The EQS Input File

We proceed by examining the link between the CFA model presented in Fig. 3.1 and the translation of its specifications into a file interpretable to EQS. This input file is shown in Table 3.2.

As described by the /TITLE paragraph, this file represents the initially hypothesized model representing a four-factor structure. The /SPECIFICATIONS paragraph indicates that (a) the sample size is 265, (b) there are 46 observed variables, (c) the method of estimation is maximum likelihood, (d) the data are in raw matrix form, and (e) the data are in fixed format, as described by the Fortran statement (40F1.0,X,6F2.0). This expression tells the program to read 40 single-digit numbers, to skip one column, and then to read six double-digit numbers. The first 40 columns represent item scores on the SPPC (not used in the present study) and the SDQ2; the remaining six scores represent scores for the MASTENG1 through SMAT1 variables (not used in the present study). Finally, note that the data reside as an external file called "ASC7INDM.ess." However, a brief explanation of this specification is in order. Installation instructions accompanying EQS6.1 recommend that all files be kept in the program folder, in which case DATA specification in the input file would read as DATA='ASC7INDM.ess'. The reason for the modified input in Table 3.2 is because I prefer to keep my working files separate from the program files. Therefore, I need to specify to the program exactly where these files can be found. Likewise, if users wish to operate in the same manner, they would simply specify the location of their data in accordance with their own computer.

By now, you will no doubt find the information specified in the next four paragraphs (/LABELS; /EQUATIONS; /VARIANCES; /COVARIANCES) to be fairly straightforward; thus, further explanation is unnecessary. However, the final two paragraphs introduced by the keywords /PRINT and /LMTEST are new and require elaboration. The /PRINT paragraph provides for printing of additional information that the manual states "make sense of a model and the quality of the estimates" (Bentler, 2005, p. 91). Some examples include the printing of a specified number of digits (DI=n; default=3), effect decomposition (EF=YES; Default=No), and additional goodness-of-fit indexes (FIT=ALL), which is the case with this input file.[4] The /PRINT paragraph also allows for the generation of a RETEST file in which start values are automatically assigned to all estimated parameters by the program, a function that is illustrated in chap. 6.

The /LMTEST keyword requests that the Lagrange Multiplier Test (LM Test) be implemented to test hypotheses bearing on the statistical viability of specified

[4]EQS automatically includes this /PRINT ↳ FIT=ALL paragraph when the input file is formulated using BUILD_EQS.

TABLE 3.2
EQS Input for Initially Hypothesized Four-Factor Model

```
/TITLE
 CFA OF ASC Structure - GRADE 7 "ASC7F4I"
 Initial 4-factor Model
/SPECIFICATIONS
 CASE=265; VAR=46; ME=ML; MA=RAW; FO='(40F1.0,X,6F2.0)';
 DATA='C:\EQS61\Files\Books\Data\ASC7INDM.ess';
/LABELS
 V1=SPPCN08;   V2=SPPCN18;   V3=SPPCN28;  V4=SPPCN38;  V5=SPPCN48;
 V6=SPPCN58;   V7=SPPCN01;   V8=SPPCN11;  V9=SPPCN21;  V10=SPPCN31;
 V11=SPPCN41;  V12=SPPCN51;  V13=SPPCN06; V14=SPPCN16; V15=SPPCN26;
 V16=SPPCN36;  V17=SPPCN46;  V18=SPPCN56; V19=SPPCN03; V20=SPPCN13;
 V21=SPPCN23;  V22=SPPCN33;  V23=SPPCN43; V24=SPPCN53; V25=SDQ2N01;
 V26=SDQ2N13;  V27=SDQ2N25;  V28=SDQ2N37; V29=SDQ2N04; V30=SDQ2N16;
 V31=SDQ2N28;  V32=SDQ2N40;  V33=SDQ2N10; V34=SDQ2N22; V35=SDQ2N34;
 V36=SDQ2N46;  V37=SDQ2N07;  V38=SDQ2N19; V39=SDQ2N31; V40=SDQ2N43;
 V41=MASTENG1;V42=MASTMAT1;V43=TENG1; V44=TMAT1; V45=SENG1; V46=SMAT1;
/EQUATIONS
 V25= F1+E25;
 V26= *F1+E26;
 V27= *F1+E27;
 V28= *F1+E28;
   V29= F2+E29;
   V30= *F2+E30;
   V31= *F2+E31;
   V32= *F2+E32;
     V33= F3+E33;
     V34= *F3+E34;
     V35= *F3+E35;
     V36= *F3+E36;
       V37= F4+E37;
       V38= *F4+E38;
       V39= *F4+E39;
       V40= *F4+E40;
/VARIANCES
 F1 TO F4= *;
 E25 TO E40= *;
/COVARIANCES
 F1 TO F4= *;
/PRINT
 FIT=ALL;
/LMTEST
 SET=GVF, PEE;
/END
```

restrictions in the model;[5] in a CFA model, for example, that selected indicator variables load on specific factors. The basic idea underlying this test is to determine if, in a subsequent EQS run, certain parameters were specified as free rather than fixed, would it lead to a model that better represents the data? Although we are using the LM Test only to identify which fixed parameters, if freely estimated, would lead to a significantly better-fitting model, it is also used to assess the viability of equality constraints (an issue explored in chaps. 7–10). EQS produces univariate and multivariate χ^2 statistics that permit evaluation of the appropriateness of the specified restrictions; it also yields a "parameter change statistic" that represents the value that would be obtained if a particular fixed parameter were freely estimated in a future run.

The LM Test procedure provides for several options, all of which are fully described in the manual (Bentler, 2005). One of these options, the SET command, is included in the present input. This command allows the user to limit the LM Test to a subset of only fixed parameters in the model; otherwise, the program produces numerous and often irrelevant modification indexes. In this CFA model, for example, misspecification can arise from two possible sources: (a) one or more of the item-pairs is loading on a nontarget factor, and (b) error terms associated with two or more of the indicator variables may be correlated. As such, the factor loadings and error terms that are fixed to a value of 0.0 are of substantial interest. Statistically significant LM χ^2 values would argue for the presence of factor cross-loadings (i.e., a loading on more than one factor) and error covariances (correlated errors), respectively.

EQS follows SEM convention in its coding for the SET command: a Greek letter designates the matrix of which a particular parameter is an element. However, unlike the LISREL program in which there are eight such matrices, EQS functions with only three: a variance–covariance matrix of independent factors (PHI), a regression (or coefficient) matrix involving both independent and dependent variables (GAMMA), and a regression matrix involving only dependent variables (BETA). This minimal set of matrices arises from the EQS requirement that all variables be designated as either independent or dependent variables; only dependent variables can have equations, and only independent variables can have variances and covariances. Coding for the SET command comprises three letters: the first represents the matrix (P, G, or B) and the remaining two represent a submatrix of one of those matrices. For example, the input file in Table 3.2 shows SET=GVF, PEE. The letter G represents the GAMMA matrix, and the double letters VF indicate the regression of the dependent V's on the independent F's (i.e., the factor loadings). Likewise, the letter P stands for the PHI matrix and the

[5]The LM Test is analagous to the so-called Modification Indices in LISREL. However, there is at least one very important difference between the two: whereas the LM Test operates multivariately in determining misspecifed parameters in a model, the LISREL Modification Indices operate univariately.

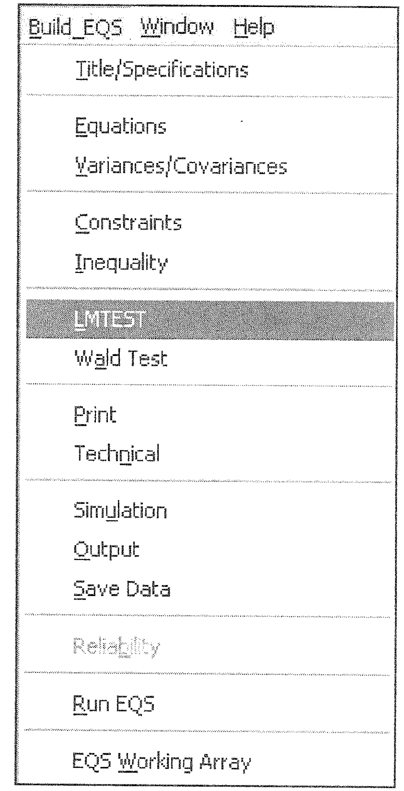

FIG. 3.2. Build EQS drop-down menu showing selection of LMTest.

double letters EE for the covariance between two error terms (i.e., correlations among the independent error terms).

In building an EQS input file, using the BUILD_EQS, specification of the LM Test is implemented following completion of the /VAR and /COV paragraphs. To begin the process, drop down the BUILD_EQS menu and select LMTEST, as highlighted in Fig. 3.2. Clicking on LMTEST subsequently yields the Build LMtest dialog box presented in Fig. 3.3. As shown here, only the boxes related to factor loadings (GVF) and error covariances (PEE) are checked. However, note that when the dialog box is first opened, you will find several other options are checked albeit not the ones that we have selected here. Simply Click on these other boxes to delete the checkmark. Once this dialog box has been completed, click OK and the /LMTEST paragraph will be added to the input file.[6]

[6]Alternatively, this choice could have been programmed via the Preference dialog box (see Fig. 2.5).

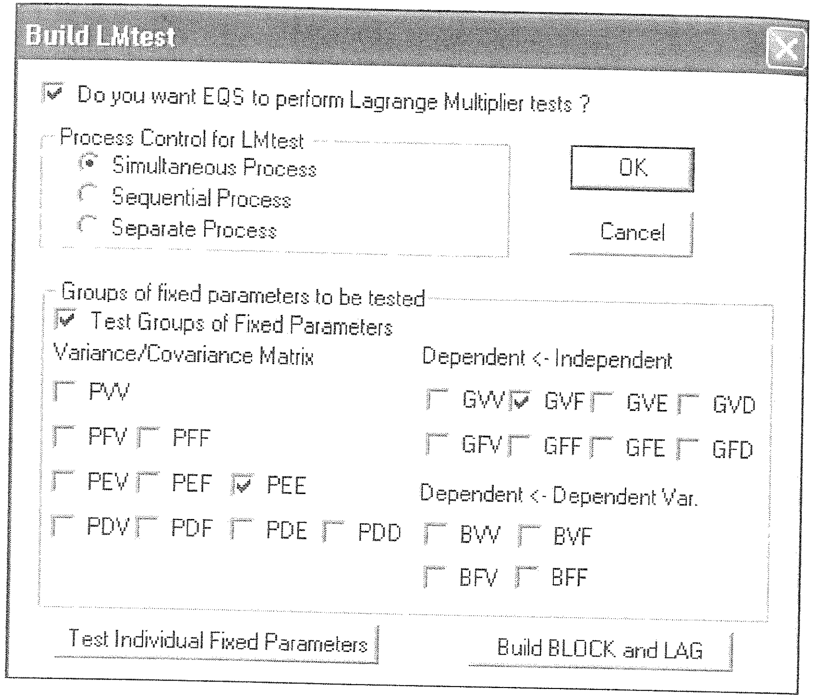

FIG. 3.3. Build LMTest dialog box showing fixed parameters under test.

Before leaving this topic of the LM Test, one vitally important caveat needs to be stressed. It bears on two factors: (a) the LM Test is based solely on statistical criteria, and (b) virtually any fixed parameter (constrained either to zero or some nonzero value) is eligible for testing. Thus, it is critical that the researcher heed the substantive theory before relaxing constraints as may be suggested by the LM statistics. Model respecification in which certain parameters have been set free must be substantiated by sound theoretical rationale; it also demands that heed be paid to the issue of identification.

The EQS Output File

We turn now to the EQS output resulting from the input file shown in Table 3.2. For didactic purposes, the entire output (except for the descriptive statistics section, which is addressed in chap. 4) is provided for the initially hypothesized model in Application 1 only; hereafter, selected portions of the output are displayed. To facilitate the presentation and discussion of results, this material is divided into three subsections: (a) model specification and analysis summary, (b) model assessment, and (c) model misspecification.

Model Specification and Analysis Summary. Given the known problems that can occur with analyses based on the correlation matrix (see, e.g., Bollen, 1989a; Boomsma, 1985; Cudeck, 1989; and Jöreskog & Sörbom, 1988), EQS automatically analyzes the covariance matrix when data are in raw matrix form. If, however, you wish to use data that are in the form of a correlation matrix, simply include the standard deviations (as shown in chap. 2) and EQS will again base the analyses on the covariance matrix. Conversely, should you wish (for any reason) to have the program base analyses on the correlation matrix, the program automatically presents a warning message advising that "statistics may not be meaningful due to analyzing a correlation matrix" (Byrne, 1994a, p. 49). Nonetheless, the program can still analyze the correlation matrix, but the ANAL=CORR command must be included, as noted in chap. 2. Shown in Table 3.3 is the covariance matrix to be analyzed in the present example.

EQS automatically decodes the input file to generate a model specification based on the Bentler–Weeks designation of dependent and independent variables. As shown in Table 3.3, there are 16 dependent variables (i.e., 16 observed variables) and 20 independent variables (i.e., four factors and 16 error terms). There are also 38 free parameters (i.e., 12 factor loadings, four factor variances, six factor covariances, 16 error variances) and 20 fixed nonzero parameters (four factor loadings, 16 error regression paths). This summary of the model is helpful in at least two ways. First, it enables you to verify that the labeled figure is consistent with the input file. In other words, is the specified model the one that you were expecting to analyze? Second, it enables you to quickly calculate degrees of freedom. In the present case, given 38 freely estimated parameters and 136 (16 [17]/2) pieces of information (see chap. 2), we know we are working with 98 (136 minus 38) degrees of freedom.

Following the Bentler–Weeks representation are two summary pieces of information: the first represents the numerical value of the matrix determinant value and the second represents a summary statement regarding the technical acceptability of the model parameters—basically, the program checks on the identification status of all parameters. Ideally, the message "PARAMETER ESTIMATES APPEAR IN ORDER, NO SPECIAL PROBLEMS WERE ENCOUNTERED DURING OPTIMIZATION" appears, as shown. It is important to locate this message prior to any interpretation of results; accordingly, we can be confident that the estimates in the present application are appropriate.

On the other hand, if the program encounters difficulties in the estimation process, the message locates the problematic parameter and prints out a Condition Code that pinpoints the obstacle contributing to its lack of identification. Basically, such problems relate to two situations. First, a parameter is linearly dependent on other parameters in the model, thereby causing the covariance matrix to be singular; the message appears as "LINEARLY DEPENDENT ON OTHER PARAMETERS." This situation occurs because either the parameter is underidentified in the model or it is empirically underidentified as a consequence of the data.

In the standardized solution, all variables are rescaled to have a variance of 1.0. In EQS, standardization is applied to all variables in the linear structural equation system, including errors and disturbances. As a result, all coefficients in the equations have a similar interpretation and the magnitude of their standardized values may be easier to interpret than that of coefficients obtained from the covariance or raw data metric (Bentler, 2005).[12] In contrast to the unstandardized solution, information related to the standardized solution is summarized on one line, along with a related R^2 value (i.e., the squared multiple correlation) appearing in the column to the right labeled R-SQUARED (see Aiken, West, & Pitts, 2003, p. 485). Each measured (or dependent, in the Bentler–Weeks sense) variable is accompanied by an R^2 value representing the proportion of variance accounted for by its related factor (or independent predictor variable). It is computed by subtracting the square of the error term from 1.0 (i.e., $1.0 - E^2$). Bentler (2005) notes that in the event that a particular R^2 cannot be computed or that it differs by more than 0.01 from the corresponding Bentler–Raykov corrected R^2 value (Bentler & Raykov, 2000), the corrected R^2 value will be printed below.

In reviewing the standardized estimates, the user should verify that particular parameter values are consistent with the literature. For example, within the context of the present application, it is of interest to inspect correlations among the SC factors for their consistency with previously reported values; in the present example, these estimates are as expected.

Three additional features of the standardized solution are note worthy. First, in the event that some variances are estimated as negative values, the standardized solution cannot be obtained because the computation requires the square roots of these values; if such is the case, no standardized solution will be printed. Second, in the standardized solution, parameters that were previously fixed to 1.0 take on new values. Finally, note the absence of output for the variances of the independent variables. This is because in standardizing the estimates, the variances automatically take on a value of 1.00.

Model Misspecification. Determination of misfitting parameters is accomplished in EQS by means of the LM Test. As discussed previously, fixed parameters—as specified in the input file—are assessed both univariately and multivariately to identify parameters that would contribute to a significant drop in χ^2 if they were to be freely estimated in a subsequent EQS run. More specifically, information is presented first for univariate LM Tests of model parameters constrained either to 0.0 or to some nonzero value. If any of the univariate tests yield statistically significant results, the program then proceeds with a

[12]The standardized solution in EQS is not the same as the one in the LISREL output. In the latter, neither the measured variables, error terms, nor disturbances in equations (not present in first-order CFA models) are standardized (Bentler, 2005).

multivariate test of fixed parameters. As such, it proceeds with a forward stepwise procedure that selects as the next parameter to be added to the multivariate test, the single fixed parameter that provides the largest increase in the multivariate χ^2 statistic (Bentler, 2005). Results related to these LM Tests are presented in Table 3.7.

Univariate Test Statistics

Review of these results shows eight columns of information. Column 1 simply assigns a number to the parameter being tested. Column 2 assigns a dual numerical code to the parameter under test. In a simultaneous test of parameters, which is the case here, the first digit will always be 2, as shown in Table 3.7. The second digit refers to the submatrix number in which the parameter resides (1 to 22). However, if the parameter has been fixed to a nonzero value, the second digit will be zero. (There is no reason to remember this information; it is presented solely in the interest of completeness.) Column 3 lists the parameter under test.

Column 4 presents the univariate LM χ^2 test statistic, which has 1 degree of freedom; Column 5 presents its related statistical probability. These values result from testing the hypothesized constraint that the selected parameter is equal to zero. Interpreted literally, given a probability of less than .05, this hypothesis must be rejected, thereby indicating some evidence of misspecification in the model. However, Bentler (2005) cautions that because these LM univariate tests are correlated and can be applied repeatedly to test a variety of single restrictions, they should not be used to determine what the simultaneous effect of several restrictions may be. Such decisions should always be based on the multivariate LM Test results.

Column 6, labeled Hancock 98 df Prob presents LM Test probabilities based on Hancock's (1999) multiple comparison rationale. This criterion was developed for use in SEM as an analog to the Scheffé test (1953) used in ANOVA to control for family-wise Type I errors. These probabilities represent an evaluation of each LM χ^2 statistic based on degrees of freedom for the current model (98 in the present case) rather than the usual 1 degree of freedom. Hancock's criterion provides for an extremely conservative approach (too conservative, in my experience) to model testing that can help control Type I error in exploratory (i.e., post hoc) model modification.

Columns 7 and 8 present the unstandardized and standardized parameter change statistic, respectively.[13] For each parameter tested via the LM Test, the parameter change statistic represents its estimated value if this parameter is freely estimated in a subsequent test of the model. Such information can be helpful in determining whether a parameter identified by the LM Test is justified to stand as a candidate for respecification as a freely estimated parameter. In other words, is the estimated

[13]This is sometimes referred to as the expected parameter change statistic.

TABLE 3.7
EQS Output for Initially Hypothesized Four-Factor Model: Modification Indexes

LAGRANGE MULTIPLIER TEST (FOR ADDING PARAMETERS)
ORDERED UNIVARIATE TEST STATISTICS

NO	CODE		PARAMETER	CHI-SQUARE	PROBABILITY	HANCOCK 98 DF PROBABILITY	PARAMETER CHANGE	STANDARDIZED CHANGE
1	2	6	E39,E38	17.753	.000	1.000	-.333	-.495
2	2	6	E27,E25	16.986	.000	1.000	.360	.319
3	2	12	V37,F2	11.205	.001	1.000	-.563	-.421
4	2	6	E39,E37	10.660	.001	1.000	.306	.546
5	2	6	E32,E29	9.264	.002	1.000	-.243	-.210
6	2	12	V37,F3	9.200	.002	1.000	-.299	-.205
7	2	6	E40,E38	8.255	.004	1.000	.222	.203
8	2	12	V39,F1	7.404	.007	1.000	.293	.238
9	2	12	V35,F4	7.313	.007	1.000	-.200	-.077
10	2	12	V35,F2	7.307	.007	1.000	-.657	-.514
11	2	12	V28,F2	6.910	.009	1.000	.491	.571
12	2	6	E29,E26	6.514	.011	1.000	.221	.177
•	•		•	•	•	•	•	•
•	•		•	•	•	•	•	•
•	•		•	•	•	•	•	•
•	•		•	•	•	•	•	•
170	2	0	V33,F3	.000	1.000	1.000	.000	.000
171	2	0	V25,F1	.000	1.000	1.000	.000	.000
172	2	0	V29,F2	.000	1.000	1.000	.000	.000

MULTIVARIATE LAGRANGE MULTIPLIER TEST BY SIMULTANEOUS PROCESS IN STAGE 1
PARAMETER SETS (SUBMATRICES) ACTIVE AT THIS STAGE ARE: PEE GVF

	CUMULATIVE MULTIVARIATE STATISTICS				UNIVARIATE INCREMENT			
							HANCOCK'S SEQUENTIAL	
STEP	PARAMETER	CHI-SQUARE	D.F.	PROB.	CHI-SQUARE	PROB.	D.F.	PROB.
1	E39,E38	17.753	1	.000	17.753	.000	98	1.000
2	E27,E25	34.739	2	.000	16.986	.000	97	1.000
3	E32,E29	44.003	3	.000	9.264	.002	96	1.000
4	V35,F4	51.317	4	.000	7.313	.007	95	1.000
5	E40,E32	58.310	5	.000	6.993	.008	94	1.000
6	E29,E26	63.870	6	.000	5.560	.018	93	1.000
7	E33,E29	68.972	7	.000	5.102	.024	92	1.000
8	E40,E36	73.905	8	.000	4.933	.026	91	1.000
9	E32,E28	78.590	9	.000	4.685	.030	90	1.000
10	V39,F1	82.726	10	.000	4.136	.042	89	1.000
11	E39,E37	87.433	11	.000	4.707	.030	88	1.000

NOTES: LAGRANGIAN MULTIPLIER TEST REQUIRED 59325 WORDS OF MEMORY.
PROGRAM ALLOCATES 2000000 WORDS.
1
Execution begins at 10:55:35
Execution ends at 10:55:37

difference in the magnitude of the parameter estimate sufficient to justify inclusion of its specification in the model?[14]

Let's review two entries in the LM Test univariate results reported in Table 3.7. In Entry No. 1, the first parameter tested is E39, E38, an error covariance between V39 and V38. The test that this parameter equals zero produced a univariate LM $\chi^2_{(1)}$ of 17.753, ($p = .000$), thereby indicating that this hypothesized restriction is not tenable. In contrast, the Hancock's Criterion shows a probability value of 1.000, indicating that the parameter is tenable and need not be considered in any respecification of the model. (This criterion is elaborated on in chap. 4 in which adherence to its results runs counter to reasonable model respecification.[15] The unstandardized parameter change statistic indicates that if this parameter were freely estimated, its estimated value would be $-.333$; the standardized value would be $-.495$. In Entry No. 170 (most parameter values were deleted from the table due to space limitations), the parameter tested is V33,F3, a factor loading that was constrained to 1.0 for purposes of model identification. Relatedly, the second digit in the code is 0, and the LM χ^2 is 0 (p=1.00), as it should be.

Immediately following the univariate test statistics, the program identifies the parameter sets, or submatrices, to be included in the analyses; in this case, the parameters of interest are the error covariances (PEE) and factor loadings (GVF).

Multivariate Test Statistics

Here, information is summarized by means of nine columns. Column 1 represents the step in the forward stepwise procedure at which the selected parameter is included in the analysis. Column 2 identifies this parameter, and Columns 3, 4, and 5 cite the multivariate LMχ^2 statistic, degrees of freedom, and probability value, respectively. Based on the work of Bentler and Chou (1987), a unique feature of the EQS program is that it breaks down the multivariate LM Test into a series of incremental univariate tests; these results are presented in Columns 6 and 7. (For an elaboration of both the rationale and details of this procedure, see Bentler, 2005.) Decisions regarding possible misspecification followed by respecification of the model are based on these incremental univariate statistics. In targeting misfitting parameters, within the context of Columns 6 and 7, the user typically looks for parameters whose χ^2 values stand apart from the rest and probabilities <.05. For example, in Table 3.7, there is a substantial drop between the first two χ^2 values and the remaining χ^2 values. Thus, we focus on these two parameters (E39,E38; E27,E25), each of which represent error covariances. However, incremental univariate LMχ^2 values of 17.753 and 16.986, with standardized parameter

[14]Bentler (2005) cautioned, however, that because these parameter change statistics are sensitive to the way by which variables and factors are scaled or identified, their absolute value is sometimes difficult to interpret.

[15]The conditions for optimal use of this statistic remain to be determined.

change values of -.495 and .319, respectively—particularly as they relate to error covariances—can be considered of little concern and, therefore, not worthy of inclusion in an already well-fitting and adequately specified model. Finally, degrees of freedom and probability values related to the Hancock criterion are presented in Columns 8 and 9, respectively. The two columns are needed because in the sequential test of parameters, the model degrees of freedom will necessarily decrease by one with each univariate increment to the multivariate LMχ^2. As expected, the probability values in Column 9 are consistently 1.000.

Post Hoc Analyses

In general, at this point in the analysis, a researcher can decide whether or not to respecify and reestimate the model. If he or she elects to follow this route, it is important to realize that analyses are now framed within an exploratory rather than a confirmatory mode. In other words, once a hypothesized CFA model, for example, has been rejected, it spells the end of the CFA approach in its truest sense. Although CFA procedures continue to be used in any respecification and reestimation of the model, these analyses are exploratory in the sense that they focus on the detection of misfitting parameters in the originally hypothesized model. Such post hoc analyses are conventionally termed *specification searches* (MacCallum, 1986). (The issue of post hoc model-fitting is addressed further in chap. 8 in the cross-validation subsection.)

The ultimate decision underscoring whether or not to proceed with a specification search is twofold. First and foremost, the researcher must determine whether the estimation of the targeted parameter is substantively meaningful. If, indeed, it makes no sound substantive sense to free up the parameter exhibiting the largest multivariate LM χ^2 value, the researcher may consider the parameter having the next largest value (Jöreskog, 1993). Second, whether the respecified model would lead to an overfitted model needs to be considered. The issue here is tied to the idea of knowing when to stop fitting the model or, as Wheaton (1987, p. 123) phrased the problem, "knowing . . . how much fit is enough without being too much fit." In general, overfitting a model involves the specification of additional parameters in the model after having determined a criterion that reflects a minimally adequate fit. For example, an overfitted model can result from the inclusion of additional parameters that (a) are "fragile" in the sense of representing weak effects that are not likely replicable, (b) lead to a significant inflation of standard errors, and (c) influence primary parameters in the model, albeit their own substantive meaningfulness is somewhat equivocal (Wheaton, 1987). Although correlated errors often fall into this latter category,[16] there are many situations—particularly with respect to social psychological research—in which these parameters can make strong

[16]Typically, the misuse in this instance arises from the incorporation of correlated errors into the model purely on the basis of statistical fit and to achieve a better-fitting model.

substantive sense and therefore should be included in the model (Jöreskog & Sörbom, 1993).

Having laboriously worked through the process involved in evaluating the fit of a hypothesized model, what can we conclude regarding the CFA model under scrutiny in this chapter? To answer this question, we must pool all the information gleaned from our study of the EQS text output. Considering (a) the feasibility and statistical significance of all parameter estimates; (b) the substantially good fit of the model, with particular reference to the CFI (.962) and RMSEA (.048) values; and (c) the lack of any substantial evidence of model misfit, I conclude that any further incorporation of parameters into the model would result in an overfitted model. Indeed, MacCallum et al. (1992, p. 501) cautioned that "when an initial model fits well, it is probably unwise to modify it to achieve even better fit because modifications may simply be fitting small idiosyncratic characteristics of the sample." Adhering to this caveat, I concluded that the four-factor model schematically portrayed in Fig. 3.1 represents an adequate description of self-concept structure for Grade 7 adolescents.

HYPOTHESIS 2: Self-Concept Is a Two-Factor Structure

The model to be tested here postulates a priori that self-concept is a two-factor structure consisting of GSC and ASC. As such, it argues against the viability of subject-specific academic SC factors. As with the four-factor model, the four GSC measures load onto the General SC (GSC) factor; in contrast, all other measures load onto the Academic SC (ASC) factor. This hypothesized model is represented schematically in Figure 3.4; the EQS input file is shown in Table 3.8.

In reviewing these graphical and equation model specifications, two points relative to the modification of the input file are of interest. First, although the pattern of factor loadings remains the same for the GSC and ASC measures, it changes for both the English SC (ESC) and Math SC (MSC) measures in allowing them to load onto the ASC factor. Second, because only one of these eight ASC factor loadings needs to be fixed to 1.0, the two previously constrained parameters (i.e., SDQ2N10 [V33]; SDQ2N07 [V37]) are now freely estimated.

The EQS Output File

Because only the goodness-of-fit statistics are relevant to the present application, it is the only information provided in Table 3.9.

As indicated in the output, the $\chi^2_{(103)}$ value of 455.929 represents a poor fit to the data and a substantial decrement from the overall fit of the four-factor model ($\chi^2_{(98)}$=158.512). The gain of 5 degrees of freedom can be explained by the estimation of two fewer factor variances and five fewer factor covariances,

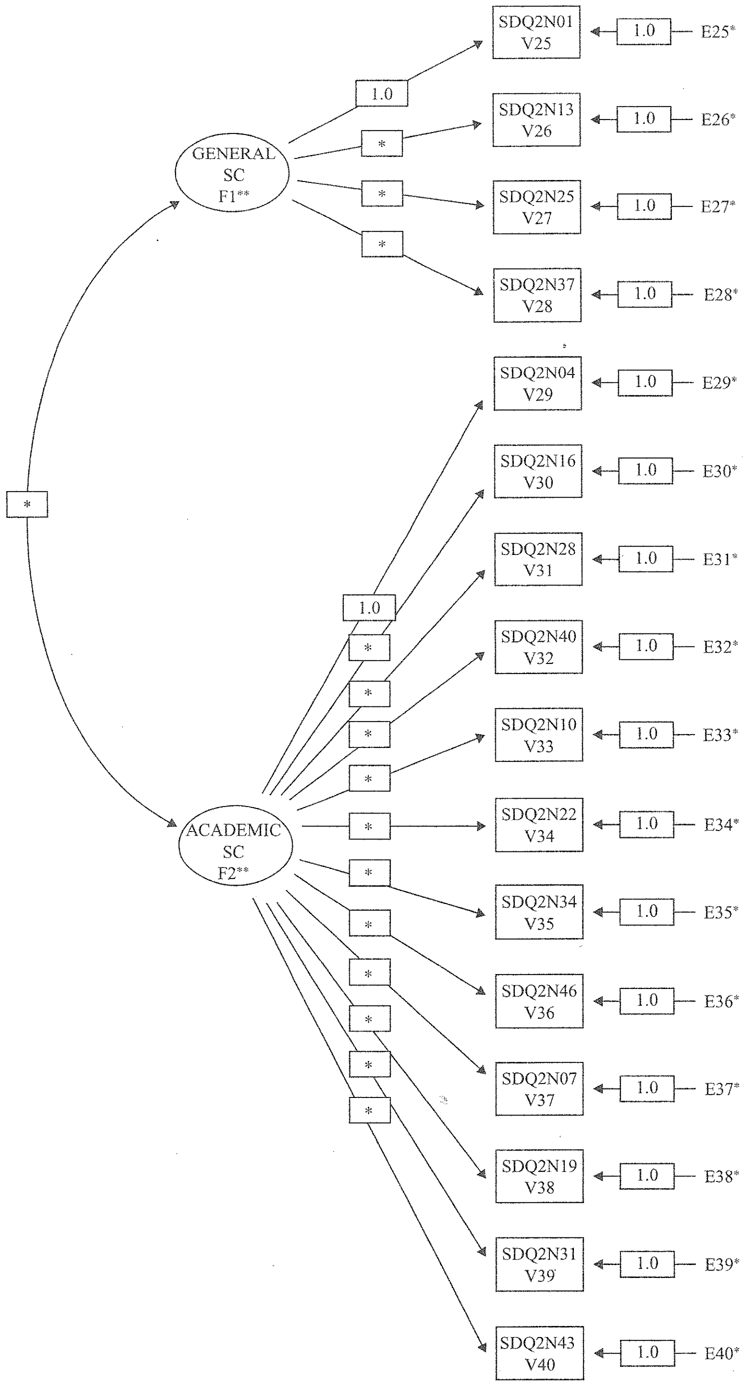

FIG. 3.4. Hypothesized two-factor model of self-concept.

TABLE 3.8
EQS Input for Two-Factor Model

```
/TITLE
 CFA OF ASC Structure - GRADE 7 "ASC7F2"
 2-Factor Model
/SPECIFICATIONS
 CASE=265; VAR=46; ME=ML; MA=RAW; FO= '(40F1.0,X,6F2.0)' ;
 DATA= 'C:\EQS61\Files\Books\Data\ASC7INDM.ess' ;
/LABELS
 V1=SPPCN08;  V2=SPPCN18;  V3=SPPCN28;  V4=SPPCN38;  V5=SPPCN48;
 V6=SPPCN58;  V7=SPPCN01;  V8=SPPCN11;  V9=SPPCN21;  V10=SPPCN31;
 V11=SPPCN41; V12=SPPCN51; V13=SPPCN06; V14=SPPCN16; V15=SPPCN26;
 V16=SPPCN36; V17=SPPCN46; V18=SPPCN56; V19=SPPCN03; V20=SPPCN13;
 V21=SPPCN23; V22=SPPCN33; V23=SPPCN43; V24=SPPCN53; V25=SDQ2N01;
 V26=SDQ2N13; V27=SDQ2N25; V28=SDQ2N37; V29=SDQ2N04; V30=SDQ2N16;
 V31=SDQ2N28; V32=SDQ2N40; V33=SDQ2N10; V34=SDQ2N22; V35=SDQ2N34;
 V36=SDQ2N46; V37=SDQ2N07; V38=SDQ2N19; V39=SDQ2N31; V40=SDQ2N43;
 V41=MASTENG1; V42=MASTMAT1; V43=TENG1; V44=TMAT1; V45=SENG1; V46=SMAT1;
/EQUATIONS
 V25= F1+E25;
 V26= *F1+E26;
 V27= *F1+E27;
 V28= *F1+E28;
   V29= F2+E29;
   V30= *F2+E30;
   V31= *F2+E31;
   V32= *F2+E32;
   V33= *F3+E33;
   V34= *F3+E34;
   V35= *F3+E35;
   V36= *F3+E36;
   V37= *F4+E37;
   V38= *F4+E38;
   V39= *F4+E39;
   V40= *F4+E40;
/VARIANCES
 F1 TO F2= *;
 E25 TO E40= *;
/CONSTRAINTS
 F1 TO F2= *;
/PRINT
 FIT=ALL;
/LMTEST
 SET=GVF, PEE;
/END
```

TABLE 3.9
EQS Output for Two-Factor Model: Goodness-of-Fit Statistics

```
GOODNESS OF FIT SUMMARY FOR METHOD = ML

INDEPENDENCE MODEL CHI-SQUARE     =  1696.728 ON   120 DEGREES OF FREEDOM

INDEPENDENCE AIC =  1456.72831  INDEPENDENCE CAIC =  907.16073
       MODEL AIC =   249.92879         MODEL CAIC = -221.78339

CHI-SQUARE =      455.929 BASED ON    103 DEGREES OF FREEDOM
PROBABILITY VALUE FOR THE CHI-SQUARE STATISTIC IS       .00000
THE NORMAL THEORY RLS CHI-SQUARE FOR THIS ML SOLUTION IS        688.051.

FIT INDICES
-----------
BENTLER-BONETT NORMED FIT INDEX =       .731
BENTLER-BONETT NON-NORMED FIT INDEX =   .739
COMPARATIVE FIT INDEX (CFI)      =      .776
BOLLEN (IFI) FIT INDEX          =       .779
MCDONALD (MFI) FIT INDEX         =      .514
LISREL GFI FIT INDEX         =      .754
LISREL AGFI FIT INDEX        =      .676
ROOT MEAN-SQUARE RESIDUAL (RMR)   =       .182
STANDARDIZED RMR               =      .101
ROOT MEAN-SQUARE ERROR OF APPROXIMATION (RMSEA) =       .114
90% CONFIDENCE INTERVAL OF RMSEA (       .103,       .124)
```

ITERATIVE SUMMARY

ITERATION	PARAMETER ABS CHANGE	ALPHA	FUNCTION
1	.439992	1.00000	2.31433
2	.149129	1.00000	1.88294
3	.062831	1.00000	1.79004
4	.035740	1.00000	1.75530
5	.023792	1.00000	1.73949
6	.016281	1.00000	1.73238
7	.010849	1.00000	1.72927
8	.007131	1.00000	1.72794
9	.004625	1.00000	1.72738
10	.002978	1.00000	1.72715
11	.001907	1.00000	1.72706
12	.001217	1.00000	1.72702
13	.000775	1.00000	1.72700

albeit the estimation of two additional factor loadings (formerly SDQ2N10 [V33]; SDQ2N07 [V37]). As expected, all other indexes of fit reflect the fact that self-concept structure is not well represented by the hypothesized two-factor model. In particular, the CFI value of .776 and RMSEA value of .114 are strongly indicative of inferior goodness-of-fit between the hypothesized two-factor model and the sample data.

HYPOTHESIS 3: Self-Concept Is a One-Factor Structure

Although it now seems obvious that a multidimensional model best represents the structure of SC for Grade 7 adolescents, some researchers still contend that self-concept is a unidimensional construct. Thus, for purposes of completeness and to address the issue of unidimensionality, Byrne and Worth Gavin (1996) proceeded in testing this hypothesis. However, because the one-factor model represents a restricted version of the two-factor model and thus cannot possibly represent a better-fitting model, these analyses are not presented herein due to space limitations.

In summary, it is evident from these analyses that both the two-factor and one-factor models of self-concept represent a misspecification of factorial structure for early adolescents. Based on these findings, Byrne and Worth Gavin (1996) concluded that self-concept is a multidimensional construct that, in their study, comprised the four facets of general, academic, English, and mathematics self-concepts.

variance to be considered as "true" variance, Rho is the most appropriate coefficient to use.

Three other reliability options are available to the researcher. In contrast to the Rho coefficient, which is a model-based statistic, these coefficients are not bound to the input model structure. Nonetheless, they do assume some type of factor structure with a large but unspecified number of latent factors and do consider all sources of covariance as true variance. The first, the Greatest Lower Bound Reliability, requires that all error variances be non-negative (i.e., they exhibit no Heywood cases).[4] The second option, Bentler's Dimension-Free Lower Bound Reliability does not have this restriction. As shown in Table 4.4, coefficients derived from each of these reliability computations were identical at a value of .924. The final reliability coefficient, Shapiro's Lower Bound Reliability, is based on a weighted sum of the variables (i.e., the variables are weighted differentially to achieve a higher reliability). Following the reported coefficient value of .963, the program then lists the weights that were applied in its computation. With respect to the present example, Bentler's Dimension-Free Lower Bound Reliability coefficient seems to be the most appropriate choice, with a value of .924 indicative of high internal consistency among the MBI items, regardless of the number of postulated factors of burnout. (For an extensive discussion of these reliability coefficients, see Bentler, 2005.)

Modification Indexes

Recall that in the initial EQS input file, the SET command was used to limit the search for misfitting parameters to only factor loadings (GVF) and error covariances (PEE); these parameters, then, are the only ones identified in the portion of the output bearing on the LM Test statistics shown in Table 4.5. Review of the ordered univariate test statistics in the upper portion of the table identifies two parameters (E16,E6; E2,E1) whose LM Test χ^2 values, at 91.038 and 82.228, stand apart from the rest; both represent error covariances. Under the Parameter Change column, we see that if an error covariance between Items 16 and 6 were specified and freely estimated in a subsequent run, the value of the resulting parameter would be approximately .735; for E2,E1, the value would be .614.

Turning to the multivariate portion of Table 4.5 and then to the multivariate χ^2 values under the heading Cumulative Multivariate Statistics, we observe that if both error covariances were freely estimated, the approximate drop in the overall χ^2

[4]Heywood cases are phenomena associated with CFA models that represent improper solutions in which the absolute value of an estimated error variance is negative or an estimated correlation is greater than 1.00. For an elaboration on the causes of Heywood cases, see Kline (1998) and Dillon, Kumar, and Mulani (1987).

TABLE 4.5
Selected EQS Output for Initially Hypothesized Model: Modification Indexes

LAGRANGE MULTIPLIER TEST (FOR ADDING PARAMETERS)
ORDERED UNIVARIATE TEST STATISTICS:

NO	CODE		PARAMETER	CHI-SQUARE	PROB.	HANCOCK 206 DF PROB.	PARAMETER CHANGE	STANDARDIZED CHANGE
1	2	6	E16,E6	91.038	.000	1.000	.735	.529
2	2	6	E2,E1	82.228	.000	1.000	.614	.549
3	2	12	V12,F1	41.402	.000	1.000	-.313	-.206
4	2	6	E11,E10	37.955	.000	1.000	.581	.524
5	2	6	E21,E7	33.441	.000	1.000	.264	.326
6	2	6	E7,E4	33.345	.000	1.000	.210	.324
7	2	12	V1,F3	28.654	.000	1.000	.871	1.193
8	2	6	E19,E18	18.558	.000	1.000	.250	.285
9	2	6	E6,E5	17.145	.000	1.000	.355	.232
•			•	•	•	•	•	•
•			•	•	•	•	•	•
•			•	•	•	•	•	•
•			•	•	•	•	•	•
274	2	12	V15,F1	.001	.976	1.000	-.002	-.001
275	2	6	E21,E2	.000	.991	1.000	-.001	-.001
276	2	0	V1,F1	.000	1.000	1.000	.000	.000

MULTIVARIATE LAGRANGE MULTIPLIER TEST BY SIMULTANEOUS PROCESS IN STAGE 1
PARAMETER SETS (SUBMATRICES) ACTIVE AT THIS STAGE ARE: PEE GVF

	CUMULATIVE MULTIVARIATE STATISTICS				UNIVARIATE INCREMENT			
STEP	PARAMETER	CHI-SQUARE	D.F.	PROB.	CHI-SQUARE	PROB.	HANCOCK'S SEQUENTIAL D.F.	PROB.
1	E16,E6	91.038	1	.000	91.038	.000	206	1.000
2	E2,E1	169.789	2	.000	78.751	.000	205	1.000
3	V12,F1	211.191	3	.000	41.402	.000	204	1.000
4	E11,E10	249.146	4	.000	37.955	.000	203	1.000
5	E21,E7	281.839	5	.000	32.692	.000	202	1.000
6	E7,E4	319.400	6	.000	37.561	.000	201	1.000
7	V1,F3	344.589	7	.000	25.189	.000	200	1.000
8	E21,E4	365.388	8	.000	20.798	.000	199	1.000
9	E6,E5	382.056	9	.000	16.668	.000	198	1.000
10	E3,E1	397.791	10	.000	15.735	.000	197	1.000
11	V2,F3	413.134	11	.000	15.344	.000	196	1.000
12	E13,E12	428.093	12	.000	14.959	.000	195	1.000
13	E14,E2	441.824	13	.000	13.731	.000	194	1.000
14	E19,E18	453.132	14	.000	11.308	.001	193	1.000
15	E19,E9	463.201	15	.000	10.069	.002	192	1.000
16	V14,F3	473.213	16	.000	10.012	.002	191	1.000
17	E20,E13	481.627	17	.000	8.414	.004	190	1.000
•	•	•	•	•	•	•	•	•
•	•	•	•	•	•	•	•	•
•	•	•	•	•	•	•	•	•
•	•	•	•	•	•	•	•	•
27	E15,E7	558.037	27	.000	5.357	.021	180	1.000
28	E17,E6	562.727	28	.000	4.690	.030	179	1.000
29	E12,E3	566.841	29	.000	4.114	.043	178	1.000

value for the model as a whole would be 169.789. To determine which parameters to free in the respecification of the model, turn to the Univariate Increment column and base the decision on the LMχ^2 statistic and related probability value. Consistent with the ordered univariate statistics presented in the upper part of Table 4.5, values for the same two error covariances are substantially higher than those for the remaining parameters. That the value here for E2,E1 (78.751) differs from its univariate value (82.228) reported previously arises from its computation as a univariate increment based on the multivariate LM Test simultaneous analysis. Although the overall univariate LM Test results parallel those for the multivariate LM Test, decisions regarding which parameter(s) to freely estimate in subsequent respecification of a model should be based on the multivariate LM Test results.

These error covariances represent systematic rather than random measurement error in item responses, and they may derive from characteristics specific either to the items or the respondents (Aish & Jöreskog, 1990). For example, if these parameters reflect item characteristics, they may represent a small omitted factor. Conversely, if they represent respondent characteristics, they may reflect bias such as yea-/nay-saying, social desirability, and the like. Another type of method effect that can trigger correlated errors is a high degree of overlap in item content. Such redundancy occurs when an item, although worded differently, essentially asks the same question; the latter situation seems to be the case here. For example, Item 16 asks whether working directly with people puts too much stress on the respondent, whereas Item 6 asks whether working with people all day puts a real strain on the respondent. Likewise, Item 2 queries if the respondent feels used up at the end of the workday, whereas Item 1 queries if the respondent feels emotionally drained from his or her work.[5]

The question now, of course, is how to proceed from here? Having determined (a) inadequate fit of the hypothesized model to the sample data, and (b) at least two misspecified parameters in the model (i.e., the two error covariances were specified as zero), it seems both reasonable and logical to move into exploratory mode and attempt to modify this model in a sound and responsible manner. Model respecification that includes correlated errors, as with other parameters, must be supported by a strong substantive and/or empirical rationale (Jöreskog, 1993); it appears that this condition exists here. In light of (a) apparent item content overlap, (b) the replication of these same error covariances in previous MBI research (e.g., Byrne, 1991, 1993), and (c) Bentler and Chou's (1987) admonition that forcing large error terms to be uncorrelated is rarely appropriate with real data, I consider respecification of this initial model, with E16,E6 and E2,E1 freely estimated, to be justified. Testing of this respecified model (Model 2) now falls within the framework of post hoc analyses.

[5]Unfortunately, refusal of copyright permission by the MBI test publisher prevented the actual item statements from being presented.

Before moving on to these analyses, however, it is important to clarify two questions that may have been raised in the previous discussion: (a) Why respecify two parameters rather than just one in the respecification of Model 2?, and (b) Why not compute the difference in S-Bχ^2 values between Models 1 and 2? Answers to these queries follow.

Question 1: The reason that respecification of both error covariance parameters is possible with EQS is that the LM Test (see chap. 3) operates multivariately in the computation of modification indexes that point to misspecified parameters in the model. In contrast, modification indexes for both LISREL and AMOS are computed univariately, thereby dictating that only one fixed parameter can be freely estimated at a time in the search for optimal model fit.

Question 2: In working with EQS, there is no need to compute the χ^2 difference (D) value between nested models in determining fixed parameters to be freely estimated in the respecification of a model. The rationale in support of this claim derives from statistical theory that has verified the asymptotic equivalence of the D and LM Tests (see, e.g., Buse, 1982; Lee, 1985; and Satorra, 1989). What these statistical findings mean for the LM multivariate statistic is that its value can be interpreted as an approximate decrease in the χ^2 statistic of overall model fit resulting from the respecification of a model in which certain fixed parameters are instead freely estimated. As Bentler (2005, p. 163) has so cogently noted, it is not necessary to actually estimate alternative models to obtain statistics needed to compute the D test because, in principle, the D statistic "is no more accurate or meaningful as a test on the model-differentiating parameters than are the LM and W tests" (see also Yuan & Bentler, 2004a).

POST HOC ANALYSES

Model 2

The EQS Input File

The model specification portion of the input file for Model 2 is presented in Table 4.6, which shows only two differences between this input and the input for the initially hypothesized model. First, note a modification to the method, which now reads as METHOD=ML,ROBUST; second, note the addition of the two error covariance parameters (E16,E6; E2,E1) in the /COVARIANCES paragraph. While you will likely have no difficulty interpreting the specification of the error terms, modification to the Method command requires further explanation, which follows before proceeding with Model 2.

In reviewing the descriptive sample statistics presented previously, evidence of moderate kurtosis associated with five MBI items was noted. The effect of these

The EQS Output File

As shown in the goodness-of-fit summary in Table 6.23, incorporation of the path F11,F1 resulted in virtually no change in overall model fit from the previous model (i.e., Model 5). Thus, although the LM Test Statistics shown in Table 6.24 suggested another structural path to be incorporated into the model, this addition was not considered.

Thus far in this chapter, discussion related to model fit has considered only the addition of parameters to the model. However, another side to the question of fit—particularly as it pertains to a full causal model—is the extent to which certain initially hypothesized paths and possibly post hoc additional paths may be redundant to the model. One way to determine such redundancy is to examine the statistical significance of all structural parameter estimates. This information, as derived from the estimation of Model 6, is presented in Table 6.25.

Examining z-statistics associated with these structural estimates, we can determine five that are nonsignificant; these parameters are circled in Table 6.25 and represent structural paths flowing from F7 to F8, F1 to F11, F6 to F11, F10 to F12, and F1 to F12. The limiting factor in using these statistics as a basis for pinpointing redundant parameters, however, is that they represent univariate tests of significance. When sets of parameters are to be evaluated, a more appropriate approach is to implement a multivariate test of statistical significance. Indeed, the EQS program is unique in its provision of the Wald Test (WTest; Wald, 1943) for

TABLE 6.22
Selected EQS Input: Model 6

```
/TITLE
 FULL BURNOUT MODEL FOR SECONDARY TCHRS (GRP1); "BURNHS6.EQS"
 MODEL 6
 ADDED:  F3 to F11 (Work -> DP)
 ADDED:  F8 to F9 (SE -> XLOCUS)
 ADDED:  F5 to F12 (SSUP->PA; F2 to F9 (ROLEC->XLOCUS); F6 to F10 (PSUP->EE);
         F3 to F12 (WORK->PA); F6 to F11 (PSUP->DP)
 ADDED:  F8 to F10 (SE -> EE)
 ADDED:  F1 to F11 (ROLEA -> DP)
     .
     .
/EQUATIONS
     .
     .
 F8 =  .363*F5 -.114*F6 -.044*F7 + 1.000 D8;
 F9 = -.262*F5 + *F8 + *F2 + 1.000 D9;
 F10 = -.128*F2 + .745*F3 -.898*F4 + *F6 + *F8 + 1.000 D10;
 F11 = .549*F10 + .147*F2 + *F3 + *F6 + *F1 + 1.000 D11;
 F12 = .512*F8 -.188*F9 + .019*F10 -.195*F11 -.041*F1 + *F5 + *F3 + 1.000 D12;
     .
     .
/LMTEST
 SET=GFF, BFF, PDD;
/END
```


TABLE 6.23
Selected EQS Output for Model 6: Goodness-of-Fit Statistics

```
              GOODNESS OF FIT SUMMARY FOR METHOD = ML

CHI-SQUARE =      889.534 BASED ON    417 DEGREES OF FREEDOM
PROBABILITY VALUE FOR THE CHI-SQUARE STATISTIC IS      .00000

FIT INDICES
-----------
BENTLER-BONETT      NORMED FIT INDEX =      .927
BENTLER-BONETT NON-NORMED FIT INDEX =      .952
COMPARATIVE FIT INDEX (CFI)         =      .960
ROOT MEAN-SQUARE RESIDUAL (RMR)     =      .032
STANDARDIZED RMR                    =      .040
ROOT MEAN-SQUARE ERROR OF APPROXIMATION (RMSEA)    =     .040
90% CONFIDENCE INTERVAL OF RMSEA   (       .036,      .043)

              GOODNESS OF FIT SUMMARY FOR METHOD = ROBUST

SATORRA-BENTLER SCALED CHI-SQUARE =   802.7997 ON   417 DEGREES OF FREEDOM
PROBABILITY VALUE FOR THE CHI-SQUARE STATISTIC IS      .00000

FIT INDICES
-----------
BENTLER-BONETT      NORMED FIT INDEX =      .921
BENTLER-BONETT NON-NORMED FIT INDEX =      .952
COMPARATIVE FIT INDEX (CFI)         =      .960
ROOT MEAN-SQUARE ERROR OF APPROXIMATION (RMSEA)    =     .036
90% CONFIDENCE INTERVAL OF RMSEA   (       .032,      .040)
```

TABLE 6.24
Selected EQS Output for Model 6: Modification Indexes

```
 MULTIVARIATE LAGRANGE MULTIPLIER TEST BY SIMULTANEOUS PROCESS IN STAGE 1
   PARAMETER SETS (SUBMATRICES) ACTIVE AT THIS STAGE ARE:
     PDD GFF BFF

      CUMULATIVE MULTIVARIATE STATISTICS     UNIVARIATE INCREMENT
      ----------------------------------     ------------------------------
                                                                 HANCOCK'S
                                                                 SEQUENTIAL
STEP  PARAMETER  CHI-SQUARE  D.F.  PROB.     CHI-SQUARE  PROB.  D.F.  PROB.
----  ---------  ----------  ----  -----     ----------  -----  ----  -----
  1     F9,F3       3.870      1   .049         3.870    .049   417   1.000
```

this very purpose. Essentially, the WTest ascertains whether sets of parameters, specified as free in the model, can in fact be simultaneously set to zero without substantial loss in model fit. It does so by taking the least significant parameter (i.e., the one with the smallest z-statistic) and adding other parameters in such a way that the overall multivariate test yields a set of free parameters that with high probability can simultaneously be dropped from the model in future EQS runs without significant degradation in model fit (Bentler, 2005). In other words, this

TABLE 6.25
Selected EQS Output for Model 6: Structural Path Estimates

```
CONSTRUCT EQUATIONS WITH STANDARD ERRORS AND TEST STATISTICS
STATISTICS SIGNIFICANT AT THE 5% LEVEL ARE MARKED WITH @.
(ROBUST STATISTICS IN PARENTHESES)

SELF  =F8   =      .360*F5   -   .120*F6   -  .047*F7   +  1.000 D8
                   .060          .031          .034
                  5.984@       -3.827@       -1.374
               (   .068)    (    .035)       (.042)
               (  5.310@    (  -3.405@      (-1.120)

XLOC  =F9   =    -.269*F8   +   .131*F2   -    .081*F5   +  1.000 D9
                   .057          .037           .039
                 -4.672@        3.553@        -2.076@
               (   .072)    (    .036)    (     .040)
               ( -3.738@    (   3.641@    (   -2.033@

EE    =F10  =    -.828*F8   -  2.118*F2   +   2.223*F3   -   .929*F4
                   .133          .650           .548          .178
                 -6.247@       -3.259@         4.057@       -5.212@
               (   .168)    (    .687)    (     .569)    (    .187)
               ( -4.934@    (  -3.084@    (    3.907@    (  -4.957@

               -   .269*F6   +  1.000 D10
                   .108
                 -2.487@
               (   .126)
               ( -2.132@

DP    =F11  =     .996*F10  -   .452*F1   +   4.213*F2   -  3.548*F3
                   .177          .233          1.493         1.244
                  5.623@       -1.942          2.822@       -2.852@
               (   .194)    (    .241)    (    1.598)    (   1.307)
               (  5.124@    (  -1.874)    (    2.637@    (  -2.715@

               +   .276*F6   +  1.000 D11
                   .210
                  1.313
               (   .236)
               (  1.170)

PA    =F12  =     .465*F8   -   .174*F9   -    .017*F10  -   .159*F11
                   .102          .075           .049          .035
                  4.541@       -2.317@         -.345        -4.523@
               (   .132)    (    .074)    (     .051)    (    .041)
               (  3.521@    (  -2.360@    (    -.334)    (  -3.893@

               +   .043*F1   +   .165*F3   +    .268*F5   +  1.000 D12
                   .103          .064           .072
                   .411         2.596@         3.708@
               (   .118)    (    .067)    (     .078)
               (   .362)    (   2.476@    (    3.419@
```


TABLE 6.26
Selected EQS Output for Model 6: Wald Test Results

WALD TEST (FOR DROPPING PARAMETERS)
ROBUST INFORMATION MATRIX USED IN THIS WALD TEST
MULTIVARIATE WALD TEST BY SIMULTANEOUS PROCESS

	CUMULATIVE MULTIVARIATE STATISTICS				UNIVARIATE INCREMENT	
STEP	PARAMETER	CHI-SQUARE	D.F.	PROBABILITY	CHI-SQUARE	PROBABILITY
1	F12,F10	.111	1	.739	.111	.739
2	F12,F1	.186	2	.911	.074	.785
3	F11,F6	1.511	3	.680	1.325	.250
4	F8,F7	2.895	4	.576	1.385	.239
5	F11,F1	6.048	5	.302	3.152	.076

multivariate WTest operates in a stepwise manner that is analogous to stepwise backward regression. In contrast, the stepping procedure for the LM Test is forward. The value of this stepwise implementation in EQS is that it may determine that only a few parameters actually carry all the weight in the multivariate test (Bentler, 2005). Implementation of the WTest is simple and involves only the typing of a separate line, as follows: /WTEST. Essentially, this specification replaces the /LMTEST specification.

To test multivariately for redundant structural paths in the model, the /WTEST paragraph was added to the EQS input for Model 6 and the model was reestimated; for this run also, there was no specification of LM Test statistics. Results from this invocation of the WTest are presented in Table 6.26.

Interestingly, the WTest identified the same five parameters noted in Table 6.25 as being redundant to the model. Of the five nonsignificant parameters, three represent structural paths present in the originally hypothesized model (F7 ->F8; F10 ->F12; F1 ->F12) and two represent paths added during the post hoc model-fitting stage (F1 ->F11; F6 ->F11).

Revision of the model in accordance with these results led to deletion of structural paths describing the impact of: Role Ambiguity on Personal Accomplishment, Role Ambiguity on Depersonalization, Superior Support on Depersonalization, Peer Support on Self-esteem, and Emotional Exhaustion on Personal Accomplishment. These deletions resulted in the Role Ambiguity and Peer Support constructs being totally eliminated from the causal model. To obtain fit statistics and estimates for this final model of burnout for secondary school teachers, Model 6 was respecified with these five parameters deleted and labeled Model 7, which was then estimated. Goodness-of-fit statistics related to this final model of burnout are presented in Table 6.27.

Of import in reviewing these statistics is the fact that both the *CFI and the *RMSEA values remained unchanged (.960 and .036, respectively) from those for Model 6 in which these five structural paths were estimated. Although there was a