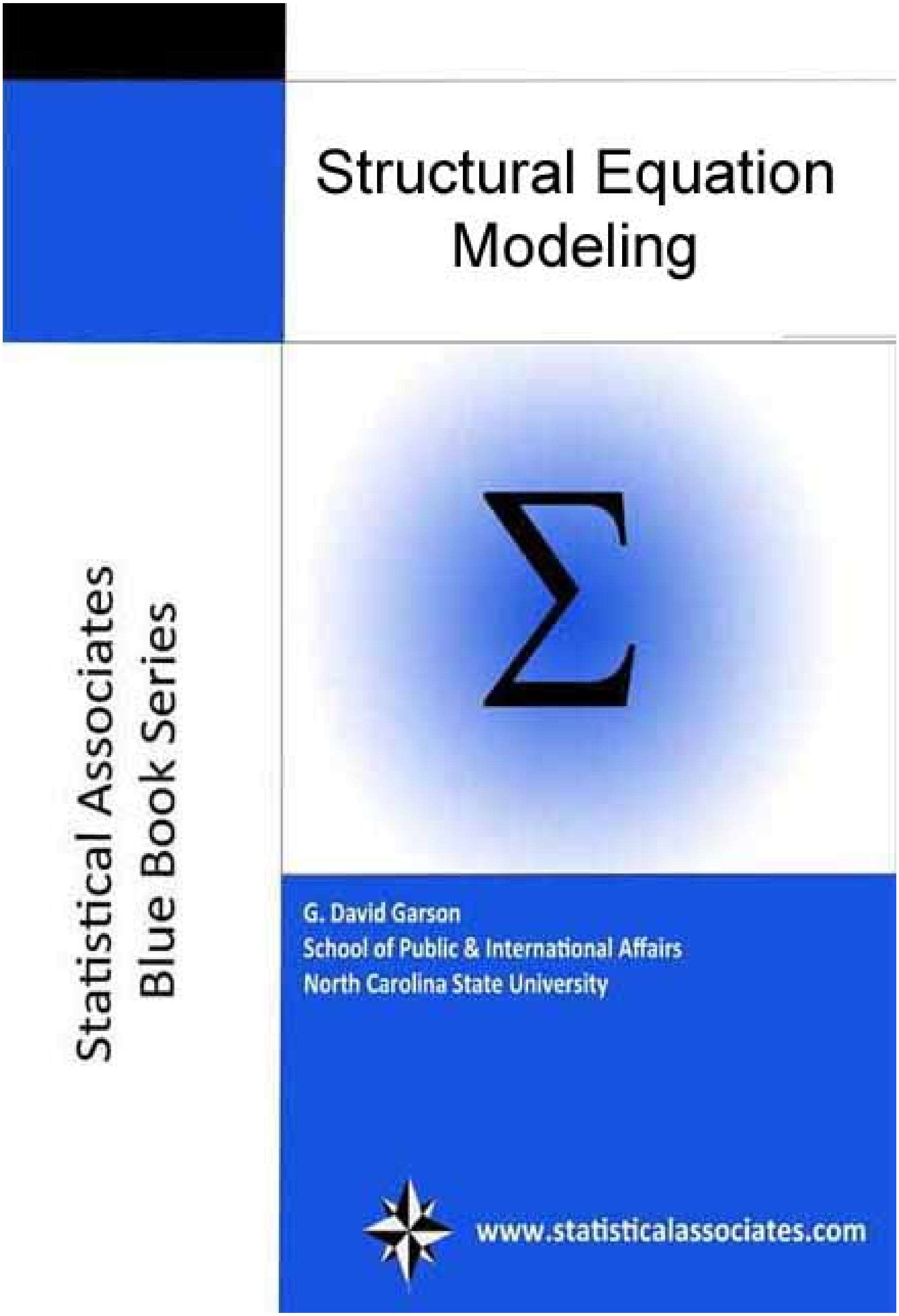

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PREVIEW OF FIRST 33 PAGES

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Contact:

G. David Garson, President
Statistical Publishing Associates
274 Glenn Drive
Asheboro, NC 27205 USA

Email: sa.publishers@gmail.com
Web: www.statisticalassociates.com

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Structural Equation Modeling

Overview

Structural equation modeling (SEM) grows out of and serves purposes similar to multiple regression but in a more powerful way which takes into account multiple latent independent variables, each measured by multiple indicators; one or more latent dependent variables also each with multiple indicators; the modeling of mediators as both causes and effects; and modeling of interaction terms; modeling, nonlinearities; modeling correlated independent variables and correlated error; and modeling measurement error. SEM may be used as a more powerful alternative to multiple regression, path analysis, factor analysis, time series analysis, and analysis of covariance. In fact, these procedures may be seen as special cases of SEM.

Models which may be implemented by SEM, depending on the capabilities of the statistical package, include:

- Linear and generalized multiple linear regression
- Linear and generalized multivariate linear regression (multiple dependent variables)
- ANOVA
- Confirmatory factor analysis (CFA, which is SEM for measurement models)
- Reliability analysis
- Path analysis using measured variables
- Structural equation modeling of measured and latent variables (SEM for structural models)
- Multi-group modeling of measurement and structural models
- Latent growth curve models
- Multilevel models

Advantages of SEM compared to multiple regression include more flexible assumptions; allowing interpretation even in the face of multicollinearity; use of confirmatory factor analysis to reduce measurement error; testing models overall

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rather than testing coefficients individually; testing models with multiple dependent variables; modeling complex causal paths taken by mediating variables; ability to go beyond the ordinary least squares (OLS) additive model which makes the dependent variable a function of the sum of effects; the ability to model error terms; the ability to test coefficients across multiple between-subjects groups; and ability to handle difficult data such as time series with autocorrelated error, non-normal data, and incomplete data. Moreover, where regression is highly susceptible to error of interpretation due to misspecification, the SEM strategy of comparing alternative models to assess relative model fit makes it more robust. In addition to all this, there is the attraction of being able to create and test models using a graphical modeling interface.

SEM is usually viewed as a confirmatory rather than exploratory procedure, using one of three approaches:

1. *Strictly confirmatory approach*: A model is tested using SEM goodness-of-fit tests to determine if the pattern of variances and covariances in the data is consistent with a structural (path) model specified by the researcher. However as other unexamined models may fit the data as well or better, an accepted model is only a not-disconfirmed model.

2. *Alternative models approach*: The researcher may test two or more causal models to determine which has the best fit. There are many goodness-of-fit measures, each reflecting different considerations. Usually three or four fit measures are reported by the researcher. Although desirable in principle, this approach runs into the real-world problem that in specific research areas, the researcher may not find in the literature two well-developed alternative models to test.

3. *Model development approach*: In practice, a great many instances of SEM research combine confirmatory and exploratory purposes: a model is tested using SEM procedures, found to be deficient, and an alternative model is then tested based on changes suggested by modification indexes and other statistical output generated by SEM. The problem with the model development approach is that models

confirmed in this manner are post-hoc ones which may not be stable (may not fit new data, having been created based on the uniqueness of an initial dataset). Researchers may attempt to overcome this problem by using a cross-validation strategy under which the model is developed using a calibration data sample and then confirmed using an independent validation sample.

Regardless of approach, SEM cannot itself draw causal arrows in models or resolve causal ambiguities. It is entirely possible that one model with arrows drawn in the opposite direction from a second model may fit the data equally well. Theoretical insight and judgment by the researcher is still of utmost importance.

SEM is a family of statistical techniques which incorporates and integrates path analysis and factor analysis. In fact, use of SEM software for a model in which all variables are simple observed variables is a type of path analysis. Use of SEM software for a model in which each latent construct has multiple indicators but there are no direct effects (arrows) connecting the latent constructs is a type of factor analysis. Usually, however, SEM refers to a hybrid model with both multiple indicators for each variable (called latent variables or factors) and paths specified connecting the latent variables. Synonyms for SEM are covariance structure analysis, covariance structure modeling, and analysis of covariance structures. Although these synonyms rightly indicate that analysis of covariance is the focus of SEM, be aware that SEM can also analyze the mean structure of a model.

See also partial least squares regression, which is an alternative method of modeling the relationship among latent variables, also generating path coefficients for a SEM-type model but without SEM's data distribution assumptions. PLS path modeling is sometimes called "soft modeling" because it makes soft or relaxed assumptions about data. See the separate Statistical Associates “Blue Book” volume on “Partial Least Squares.”

Data examples in this volume

The example datasets used in this volume are listed below in order of use, with versions for SPSS (.sav), SAS (.sas7bdat), and Stata (.dta).

The Wheaton dataset is a classic dataset described below. See Wheaton, Muthén, Alwin, & Summers (1977).

- Right-click here download wheaton.sav for SPSS Amos. This illustrates correlation matrix input.
- The Wheaton data for SAS is read in using a DATA step, discussed below. (There is no file). This illustrates covariance matrix input. Results are almost identical to correlation matrix input but covariance matrix input is preferred as it is possible for correlation matrix input to result in estimated standard errors being incorrect (cf. Cudeck, 1989).
- Right-click here to download sem_sm2.dta (the version of the Wheaton data distributed by Stata). This illustrates correlation matrix input.

The Wheaton dataset is also used in the section on confirmatory factor analysis (CFA) below.

For the sections on structural modeling and specification search, a subset of the General Social Survey 2012 was used for which missing values were imputed using the SPSS multiple imputation module. Variables are described below.

- Click here to download GSSsubset2012imputed.sav for SPSS Amos.
- Click here to download GSSsubset2012imputed.sas7bdat for SAS.
- Click here to download GSSsubset2012imputed.dta for Stata.

The section on specification search, which is only available in SPSS Amos, uses the following file. Variables are described below.

- Click here to download structur1.sav for SPSS Amos.

The section on multi-group analysis uses a confirmatory factor analysis model on types of music. Variables are described below.

- Click here to download music.sav for SPSS Amos.
- Click here to download music.sas7bdat for SAS.
- Click here to download music.dta for Stata.

The section on latent growth curve analysis uses a dataset focused on a medical example involving growth of dental features in children. Variables are described below.

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- Click here to download royfm.sav for SPSS Amos.
- Click here to download royfm.sas7bdat for SAS.
- Click here to download royfm.dta for Stata.

The section on Bayesian structural equation modeling used a subset of the General Social Survey 1993. Variables are described below.

- Click here to download GSS93subset.sav for SPSS Amos.

The section on mixture modeling/latent class analysis used a version of the "Iris" sample file supplied with SPSS Amos. Variables are described below.

- Click here to download iris3.sav for SPSS Amos.

The section on mean structure analysis used a version of the "GSS93subset" sample file supplied with SPSS Amos. Variables are described below.

- Click here to download GSS93 subset males imputed.sav for SPSS Amos.
- Click here to download GSS93 subset females imputed.sav for SPSS Amos.
- Click here to download GSS93subsetmergedimputed.sas7bdat for SAS.
- Click here to download GSS93 subset merged imputed.dta for Stata.

The section on generalized SEM uses a fictional dataset in which the latent variables Knowledge and Motivation are measured by 6 binary and 5 ordinal indicators respectively. At this writing, Stata supports GSEM but not SPSS or SAS. Variables are described below.

- Click here to download gsemcfa.dta for Stata.

Key Concepts and Terms

The structural equation modeling process

The researcher starts a SEM project by specifying a model on the basis of theory. Typically, each variable in the model is conceptualized as a latent construct measured by multiple indicators (e.g., stress as a latent variable measured by several survey items). Multiple indicators are developed for each latent variable,

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with at least two and preferably three or more indicators per latent variable. Simple one-measure variables such as gender may also be in the model.

Based on a large representative sample, a type of factor analysis analogous to common factor analysis (principal axis factoring), not principle components analysis, is used to establish that indicators seem to measure the corresponding latent variables. The researcher proceeds only after the measurement model has been validated. Two or more alternative models (one of which may be the null model) are then compared in terms of model fit, measures for which assess the extent to which the covariances predicted by the model correspond to the observed covariances in the data.

Indicator variables

Indicator variables are observed variables, sometimes called manifest variables or reference variables. Items in a survey instrument may be indicator variables, for instance. Four or more indicators are recommended, though three is acceptable and common practice. As few as two indicators or even a single indicator may be acceptable if the researcher is confident in the measure's validity and reliability.

The prime consideration in selecting indicators is whether they are theoretically sound and reliably measured. Also, allowing one- and two-indicator latent variables to a model may allow the testing of theoretically important latent-level control relationships which otherwise might not be possible. However, with one indicator, error cannot be modeled but rather one must specify a fixed measurement error variance. Also, models using only two indicators per latent variable are more likely to be under-identified and/or fail to converge and error estimates may be unreliable. Ideally, indicators should have pattern coefficients (factor score weights) of .7 or higher on their latent factors, though this is a stringent test. A less stringent criterion is the that standardize path weights from the latent variables to their indicator variables should be .7 or higher.

Indicator variables cannot be combined arbitrarily to form latent variables. For instance, combining gender, race, or other demographic variables to form a latent variable called "background factors" would be improper because it would not represent any single underlying continuum of meaning. The confirmatory factor analysis step in SEM is a test of the meaningfulness of latent variables and their indicators but the researcher may wish to apply reliability tests (ex., Cronbach's alpha or ordinal item alpha) or conduct traditional factor analysis (ex., principal axis factoring) as well.

Latent variables

Latent variables are the unobserved variables/constructs/factors which are measured by their respective indicators. Latent variables include both independent, mediating, and dependent variables. Those with no prior causes are called exogenous variables while mediating and dependent variables are called endogenous variables.

Exogenous variables

Exogenous variables are independent variables with no prior causal variable (though they may be correlated with other exogenous variables, depicted by a double-headed arrow). In fact it is usual to assume that all exogenous variables are correlated (connected by a double-headed covariance arrow) unless there is theoretical reason not to. If two exogenous variables are connected by a covariance arrow, there cannot also be a straight (regression path) arrow nor can the researcher place a covariance arrow connecting an exogenous variable to an endogenous variable. Exogenous latent variables are sometimes denoted by the Greek letter ksi (ξ).

Endogenous variables

Endogenous variables are dependent or mediating variables (variables which are both effects of other exogenous or mediating variables, and are causes of other mediating and dependent variables). Dependent variables have incoming causal effects but no outgoing causal effects (other than to their own indicator variables). Thus endogenous variables are on the receiving end of single-headed straight arrows indicating a regression path and implying a causal relationship. The path to the endogenous variable may come from an exogenous variable or another endogenous variable. Endogenous constructs are sometimes denoted by the Greek letter eta (η). Variables in a model may be "upstream" or "downstream" depending on whether they are being considered as causes or effects respectively.

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While SEM packages are used primarily to implement models with latent variables (see below), it is possible to run regression models or path models using only simple indicator variables.

Regression models, path models, and SEM models

In one sense, all regression models are path models and are a subset of SEM models. However, for those who wish to distinguish rather than conflate these three terms, the following differences are implied.

- *Regression models*: In regression models, only observed variables are modeled and only the dependent variable in regression has an error term. Independent variables are assumed to be modeled without error. The only possible model is graphically a "star," with the arrows from all independent variables ending at the dependent variable. The partial coefficient for any independent variable controls for all other independents, whether or not an actual causal control effect is plausible.
- *Path models:* Path models also contain only observed variables (there are no latent variables). Unlike regression models but like structural equation models, independent variables can be both causes and effects of other variables. That is, path models are like SEM models in having circle-and-arrow causal diagrams, not just the "star" design of regression models. Only the endogenous variables in path models have error terms. Unlike SEM models, exogenous variables in path models are assumed to be measured without error. Partial coefficients are calculated using only the independent variables in a direct path to the endogenous variable. Using SEM packages for path models instead of doing path analysis using traditional regression procedures has the benefit that measures of model fit, modification indexes, and other aspects of SEM output discussed later become available.
- *SEM models:* SEM models contain one or more latent variables. Typically, all variables in the structural model are latent variables though it is permissible to include simple/observed variables such as “Gender”. SEM models also support complex paths connecting variables in the model and support multiple dependent variables. Unlike path models with only observed variables, SEM models allow error associated with variables in the model to be themselves modeled (ex., models may be compared with and

without an assumption of error covariance between variables, or with equality or other constraints for pairs of error terms).

Model specification

Model specification is the process by which the researcher lists variables in the model and lists which effects among latent variables are null, which are fixed to a constant (usually 1.0), and which vary. That is, three types of relationships may connect specified variables:

- In a SEM model, most straight (path) arrows indicate a regression relationship which is unconstrained and must be estimated. Likewise, double-headed covariance arrows indicate a correlation which is unconstrained and must be estimated.
- The absence of path and covariance arrows connecting two variables stipulates that the path or covariance weight is 0, representing no direct relationship (independence).
- It is also possible for the researcher to constrain a path or covariance to a particular value. For instance, it is almost always the case that the path from a latent variable to one of its indicator variables is constrained to 1, in order to set the metric for the latent variable (see below). In fact, this is typically done by software automatically.

Model parsimony

A model in which no effect is constrained to 0 (every variable has a direct arrow connecting it to every other variable) is a “saturated” model which will always fit the data perfectly, even when the model makes no sense. The closer the researcher's default model is to this most-complex model, the better will be the fit. That is, adding paths will tend to increase fit. This is why a number of goodness of fit measures discussed later below penalize for lack of parsimony.

A corollary is that if the researcher’s model is the saturated model, it cannot usefully be tested by SEM. The researcher’s model of interest must be more parsimonious than the saturated model.

Note lack of parsimony may be a particular problem for models with few variables. If there are only three variables, for instance, it may be tempting to

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have arrows connecting each variable with each other variable, but the researcher's default model must be more parsimonious than the saturated model (the model with all possible direct arrows). Ways to increase parsimony are erasing direct effects (straight arrows) connecting one latent variable to another or erasing covariance arrows. In each case, arrows should be erased from the model only if there is no theoretical reason to suspect that the effect or correlation exists. Customarily, the researcher seeks the most parsimonious well-fitting model.

Is the most parsimonious model the one with the fewest terms and fewest arrows? Yes, but a broader view should be taken. Much more weight should be given to parsimony with regard to structural arrows connecting the latent variables (and simple variables, if any) than to measurement arrows from the latent variables to their respective indicators. Indeed, having more than the minimum number of indicator variables per latent variable is desirable. Also, if there are fewer exogenous and mediating variables in the model and yet the dependent variable or variables is/are equally well explained, that is parsimony also since fewer predictor variables will almost always mean fewer arrows.

Model development

The measurement model versus the structural model

SEM analysis typically proceeds in two steps: validation of the measurement model, then testing the structural model. Both steps are discussed much more fully in a later section.

The measurement model consists of the latent variables and their indicator variables. Connections among the latent variables are not considered. The measurement model step is called "confirmatory factor analysis" (CFA) because its purpose is to validate (confirm) the way the researcher has measured the latent variables (factors) in the model. If SEM analysis shows good fit, this is an indication that indicator variables reflect the latent variables they are supposed to and that the latent variables are different from each other. That is, CFA establishes convergent and divergent validity in the proposed model.

If CFA upholds the measurement model, then the researcher proceeds to test the structural model. The structural model is the measurement model plus the latent variables and the paths and covariances connecting them. The same goodness-of-

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fit coefficients available in CFA are available for the structural step as well. The researcher is seeking to establish that the structural model has good fit to the data or, better yet, that one model fits the data better than another model.

Model trimming versus model building

After the structural model is run, it is necessary to evaluate it and consider modifying it. In fact, a common type of SEM article tests a model taken from the literature, finds it deficient in some way, then proposes a modified model which fits the data better than the original model. In modifying an existing model, it is possible to add paths and/or covariance (model building or model growing), or the researcher may remove paths and/or covariances (model trimming).

Although both strategies may be pursued in any order, a common convention is to grow the model using modification indexes and then to trim the model using significance tests of the path (regression) coefficients. Of course, additions to and deletions from the model should make theoretical sense. For instance, adding an arrow from a variable associated with a later time to a different variable associated with an earlier time is a chronological impossibility, no matter what a modification index suggests. Modification indexes are discussed below.

The usual procedure is to overfit the model, then change only one parameter at a time. That is, the researcher first adds paths one at a time based on theory and on the modification indexes (MI's), then drops paths one at a time based on the likelihood ratio (chi-square difference) test or Wald tests of the significance of the structural coefficients, discussed below. Modifying one step at a time is important because the MI's are estimates and will change each step, as may the structural coefficients and their significance.

As paths are added to the model, chi-square tends to decrease, indicating a better fit and also increasing the chi-square difference. That is, a significant chi-square difference indicates the fit of the more complex model is significantly better than for the simpler one. Adding paths should be done only if consistent with theory and face validity.

When the model growing process has gone as far as judicious, then the researcher may erase one arrow at a time based on non-significant structural paths, again taking theory into account in the trimming process. Some authors, such as Ullman (2001), recommend that the alpha significance cutoff deleting

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model effects (arrows) be set at a more stringent .01 level rather than the customary .05, on the rationale that after having added parameters on the basis of theory, the alpha significance for their deletion should involve a low Type I error rate. More than one cycle of building and trimming may be needed before the researcher settles on the final model.

Modification indexes and parameter change

Modification indexes (MI) are used in conjunction with parameter change coefficients to judge whether the model would be improved significantly by adding arrows. Note that in Amos, the MI table is not computed if the dataset contains missing values. There is more than one table of MI coefficients:

- MI's for regression weights (paths(): In the case of MI for estimated regression weights, the MI has to do with the change in chi-square if the path between the two variables is added to the model, with larger MI suggesting stronger reason to add the path.
- MI's for covariances: In the case of modification indexes for covariances, the MI has to do with the decrease in chi-square if two error term variables are allowed to correlate. For instance, if the MI for a covariance is 24 and the "Par Change" is .8, this means that if the model is respecified to allow the two error terms to covary their covariance would be expected to change by .8, leading to a reduction of model chi-square by 24 (lower is better fit). Even if MI and Par Change indicate that model fit will increase if a covariance arrow is added between indicator error terms, the standard recommendation is not to do so unless there are strong theoretical reasons in the model for expecting such covariance (ex., the researcher has used a measure at two time periods, where correlation of error would be predicted). That is, error covariance arrows should not be added simply to improve model fit.
- MI's for error terms: MI's may suggest adding covariance arrows connecting error terms. Generally, the researcher does not want to add a covariance arrow between the error term for an indicator variable for one latent variable and the error term for an indicator variable for a different error term. Rather, the researcher generally wishes the indicator variables for different latent variables to be uncorrelated, and for their error terms to be uncorrelated as well, so as to preserve the conceptual distinction between latent variables. If the suggested covariance is between error

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terms of two indicator variables for the same latent variable, this means that once the latent cause of correlation of the two indicator variables is accounted for (by the latent variable), there is still an unmeasured influence connecting the two indicator variables. This influence might be that one indicator causes the other, or they may share an unmeasured common influence connecting them. Further investigation is warranted. An alternative strategy might be to drop one of the indicator variables, but this runs the risk of reducing the reliability of the latent variable as a measure.

MI coefficients may be used to alter models to achieve better fit but this must be with theoretical justification. Some oppose use of MI's altogether on the ground that all model specifications should be theory-driven, not data driven. Blind use of MI runs the risk of capitalization on data noise and model adjustments which make no substantive sense. Simulation studies by Silvia and MacCallum (1988; see also MacCallum, 1986) found most MI-suggested model changes to misspecified models were incorrect and did not reproduce the model known to be true and which generated the data. Moreover, when n is large, even very small discrepancies between the model-implied and the observed covariance matrix may trigger an MI flag. The researcher should be aware that MI's are just flags to consider adding a direct path or covariance and may represent mistaken suggestions.

If MI's are used, the researcher should also take into account the effect size of the arrow to be added as indicated by the parameter change coefficient. "Par change" is the estimated path coefficient change when adding arrows. Since absence of an arrow corresponds to a 0 path coefficient weight, "Par change" <u>is</u> the regression coefficient for the added arrow. "Par change," also called "expected parameter change" (EPC) in Stata and some other software, is an effect size measure. Most SEM software will list the expected parameter change and its significance level along with the MI for that path. If the given arrow is added, the actual new parameter value may differ somewhat from the "Par Change" estimate. The researcher may decide not to add an arrow flagged by MI if the parameter change is trivial. Likewise, the researcher may wish to add an arrow where the parameter change is large in absolute size even if the corresponding MI is not the largest one.

How large is a "large" MI? The minimum value would be 3.84, since chi-square must drop that amount simply by virtue of having one less parameter (path) in the model. This is why the default threshold is set to 4 in Amos and most SEM software. The researcher can set a higher value if wanted, causing MI's below the specified level not to be output.

To summarize, the researcher may consider adding an arrow to the model if the MI is high and the parameter change coefficient is high and it makes theoretical sense. A variety of criteria have been used:

- Consider adding a path if the modification index exceeds 100.
- Consider adding a path for the largest MI which also is associated with a large enough parameter change to affect substantive interpretations of effects in the researcher's particular context.
- On an exploratory basis, the researcher may assess adding which arrows, if any, causes fit indexes to reach acceptable levels.

Although a number of criteria have also been suggested as rules-of-thumb for a "large" MI (> 4, >10, >30, and >100 have been mentioned), such criteria are beside the point, which is to consider adding arrows to the model if justified by theory and if adding the arrow will cause model fit to reach acceptable levels. The MI is simply a flag which suggests to the researcher which arrows to consider. The less certain the theoretical justification for adding an MI-flagged path or covariance, the greater the need for cross-validation of the model on other data than the model-development data.

The Lagrange multiplier coefficient

SAS and Stata output the Lagrange multiplier (LM) statistic rather than the MI statistic, though both serve the same function. The LM statistic is sometimes called "multivariate MI," and serves the same function in SAS and Stata output. In fact, Stata labels the LM statistic as "MI", though SAS labels it "LM". While univariate MI in Amos and multivariate MI (LM) in SAS and Stata frequently lead to the same conclusions, this is not always the case as an example later on below demonstrates.

LM would is especially appropriate if the researcher is considering adding an entire set of arrows to the model since different conclusions might arise from the multivariate LM approach as compared with a series of individual MI decisions. On the other hand, larger LM or MI both flag possible arrows to add to a model and the usual procedure is to add arrows one at a time, rerunning the model after each addition.

Path significance and critical ratios

Model trimming usually centers on deleting arrows in the model which are not significant, provided it makes theoretical sense to do so. For regression paths, most SEM software will print out the p significance level and in social science, p values above .05 flag non-significant paths.

If the p value is not available, paths with a critical ratio greater than 1.96 indicate that path is significant at the .05 level or better. Significance of covariances is interpreted in the same manner. Greater than 2.58 indicates significance at the .01 level or better. Amos and some other packages indicate the .05 level with one asterisk, the .01 level with two asterisks, and the ,001 level with three asterisks. The significance of the standardized and unstandardized estimates will be identical so some statistical packages, including Amos, do not print the significant level for standardized coefficients.

Model fit

A quite large number of different types of goodness-of-fit coefficients are available to assess both confirmatory factor analysis and structural models. The correspondence of these fit measures to true causality is a subject of great controversy, with positions ranging from rejection of any use of fit measures to embrace of their use. Understanding this controversy is important to proper use of fit measures. As a practical matter, however, the great majority of SEM studies finding their way to publication report goodness of fit measures. Meeting goodness of fit criteria does not assure that the causal model is true, but failing to meet fit criteria is reason to strongly suspect the model is false. This topic is explored at greater length in a later section.

Non-hierarchical model comparisons

Model-building and model-trimming, discussed above, involve comparing a model which is a nested subset of another. If modeling does not simply involve adding and subtracting path and covariance arrows in the model, then one model may not be nested within another. The likelihood ratio test of model chi-square difference cannot be used directly for non-hierarchical models, only nested models. This is because model fit by chi-square is partly a function of model complexity, with more complex models fitting better. For non-hierarchical model comparisons, the researcher should use information theory goodness of fit measures which penalize for complexity (reward parsimony), such as AIC or BIC, since these handle comparison of non-nested models (however, see discussion below).

Software packages

This volume covers structural equation modeling in SPSS, SAS, and Stata. While all three packages can implement most SEM models, at this writing Stata is the most comprehensive package insofar as it supports generalized SEM (support for non-normal distributions and a variety of link functions) and hierarchical SEM (support for multilevel/linear mixed SEM modeling).

- SPSS. Amos (Analysis of MOment Structures) is the SPSS SEM module. It features a user-friendly graphical interface and has become popular as a relatively easy way to specify models. However, also available in Amos is a BASIC programming mode. At this writing, Amos does not support generalized SEM or hierarchical SEM.
- *SAS*. SEM is implemented in SAS using PROC CALIS. SAS briefly supported PROC TCALIS on an experimental basis, handling multi-group SEM and analysis of mean structures, but its features have now been folded back into PROC CALIS. At this writing, SAS does not support generalized SEM or hierarchical SEM.
- *Stata*: The Stata `sem` command implements structural equation models for normally distributed data. The `gsem` command implements generalized SEM, which supports non-normal distributions and a variety of link functions. In addition, starting with Version 13, Stata supports hierarchical structural equation modeling, including hierarchical generalized SEM. An extension for generalized linear latent and mixed models (GLLAMM) supports multilevel models, generalized models, latent class models, item response models, factor models, and structural models. GLLAMM programs for Stata are documented at http://www.gllamm.org/ and in Rabe-Hesketh, Skrondal, & Pickles (2004, 2005). Type `net install gllamm` to install this user-written add-on and then type `help gllamm` from the Stata command prompt.

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Other statistical packages.

- Mplus software (developed by Muthén, 2002a, 2002b) supports more complex models involving a mix of nominal ordinal, and continuous variables, including multilevel (hierarchical) data and random effects. MPlus also handles generalized SEM and discrete-time survival models.
- xxM is an R-language package which supports multilevel structural equation modeling, cross-classified models, longitudinal models, and linear growth models. At this writing it was free.
- Lisrel popularized SEM in sociology and the social sciences and is still the package of reference in many articles employing structural equation modeling.
- EQS is another long-standing and widely used SEM package.

User interfaces for SEM

In most statistical packages, structural equation models may be entered graphically, as illustrated below using the Wheaton data. This classic dataset is used by Amos, SAS, Stata, MPlus, and numerous other packages and textbooks to illustrate a simple SEM model. In this model, focusing on the stability of "Alienation" as a construct between 1967 and 1971, the following variables are used:

- anomia67 and powles67: observed indicators of "Alienation67"
- anomia71 and powles71: observed indicators of "Alienation71"
- educatio and sei: observed indicators of "SES", which is socioeconomic status.

The model posits that Alienation71 is caused by Alienation67, and both are caused by SES. Also posited in this version of the model are covariances between anomia67 and anomia71; and between powles67 and powles71.

The SPSS Amos interface

Most Amos users employ the Amos graphical user interface shown below. Using menu choices and tools shown on the left of the figure below (tools also may be invoked using the Diagram menu choice), the structural equation model is drawn.

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- Selecting View > Variables in the Data causes a variable list to pop up. Variables may be dragged to the rectangles, which are the measured variables.
- Using View > Object Properties, names may be given to the ovals, which are the latent variables.
- Using Plugins > Name Unobserved Variables, the error terms shown as small circles may be labeled.
- The single black arrow tool in the upper left, second row of icons, is used to draw hypothesized causal arrows.
- The double-headed arrow tool next to it is used to draw covariance relationships.

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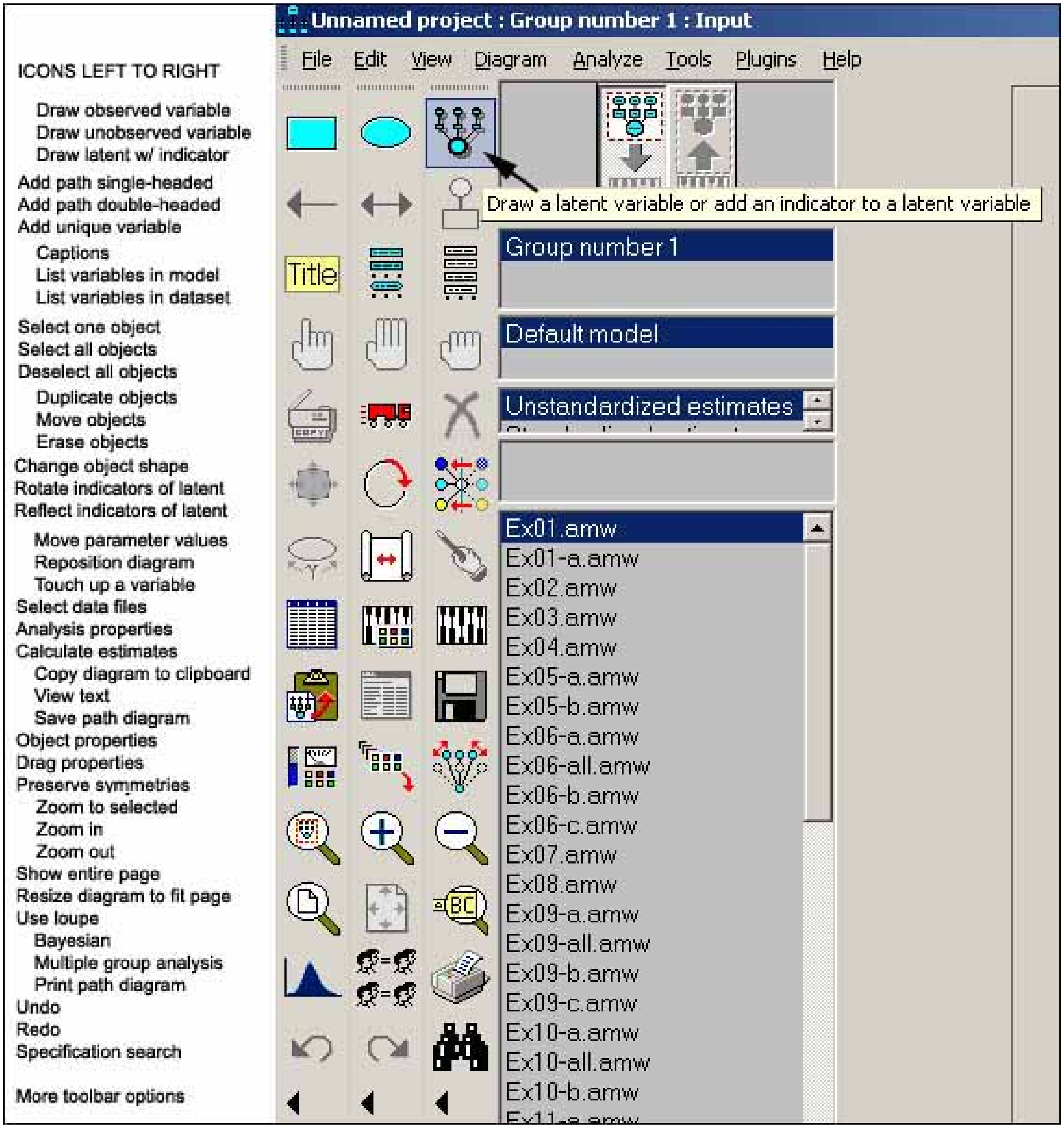

In Amos, the general process of structural modeling is to use the icons above to draw a circle-and-arrow path diagram, associated the diagram with data (a correlation matrix or raw data). When the model is fully drawn and analysis and output options are selected, the Analyze > Calculate Estimates menu selection runs the model. View > Text Output enables the researcher to view and print results.

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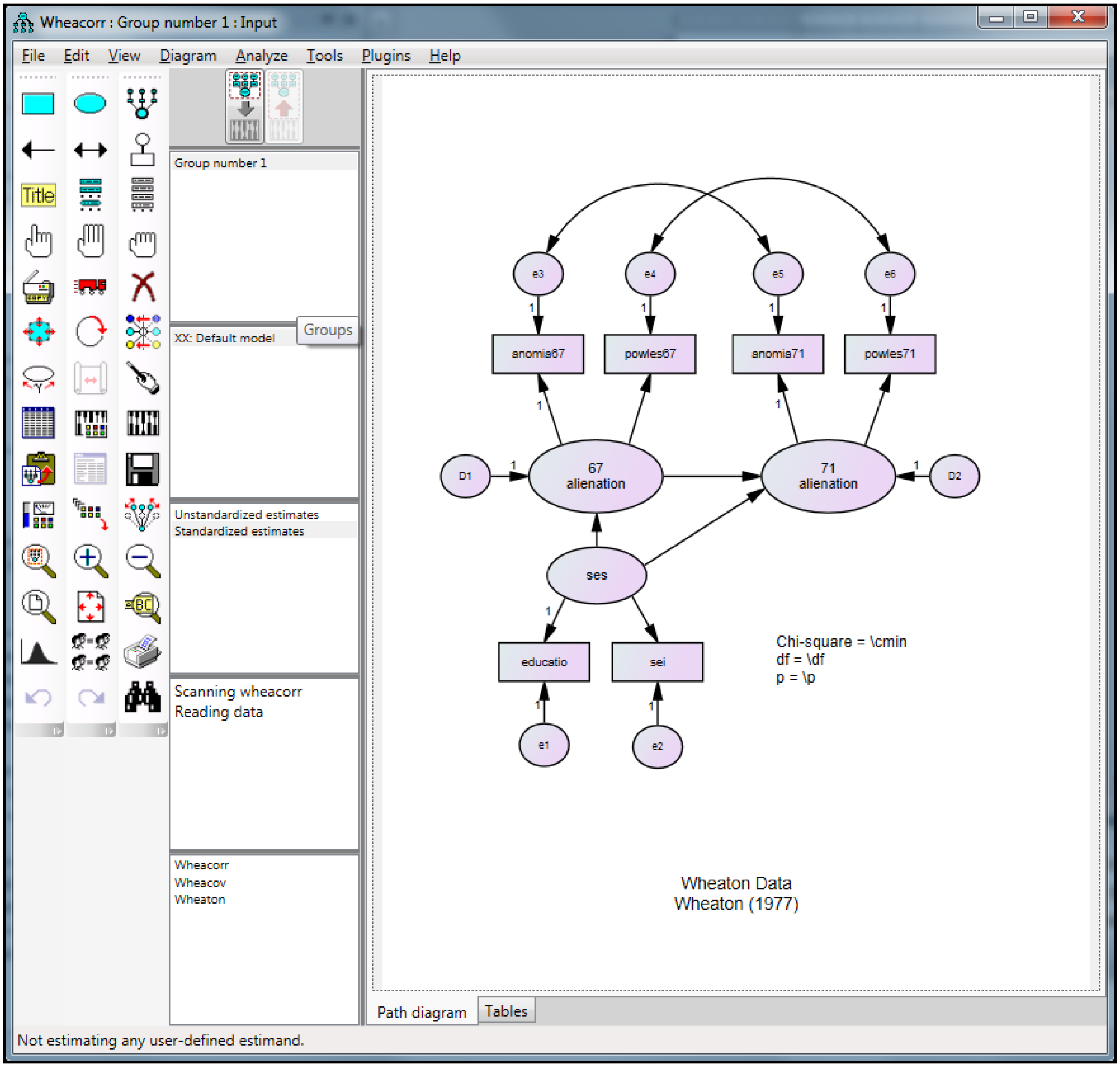

In tandem with using the Amos graphical interface to draw a model, the File > Data Files menu choice is used to specify the data. Below is the data file for the Wheaton example. As can be seen Amos accepts covariance or correlation matrix input, not just raw data.

END OF PREVIEW OF FIRST 33 PAGES

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