

Method Variance and Big Five Correlations

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Abstract

Recently DeYoung (2006) proposed that the Big Five dimensions exhibit a two factor structure with a higher order factor he called Stability indicated by Agreeableness, Conscientiousness, and Neuroticism and another called Plasticity indicated by Extraversion and Openness. DeYoung's evidence for the two-factor structure was based primarily on multiple-rater analyses of whole scale scores. His results and others have suggested that method bias might affect estimated correlations of the Big Five dimension. The study presented here investigated the relationship of Big Five correlations to estimation of method bias when individual items or parcels were modeled. A confirmatory factor analytic model was applied to data of a Big Five questionnaire in which a Method latent variable was included to model method biases of individual raters. The six-factor CFA was applied to the data of four samples ranging in size from 166 to 360. Indicators of the latent variables were either individual items or two-item parcels from the 50-item Big Five scale available on the IPIP web site. Inclusion of a Method latent variable was associated with significant improvements in fit of the model to each dataset. Mean correlations between the Big Five scales were .255, .142, .242, and .234 for the four samples. For the method bias model applied to individual items, corresponding mean correlations were .090, -.121, .083, and .043. For the model applied to parcels they were -.022, -.020, -.118, and -.023. However, even when a Method latent variable was included, models that constrained Big Five covariances to zero fit significantly worse than those in which the covariances were estimated. Implications of the results are discussed.

Method Variance and Big Five Correlations

Michael D. Biderman

In the past 25 years the Big 5 model of normal personality traits has received increasing support, to the extent that it is now the commonly accepted view of the dimensionality of normal personality (Costa & McCrae, 1992, Goldberg, 1993). Although there is less agreement on the orthogonality of the five dimensions, at the present time there is mounting evidence that, in fact, the five dimensions are not orthogonal, but instead form two higher order factors. Recent studies (DeYoung, Peterson, & Higgins, 2002; DeYoung, 2006; Digman, 1997). have suggested that the five dimensions are themselves indicators of two higher-order dimensions. The first higher order dimension is indicated by Agreeableness (A), Conscientiousness (C), and Emotional Stability (S). DeYoung (2006) has labeled this higher order dimension, Stability. The second higher order dimension, indicated by Extraversion (E) and Openness (O) has been called Plasticity by DeYoung (2006).

DeYoung (2006) has provided the strongest evidence to date for the higher order structure. In this study, confirmatory factor analyses of descriptions of the same participants from four different sources were conducted on data from two different instruments – the Big Five Inventory (BFI; John & Srivastava, 1999) and the Mini-Markers (Saucier, 1994). In a correlated-traits correlated-uniquenesses analysis, evidence for the hypothesized hierarchical factor structure was obtained. In this model, method biases associated with different raters were represented by the correlated uniquenesses. The partialling out of method biases is important because it is well-known that correlations among paper-and-pencil questionnaire scales can be strongly related to biases associated with the questionnaire method. For example, Podsakoff, MacKenzie, Lee, & Podsakoff (2003) noted that the percentage of variance shared by measures of different variables dropped from 35% to 11% after method variance was taken into account.

Accounting for method effects in analyses of Big Five data requires at least two indicators of each dimension in order to prevent the model from being underidentified. DeYoung (2006; see also Barbaranelli & Caprara, 2000) provided multiple indicators by having four persons provide ratings. Others have used scores from two or more measures to insure model identification (Lim & Ployhart, 2006; McCrae & Costa, 1987). Both DeYoung (2006) and Lim & Ployhart (2006) estimated method effects. In both studies, single scores on each of the Big Five dimensions for each instrument served as the basic data for the models estimating method effects. Another way of providing multiple indicators per dimension is to analyze the individual items making up the scale for each dimension or to analyze parcels or testlets formed by summing or averaging responses to groups of items from each scale. An advantage of this method is that it does not require the use of multiple observers or multiple questionnaires. A disadvantage of analyses of smaller “pieces” of a questionnaire is that goodness-of-fit of models applied to item or parcel data are typically poorer than when applied to whole-scale score data., leaving researchers with the question of whether poor goodness-of-fit is due to fundamental

misspecification of a model or to more harmless misspecification of idiosyncratic relationships among individual items or parcels. While analyses of items or parcels have been considered for many years there have been few analyses of Big Five data in which method biases were estimated from parceled data (Biderman & Nguyen, 2006; Burns & Christensen, 2007). To address this issue the present study investigated the feasibility of a model of method biases using individual item and parcel data and examined the effect of including method biases on the correlations among the Big Five latent variables.

For the data analyzed here, two datasets were created. The first consisted of 10 individual items for each of the Big Five dimensions. The second consisted of five two-item parcels created by averaging pairs of items. There is a growing literature on the positive and negative aspects of using parcels, as opposed to whole scores or individual items in CFA and SEM applications (e.g., Bandalos, 2002; Sass & Smith, 2006). For example, an advantage of parceling is creation of indicators that more nearly approximate normality. Our reading of the consensus is that parceling is appropriate as needed when items are unidimensional. Given the generally accepted consensus on the factor structure of the Big Five, the present data seemed to meet this criterion. Our experience has been that models of parcels as opposed to individual items have been more likely to yield convergence in the iterative processes required for confirmatory factor analysis. The convergence issue was the reason for the use of two-item parcels in addition to individual items in the present study.

The method bias model used in the present study involved adding a single Method latent variable to the typical five-latent variable CFA. Loadings of all items or parcels on the Method variable were estimated as were loadings on the Big 5 latent variables. The model for a dataset with five two-item parcels per dimension is illustrated in Figure 1.

The present study compared correlations between the Big 5 dimensions in a model in which method bias was not estimated with correlations when a method bias latent variable was estimated. In addition, confirmatory factor analysis models in which the Big 5 dimensions were assumed to be orthogonal were compared to models in which the dimensions were allowed to correlate freely using chi-square difference tests. If correlations between the Big 5 latent variables are due only to method bias, then those correlations should be essentially zero when a Method latent variable is included in the model and restricting them to zero should have negligible effects on goodness-of-fit. Specifically, a method bias model in which the covariances were restricted to zero should fit no worse than a method bias model in which there were no restrictions on the covariances of the Big 5 latent variables.

A finding of essentially zero covariances among the Big Five latent variables in the method variance model would of course suggest that there can be no higher order factors of the Big Five, since there is no covariance for them to explain. On the other hand, finding that even when method variance is accounted for the correlations among the Big Five latent variables fit the pattern of correlations consistent with the higher order factor structure would bolster the case for that structure.

Method

Samples. The data of four different samples involving administration of a Big Five questionnaire were analyzed. The first three samples were gathered as part of research studying the faking of personality items. The fourth was gathered as part of an investigation of mediation of the conscientiousness – performance relationship. The first dataset was that reported upon by Biderman & Nguyen (2004). It was comprised of 203 undergraduate and graduate student participants from two southeastern universities. Participants were given a Situational Judgment Test and the Big 5 questionnaire twice, once with instructions to respond honestly and again with instructions to respond in a fashion that would increase the participant's chances of obtaining a customer service job. Half the participants were given the honest condition first. Only the honest condition data of this sample are presented here. Participants were given the Wonderlic Personnel Test (WPT: Wonderlic, 1999) prior to the experimental manipulation.

The second dataset was similar to the first, with an honest-response and a fake-good condition (Wrensen & Biderman, 2005) with order of presentation of the conditions counterbalanced. Several other questionnaires including the WPT were given prior to the experimental manipulation. Sample size was 166. Only the honest condition data were analyzed here.

For the third dataset (Damron, 2004) participants were given the WPT, then the Big Five with instructions to respond honestly. Following that condition, participants were instructed to fake toward one of four different jobs. The honest response condition was first for all participants and only the data of that condition were analyzed. Sample size was 360.

For the final dataset (Biderman, Sebren, & Nguyen, 2007) participants were given the WPT and the Big Five questionnaire with instructions to respond honestly. After the administration of the Big 5, an email with a questionnaire concerning study habits was sent to each participant. Sample size was 185.

Questionnaire. The questionnaire used for each sample was the 50-item questionnaire from the IPIP web site (Goldberg, 1999). Items were administered in the order in which they are presented on the web site. For the first three samples, participants responded to each item indicating how accurate the item was as a description of the participant (from very inaccurate to very accurate) on a five-point scale. For the fourth sample, a seven-point scale was used.

It should be noted that the web site presenting the 50-item questionnaire includes a statement that the scales are not the IPIP scales measuring the NEO-PI-R domains (<http://ipip.ori.org>). The scales named there are Extraversion, Agreeableness, Conscientiousness, Emotional Stability, and Intellect or Imagination. A recent comparison of the 50-item IPIP questionnaire and the NEO-FFI (Kim & Ployhart, 2006) reported a .71 correlation between the IPIP Intellect/Imagination scale and the NEO-FFI Openness scale. The .71 value was the median of the five interscale correlations. In an overall assessment of the two questionnaires Kim and Ployhart (2006, p. 50) concluded that their study was able “to provide preliminary evidence for the convergent and discriminant validity of the IPIP scales and interchangeability of it with the NEO-FFI.”

Model. A confirmatory factor analytic model was applied to two datasets per sample. The first dataset consisted of 10 items per dimension. The second consisted of five two-item parcels per dimension. The parcels were created by computing the mean of the first and sixth, second and seventh, and so on of the 10 items for each dimension using the order of items as presented on the IPIP web page. Three models were applied to each dataset. Model 1 was an unrestricted CFA without a Method latent variable. Model 2 was identical to Model 1 with the exception that a Method latent variable on which all indicators loaded was added. The Method latent variable was estimated orthogonal to the Big Five latent variables. A chi-square difference test between Model 1 and Model 2 permitted a test of the need for such a Method latent variable. Model 3 was a method variance model identical to Model 2 with the exception that covariances between the Big Five latent variables were restricted to be zero. The comparison of most interest here was that between Model 2 – the unrestricted model with a Method latent variable – and Model 3, the method bias model restricting Big 5 latent variable covariances to 0. If method bias alone accounts for covariances of the indicators from different Big Five dimensions, then there should be only negligible difference in fit of Models 2 and 3. But if covariances among the Big Five latent variables account for across dimension covariances of the indicators then we would expect significant differences in the fit of Models 2 and 3. The models were applied using Mplus Version 4.2 (Muthen & Muthen, 2001-2006) and Amos Version 6.0 (Arbuckle, 1995-2005). The path diagram in Figure 1 is a screen shot from the Amos application.

Results

Table 1 presents goodness-of-fit values for the models applied to datasets consisting of individual items from each sample. Goodness-of-fit of the models depended on whether or not a Method latent variable was estimated and on covariance restrictions. For each sample, the best fitting model was Model 2, which included a Method latent variable and placed no restrictions on Big Five covariances. For all samples, goodness-of-fit was only marginally acceptable, a common finding when individual items are analyzed. The goodness-of-fit could certainly be improved. However given the commonly accepted structure of the Big 5, we attribute the lack of fit in the present data to unmodeled covariances among the items caused by the presence of idiosyncratic words or phrases. Although the lack of clearly acceptable fit is a serious consideration, it is our belief that lack of fit did not affect the results of the model comparisons made here. The same information for the model applied to two-item parcels is presented in Table 2. The RMSEA measure of goodness-of-fit of the models to the parcel data was about the same as for individual items for datasets 1 and 3 and slightly better for datasets 2 and 4. However, the CFI measure was considerably higher for each application to parceled data, a common finding. See Bandalos & Finney (2001) for a discussion of the implications of such improvements.

At the right side of Tables 1 and 2 are comparisons of model fit. Across all four samples and both type of indicator, the chi-square difference test comparing fit of Model 1, without a Method latent variable, with that of Model 2, which included a Method latent

variable, were significant ($p < .001$ for each comparison). This is consistent with the hypothesis that there were systematic method biases associated with the responses of individual raters in all four samples.

Also in Tables 1 and 2 are comparisons of method bias models restricting Big 5 covariances to 0 with method bias models in which the covariances are not restricted. These comparisons are of particular interest. If the Big 5 latent variables are orthogonal and only method bias accounts for covariances between across dimension parcels, we would expect only negligible differences in fit between Model 2 without restrictions and Model 3 with restrictions. Instead, in all cases, Model 3 fit significantly worse than Model 2, suggesting that at least some of the covariances between Big Five latent variables are nonzero.

Tables 3 and 4 present correlations between Big Five dimensions from application of the two models. The leftmost entries in the tables are whole-scale correlations. The middle entries are latent variable correlations from application of a CFA without a Method variance latent variable. The rightmost entries are latent variable correlations from application of the method variance CFA. Inspection of the table reveals that in almost all cases, the latent variable correlation from application of the method variance model was more negative than either the raw whole-scale correlations or the latent variable correlations estimated without a Method latent variable.

Discussion

The results of this study provide evidence of the existence of method biases in responses to questionnaire items such as those comprising the Big Five and are consistent with other analyses conducted at the level of whole scales (e.g., DeYoung, 2006; Lim & Ployhart, 2006) and of items or parcels (Burns & Christiansen, 2007; DeStefano, & Motl, 2006). The result was found for both the analyses of individual items and of two-item parcels. This should come as no surprise to those involved in the study of personality, although few studies have modeled method variance of individual raters at the item or parcel level as was done here.

A general pattern of results was that when the Method latent variable was added to create Model 2, correlations between the Big Five latent variables generally became less positive. Method effects are commonly assumed to positively bias correlations among constructs (Podsakoff, et. al., 2003) so the effect of removing them found here was expected. Although the results of the individual item analyses and the two-item parcel analyses were not identical, there were consistent individual differences in the latent variable correlations. The correlation between the forty individual item analysis latent variable correlations (10 per sample) with the 40 two-item analysis correlations was .491 ($p < .001$).

In spite of the downward shift in generally positive correlations after introduction of the Method latent variable, the results suggest that even when method effects are taken into account, covariances among the Big 5 dimensions are not essentially zero. What

those covariances are, however, is not clear from the results presented here. The downward shift in latent variable correlations after introduction of the Method latent variable reflects a compensatory relationship between the covariance pathways through loadings on the Method latent variable versus pathways through loadings on the Big 5 latent variables and their covariances. It is conceivable that the results represent a compensatory biasing of estimates of loadings on the Method latent variable and correlations between the Big Five latent variables, such that positive biases of the indicators on the method latent variable were compensated for by negatively biased covariances between the Big 5 latent variables.

Of course, it is certainly conceivable that the nonzero covariances found here are real and that the Big 5 latent variables are not orthogonal. However, the data here present a mixed picture concerning whether the nonorthogonality supports the two higher order factors hypothesized by DeYoung (2006). Consider Tables 3 and 4, presenting correlations among the Big 5 latent variables from the method variance model applied to the four samples. The correlations are grouped into two sets – those indicating DeYoung's (2006) Stability higher order factor (A, C, and S) and those indicating his Plasticity factor (E and O). Based on DeYoung's results, we would expect generally positive correlations among those within each higher order factor and essentially zero correlations between Big Five dimensions from different higher order factors. The most striking discrepancy from the expected pattern of results is the large number of negative correlations of the S dimension with the other two dimensions comprising the Stability higher order factor. Across Tables 3 and 4, all eight of the correlations of S with A and six of its correlations with C are negative. The correlations appear as if S had been incorrectly coded as Neuroticism. Almost as discrepant are the nearly zero correlations of A and C with only one out of eight correlations larger than .2. On the other hand, with one exception, E and O were positively correlated as would be expected, and the correlations between presumed indicators of the different order factors did not exhibit any clearly discernible trend.

Several possible explanations for the discrepancy between the results here and those of other studies supporting two higher order factors come to mind. First, these data might be taken as evidence against the higher order factors, specifically the Stability factor, proposed by DeYoung (2006). Second, it's possible that the method bias model is misspecified in some way that is biasing the correlations, particularly those involving S negatively. One possibility is the preponderance of negatively worded items in the IPIP 50-item S scale. It may be that method biases are multidimensional. For example, DeStefano, & Motl, (2006) found evidence for method effects specific to negative wording of items. It's possible that if method biases associated with negatively worded items were modeled separately from those associated with positively worded items, the negative correlations between S and the other variables would be reversed. A third possibility concerns the specific facets of the Big 5 dimensions tapped by the IPIP scales. It may be that the specific items represented by the items on this particular scale tap facets that obscure the correlations prerequisite for the higher order factors proposed by Digman (1997) and DeYoung (2006).

Suggestions for future research include further exploration of the nature of method biases using the estimation techniques proposed here. Part of this investigation should be of ways to identify and model idiosyncratic characteristics of items or to identify items that do not require special modeling techniques. The parcel/item modeling procedure employed here should be integrated with the multiple raters approach used by DeYoung (2006) and others. It's likely that such integrated research will result in more stable and useful estimates of the correlations between the Big 5 dimensions. Moreover, the item modeling procedure employed here should be employed with alternative measures of the Big Five, such as those employed by DeYoung (2006) and the NEO (Costa & McCrae, 1989). As this study makes abundantly clear, although the concept of method variance has been considered for many years, the effect of method variance on measurement of basic psychological constructs is still not completely understood.

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Table 1. Goodness-of-fit measures and means of Big 5 latent variable correlations for models applied to 10 items per dimension. Model 1: CFA with unrestricted covariances among Big 5 latent variables. Model 2: CFA including Method latent variable with unrestricted Big 5 covariances. Model 3: CFA including Method latent variable restricting Big 5 covariances to 0.

Sample 1: Biderman & Nguyen (2004). N=203.^a

<u>Model</u>	<u>X²</u>	<u>df</u>	<u>CFI</u>	<u>RMSEA</u>	<u>Mean r</u>	<u>X² Diff</u>	<u>p<</u>	<u>Models</u>
1	2282.954	1174	0.722	0.068	0.300			
2	2063.254	1124	0.764	0.064	0.090	219.700	0.001	1 vs. 2
3	2108.416	1134	0.756	0.065	0.0	45.162	0.001	3 vs. 2

Sample 2: Wrensen & Biderman (2005). N=166.^b

<u>Model</u>	<u>X²</u>	<u>df</u>	<u>CFI</u>	<u>RMSEA</u>	<u>Mean r</u>	<u>X² Diff</u>	<u>p<</u>	<u>Models</u>
1	2352.762	1174	0.628	0.078	0.185			
2	2267.598	1164	0.652	0.076	-0.121	85.164	0.001	1 vs. 2
3	2286.284	1174	0.649	0.076	0.0	18.686	0.050	3 vs. 2

Sample 3: Damron (2005). N=360.

<u>Model</u>	<u>X²</u>	<u>df</u>	<u>CFI</u>	<u>RMSEA</u>	<u>Mean r</u>	<u>X² Diff</u>	<u>p<</u>	<u>Models</u>
1	2839.792	1165	0.761	0.063	0.289			
2	2449.196	1115	0.810	0.058	0.083	390.596	0.001	1 vs. 2
3	2542.682	1125	0.798	0.059	0.0	93.486	0.001	3 vs. 2

Sample 4: Biderman, Sebren, & Nguyen (2007). N=185.

<u>Model</u>	<u>X²</u>	<u>df</u>	<u>CFI</u>	<u>RMSEA</u>	<u>Mean r</u>	<u>X² Diff</u>	<u>p<</u>	<u>Models</u>
1	2551.060	1165	0.622	0.080	0.309			
2	2253.012	1115	0.690	0.074	0.043	298.048	0.001	1 vs. 2
3	2280.404	1125	0.685	0.075	0.0	27.392	0.01	3 vs. 2

^a Loadings of O items fixed at 1 for all models.

^b Loadings of M items fixed at 1 for Models 2 and 3

Table 2. Goodness-of-fit measures and means of Big 5 latent variable correlations for models applied to five two-item parcels per dimension. Model 1: CFA with unrestricted covariances among Big 5 latent variables. Model 2: CFA including Method latent variable with unrestricted Big 5 covariances. Model 3: CFA including Method latent variable restricting Big 5 covariances to 0.

Sample 1: Biderman & Nguyen (2004). N=203.

<u>Model</u>	<u>X²</u>	<u>df</u>	<u>CFI</u>	<u>RMSEA</u>	<u>Mean r</u>	<u>X² Diff</u>	<u>p<</u>	<u>Models</u>
1	556.237	265	0.881	0.074	0.294			
2	443.901	240	0.916	0.065	-0.218	112.336	.001	1 vs. 2
3	474.241	250	0.908	0.066	0.0	30.34	.001	3 vs. 2

Sample 2: Wrensen & Biderman (2005). N=166.

<u>Model</u>	<u>X²</u>	<u>df</u>	<u>CFI</u>	<u>RMSEA</u>	<u>Mean r</u>	<u>X² Diff</u>	<u>p<</u>	<u>Models</u>
1	519.969	265	0.850	0.076	0.159			
2	402.410	240	0.905	0.064	-0.199	117.559	.001	1 vs. 2
3	426.118	250	0.897	0.065	0.0	23.708	.01	3 vs. 2

Sample 3: Damron (2005). N=360.

<u>Model</u>	<u>X²</u>	<u>df</u>	<u>CFI</u>	<u>RMSEA</u>	<u>Mean r</u>	<u>X² Diff</u>	<u>p<</u>	<u>Models</u>
1	733.903	265	0.892	0.070	0.288			
2	537.770	240	0.931	0.059	-0.118	196.133	.001	1 vs. 2
3	578.110	250	0.924	0.060	0.0	40.34	.001	3 vs. 2

Sample 4: Biderman, Sebren, & Nguyen (2007). N=185.

<u>Model</u>	<u>X²</u>	<u>df</u>	<u>CFI</u>	<u>RMSEA</u>	<u>Mean r</u>	<u>X² Diff</u>	<u>p<</u>	<u>Models</u>
1	620.679	265	0.814	0.099	0.258			
2	478.086	240	0.875	0.068	-0.023	142.593	.001	1 vs. 2
3	502.991	250	0.868	0.078	0.0	24.905	.01	3 vs. 2

Table 3. Correlations from application of the method variance model to individual item data. Leftmost entries are scale correlations. Middle entries are latent variable correlations from the CFA without a Method latent variable. Rightmost entries are latent variables from the method variance model. Values are from samples in the following order:

- Sample 1: Biderman & Nguyen (2004).
 Sample 2: Wrensen & Biderman (2005).
 Sample 3: Damron (2004).
 Sample 4: Biderman, Sebren, & Nguyen (2007).

Correlations of variables assumed to load on the Stability higher order factor are boldfaced in the upper part of the table. Those assumed to load on the Plasticity higher order factor are in boldface at the bottom of the table.

	C			S			E			I		
	<u>Scale</u>	<u>CFA</u>	<u>Meth</u>	<u>Scale</u>	<u>CFA</u>	<u>Meth</u>	<u>Scale</u>	<u>CFA</u>	<u>Meth</u>	<u>Scale</u>	<u>CFA</u>	<u>Meth</u>
A	.320	.363	.101	.114	.095	-.489	.230	.272	.344	.268	.318	.101
	.227	.218	-.087	-.042	-.032	-.314	.116	.207	-.191	.178	.317	-.193
	.257	.273	.231	.214	.219	-.180	.218	.243	.180	.290	.347	.301
	.297	.321	-.064	.088	.117	-.352	.286	.391	.158	.343	.443	.269
C				.272	.301	-.078	.134	.162	.035	.438	.532	.391
				.215	.288	.161	.025	.036	-.224	.186	.247	-.131
				.212	.261	-.176	.066	.080	-.023	.249	.297	.203
				.250	.298	-.150	.170	.237	-.038	.252	.360	.188
S							.247	.274	.156	.220	.278	-.001
							.040	.012	-.207	.235	.231	-.028
							.335	.380	-.106	.281	.402	.122
							.164	.218	-.045	.175	.204	.078
E										.303	.408	.344
										.239	.329	.008
										.303	.392	.279
										.311	.505	.386

Table 4. Correlations from application of the method variance model to two-item parcel data. Leftmost entries are scale correlations. Middle entries are latent variable correlations from the CFA without a Method latent variable. Rightmost entries are latent variables from the method variance model. Values are from samples in the following order:

- Sample 1: Biderman & Nguyen (2004).
 Sample 2: Wrensen & Biderman (2005).
 Sample 3: Damron (2004).
 Sample 4: Biderman, Sebren, & Nguyen (2007).

Correlations of variables assumed to load on the Stability higher order factor are boldfaced in the upper part of the table. Those assumed to load on the Plasticity higher order factor are in boldface at the bottom of the table.

	C			S			E			I		
	<u>Scale</u>	<u>CFA</u>	<u>Meth</u>	<u>Scale</u>	<u>CFA</u>	<u>Meth</u>	<u>Scale</u>	<u>CFA</u>	<u>Meth</u>	<u>Scale</u>	<u>CFA</u>	<u>Meth</u>
A	.320	.357	.097	.114	.098	-.158	.230	.264	.164	.268	.333	-.131
	.227	.237	.107	.042	-.082	-.257	.116	.173	.052	.178	.262	-.084
	.257	.292	.002	.214	.237	-.636	.218	.302	.000	.290	.367	.122
	.297	.371	.082	.088	.085	-.198	.286	.321	.153	.343	.448	.207
C				.272	.306	-.014	.134	.156	-.036	.438	.503	-.290
				.215	.222	.107	.025	.020	-.094	.186	.190	-.090
				.212	.245	-.368	.066	.070	-.227	.249	.286	.037
				.250	.259	-.090	.170	.191	-.108	.252	.242	-.274
S							.247	.275	.177	.220	.272	-.333
							.040	.007	-.112	.235	.250	-.004
							.335	.369	-.113	.281	.341	-.176
							.164	.150	-.039	.175	.162	-.141
E										.303	.379	.306
										.239	.315	.176
										.303	.368	.179
										.311	.355	.175

Figure 1. Method Variance model applied to Big 5 data with five indicators per dimension.

