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Controlling for Method Bias: A Critique and Reconceptualization of the Marker Variable Technique

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ABSTRACT

The marker variable technique is an easy-to-use technique for estimating the magnitude of method bias within a study. However, its validity has not yet been established. This paper addresses three issues assessing the validity of the technique and finds that it is subject to significant validity threats. A redefinition of the marker variable correlation is proposed, which partly addresses the theoretical critiques of the technique. The findings confirm Podsakoff et al.'s (2003) critique that the marker variable technique does not capture key sources of method bias. Implications of the findings for estimating and controlling for method bias within individual studies are addressed.

Keywords

Common method bias, marker variable technique, mono-method studies.

INTRODUCTION

The effect of method bias is a major potential validity threat to behavioral research, including research in the information systems (IS) discipline (Burton-Jones 2009; Doty and Glick 1998; Podsakoff et al. 2003; Sharma, Yetton and Crawford 2009). While the potential threat is widely acknowledged, it is rarely corrected for in research findings (Burton-Jones 2009; Sharma et al. 2009; Woszczynski and Whitman 2004). One reason for this has been the absence of a valid and easy-to-use technique to estimate the magnitude of method bias in findings of mono-method research designs. The marker variable (MV) technique proposed by Lindell and colleagues (2000; 2001) is an easy-to-use technique that has the potential to address that limitation.

In the absence of the MV or a similar technique, many empirical findings would remain beyond the reach of techniques to control for the effect of method bias. We concur with Lindell and Whitney (2001, p. 119) that the MV technique is "superior to overlooking method bias effects altogether, which seems to be a very common way of addressing the problem." This position is consistent with Malhotra et al.'s (2006) assertion that the MV technique "is one of the most practical tools available for assessing and controlling for method bias." (p. 1881). However, we also agree with Podsakoff et al. (2003) that the validity of the MV technique has not been established. Echoing this concern, Malhotra et al. (2006) repeatedly stress the need to evaluate its validity.

To do this, the paper identifies and examines three critical issues in addressing the validity of the MV technique. First, do the different definitions of the MV correlation proposed by Lindell and Whitney (2001) influence the conclusions that can be drawn from published research findings? Second, what are the implications of relaxing the constant method effect assumption? Third, does the MV correlation capture all sources of method bias?

To investigate these questions, the paper begins with a brief review of the techniques for estimating method bias. This is followed by a critique of the MV technique, in which we present an empirical illustration addressing each question. The analysis shows that the most frequently used MV technique underestimates the effect of method bias. A re-conceptualization of the MV technique is presented that estimates the method main effect on the focal correlation. This identifies the critical need for a mechanism to estimate the effects on the focal correlation of person, and person and method interaction sources of

method bias. The implications for future research are discussed, including that method bias detection approaches, such as the Harman single factor test and Confirmatory Factor Analysis (CFA) techniques, are subject to a major Type II error.

TECHNIQUES TO ADDRESS METHOD BIAS

The method employed to measure a construct has a systematic effect on observed scores. Therefore, when two constructs are measured employing similar methods, the two observed scores share systematic covariance on account of correlated method variance (Cote and Buckley 1987; Doty and Glick 1998). The correlation between observed scores is thus a biased estimate of the correlation between the underlying constructs. The challenge is to estimate and control for this method bias.

Techniques to empirically estimate the magnitude of method bias and control for it can be classified into four broad categories: the multitrait-multimethod (MTMM) technique (Campbell and Fiske 1959), the marker variable technique (Lindell and Whitney 2001), CFA-based techniques (Williams, Edwards and Vandenberg 2003), and the method-method pair technique (Sharma et al. 2009). Each technique is applicable to specific research designs and is subject to its own limitations.

The MTMM technique is generally accepted as the most rigorous technique to address potential validity threats arising from method bias (Podsakoff et al. 2003). The technique requires that each study employ multiple methods to measure each construct (Campbell and Fiske 1959; Podsakoff et al. 2003; Williams et al. 2003). However, social science research, including IS research, typically does not employ multiple methods within individual studies and, therefore, the applicability of this technique is limited in practice (Doty and Glick 1998).

The other three techniques are applicable to research designs where individual studies do not employ multiple methods. The MV technique developed by Lindell and colleagues (2000; 2001) obtains an estimate of method bias from the correlations reported in a study and employs that estimate to partial out the effect of method bias in all observed correlations. The CFA-based technique is conceptually similar to the MV technique. The critical difference is that it employs a structural equation model to estimate the magnitude of method bias. Richardson et al. (2009) investigate the validity of both techniques and conclude that both can lead to erroneous findings.

Finally, the method-method pair (MMP) technique developed by Sharma et al. (2009) is similar to the MTMM technique, relying on multiple methods to estimate the effect of method bias. However, rather than employing variability in methods within a study to estimate the effect of method bias, the MMP technique employs the variability in methods across the cumulative set of mono-method studies within a research domain. Its key limitation is that it can be used only in research domains that have a sufficiently large number of studies employing different methods to support the use of meta-analytical techniques.

The choice for researchers employing mono-method measurement is between techniques that can be employed within individual studies but whose validities are questionable, and the MMP technique, which can be applied only to well-researched theoretical domains. Despite its limitations, the MV technique potentially fills an important need because it is an easy-to-use technique to control for method bias within individual studies. To our knowledge, no other technique attempts to fulfill this need. Here, we assess the validity of the MV technique and offer suggestions for addressing its current limitations.

A CRITIQUE OF THE MV TECHNIQUE

Lindell and Whitney (2001) propose that the within-study method bias can be estimated by inspecting the correlation matrix reported in the study. They argue that, if a study includes a 'marker variable', "a scale that is theoretically unrelated to at least one other scale in the questionnaire", then there is "an a priori justification for expecting a zero correlation" (Lindell and Whitney 2001, p. 115). Hence, the lowest observed correlation of the marker variable is a reasonable proxy for the systematic covariance between observed scores due to method.

Lindell and Whitney (2001) make the additional critical assumption that method bias has the same effect on all relationships in the study and conclude that the "smallest correlation among the manifest variables provides a reasonable proxy for method bias". Finally, they propose that partialing out the lowest observed correlation from a correlation matrix provides estimates of construct score correlations that are not subject to method bias.

The form of correction proposed by the MV technique is intuitively appealing. It is consistent with the early theoretical treatment of method bias, in which it is defined as a function of the systematic covariance in construct scores due to the covariance in methods employed to measure those constructs (See, for example, Doty and Glick 1998). However, the theoretical validity of the MV technique has been challenged on a number of grounds (Podsakoff et al. 2003; Straub and Burton-Jones 2007). Here, we address three critical issues.

The first issue concerns the selection of the marker variable. Lindell and Whitney (2001) consider potential sources of bias due to their initial selection protocol. In choosing the lowest correlation in the correlation matrix, the protocol may capitalize on chance and underestimate the method bias. Lindell and Whitney address this issue by extending the MV definition to include the second lowest correlation among all research variables. They go on to note that, frequently, there are many more correlations between predictors than between predictor variables and one of the focal variables. They speculate that including all correlation, may also capitalize on chance. To address this concern, they further extend the definition of the MV correlation to include the lowest or second lowest correlation in the correlation matrix that include one of the variables used to estimate the focal correlation.

The resulting six definitions of the MV correlation raise a fundamental question for researchers: Which definition of the MV correlation should be adopted? This paper shows that this is a critical question by evaluating the consistency in the conclusions that can be drawn when employing each of the definitions.

The second issue concerns the constant method effect assumption that underpins the MV technique (Podsakoff et al. 2003). Under that assumption, all correlations in a study are subject to the same method bias, irrespective of the methods employed to measure the construct scores. Contrary to this assumption, Sharma et al. (2009) find that the specific method-method pair employed to measure construct scores has a strong influence on the magnitude of method bias. This paper relaxes the constant method effect assumption and proposes a new definition of the MV correlation: the lowest correlation in the correlation matrix that is estimated with the same method-method pair used to estimate the focal correlation. Under this definition, the focal correlation and the MV correlation would be subject to the same method effects.

The third issue concerns the sources of method bias captured by the MV correlation. While Lindell and Whitney (2001) claim that the MV correlation captures the effects of all sources of method bias, Podsakoff et al. (2003) argue that the MV correlation does not capture important sources of method bias, including, for example, the halo and implicit theories effects. This paper draws on Sharma et al.'s (2009) meta-analysis-based method-method pair (MMP) technique to identify the sources of method bias captured by the MV correlation.

ISSUE 1: EFFECT OF ALTERNATIVE DEFINITIONS OF THE MV CORRELATION ON CONCLUSIONS

While arguing for employing the lowest observed correlation as an unbiased estimate of method bias, Lindell and Whitney recognize that the "ad hoc selection of the smallest correlation provides an opportunity for capitalizing on chance" (2001, p. 115). Under that scenario, the lowest observed correlation underestimates the effect of method bias. To control for that potential bias, Lindell and Whitney suggest that the second lowest observed correlation could be employed as the MV correlation. Accepting this limitation, Malhotra et al. (2006) employ both the lowest and the second lowest observed correlations criteria in their post hoc analysis of correlation matrices.

Lindell and Whitney (2001) also consider using the lowest and second lowest correlation involving one of the focal variables as the estimator of method bias. They justify this choice on the grounds that "there almost always are fewer correlations between the predictors and the criterion than among the predictors, affording less opportunity for capitalization on chance in the selection of the smallest correlation" (p. 118).

The critical question is whether the six different definitions of the MV correlation influence significantly the conclusions that, after correcting for method bias, would be drawn from a research study.

Illustration: What are the comparative effects of adopting each of the six protocols for selecting the MV correlation?

The correlation matrices for each of the primary studies in the Sharma et al. (2009) meta-analysis of the relationship between perceived usefulness (PU) and use (U) were inspected and the MV correlations associated with each definition of the MV correlation were extracted.

Table 1 shows that the magnitudes of the average MV correlations are significantly different between the most frequently used criterion, the lowest correlation in the correlation matrix (Criterion 1 in Table 1), and the five alternative criteria proposed by Lindell and Whitney (2001).

		Criteria	Criteria for selection of marker variable correlation (r_{M})	ker variable correlat	ion (r _M)	
	Criterion 1: Lowest correlation in the full correlation matrix (rM1Full) N=67	Criterion 2: Second lowest correlation in the full correlation matrix (rM2Full) N=67	Criterion 3: Lowest correlation with PU in the full correlation matrix (r ^{M11V}) N=67	Criterion 4: Lowest correlation with U in the full correlation matrix (TM1DV) N=70	Criterion 5: Second lowest correlation with PU in the full correlation matrix (r ^{M21V)} N=67	Criterion 6: Second lowest correlation with U in the full correlation matrix (T'M2DV) N=70
r = Mean value of reported correlation between U and PU	0.37 (Range=0.06-0.68)	0.37 (Range=0.06-0.68)	0.37 (Range=0.06-0.68)	0.38 (Range=0.06-0.68)	0.37 (Range=0.06-0.68)	0.38 (Range=0.06-0.68)
$\overline{r_M}$ = Mean value of marker variable correlation across studies	0.11 (Range=0.00-0.48)	0.16 (Range=0.00-0.68)	0.18 (Range=0.00-0.68)	0.16 (Range=0.00-0.48)	0.28 (Range=0.01-0.69)	0.24 (Range=0.00-0.68)
r_A = Mean value of MV-adjusted correlation between U and PU across studies	0.29 (Range=0.00-0.66)	0.24 (Range=-0.15-0.66)	0.22 (Range=0.00-0.65)	0.25 (Range=0.00-0.66)	0.09 (Range=-0.63-0.64)	0.16 (Range=-0.24-0.66)
Result of paired-samples t-test for difference between mean value of MV correlation using Criterion 1 against other criteria	-N/A-	Difference=0.05 (t=6.58, p<0.000)	Difference=0.07 (t=7.26, p<0.000)	Difference=0.05 (t=5.37, p<0.000)	Difference=0.17 (t=13.86, p<0.000)	Difference=0.14 (t=11.17, p<0.000)
Result of paired-samples t-test for difference between mean MV-adjusted correlation for Criterion 1 against other criteria	-N/A-	Difference=0.06 (t=5.31, p<0.000)	Difference=0.07 (t=6.00, p<0.000)	Difference=0.05 (t=5.02, p<0.000)	Difference=0.20 (t=9.67, p<0.000)	Difference=0.14 (t=9.72, p<0.000)
% of significant correlations turning non- significant	24.59%	39.34%	45.90%	31.15%	60.66%	55.74%

Importantly, Table 1 also shows that the conclusions that would be drawn after the application of the MV technique vary significantly, contingent on the definition of the MV correlation selected (See Sharma et al.2010 for a discussion of these findings). Specifically, adopting the weakest form of the MV technique (See Criterion 1 in Table 1), the average observed correlation is r = 0.37, the average corrected correlation is r = 0.29, and 24.6% of the significant correlations would become non-significant after correcting for method bias. In contrast, adopting the strongest form (See Criterion 5 in Table 1), the average observed correlation is r = 0.37, the average corrected correlation is r = 0.09, and 60.7% of reported significant correlations become non-significant after correcting for method bias.

The above illustration shows that the conclusions that can be drawn from a study are substantially different between the weakest and strongest form of the MV technique. More importantly, from a theoretical perspective, it is unclear whether any of the criteria for selecting the MV correlation generate an unbiased estimate of the magnitude of method bias. This leaves researchers with no definitive guidance on the choice of the definition of the MV correlation and, therefore, is a major limitation to the practical applicability of the MV technique.

ISSUE 2: IMPLICATIONS OF THE CONSTANT METHOD EFFECT ASSUMPTION

Whatever definition of the MV correlation is adopted, the MV technique assumes that the method factor has a constant effect on all correlations in the correlation matrix. Lindell and Whitney (2001) acknowledge that this assumption is unrealistic and may be technically incorrect. However, they defend the assumption on the ground that it provides a reasonable approximation of the data. More importantly, they argue that violations of the assumption are unlikely to affect the conclusions drawn.

Contrary to Lindell and Whitney's (2001) claim that the constant method effect assumption is unlikely to affect the conclusions drawn, Sharma et al. (2009) find that the method-method pair used to measure the focal correlation has a powerful and significant effect on reported correlations. Specifically, they find that the method-method pair used to measure the focal correlation explains 56.1% of the variance in reported correlations between PU and U.

Methods vary in the extent to which they are susceptible to method variance (Cote and Buckley 1987; Sharma et al. 2009). Accordingly, a critical limitation of the MV technique arising from the constant method effect assumption is that the MV correlation is defined independently of the methods employed to measure the constructs in the focal correlation. It is surprising that the definition of a method-based effect makes no reference to method.

Addressing this limitation, and relaxing the strong constant method effect assumption, we propose a new definition of the MV correlation. Drawing on Sharma et al.'s (2009) framework, the MV correlation is re-defined as the lowest correlation between constructs that are expected to be unrelated and that employ the same method-method pair used to measure the focal correlation. This definition addresses Podsakoff et al.'s (2003) criticism that the marker variable correlation proposed by Lindell and Whitney (2001) cannot be expected to be subject to the same method bias as the focal correlation.

Illustration: What are the implications of relaxing the constant method effect assumption?

Here, we extend the analysis reported in Table 1. Specifically, we inspected all the correlation matrices to identify the MV/MMP correlation, the lowest correlation containing the same method-method pair used to estimate the focal correlation. Figure 1 graphs the relationship between the MV/MMP correlation and the MV/L correlation (the lowest correlation in the correlation matrix – Criterion 1 in Table 1) for each of the primary studies in the Sharma et al. (2009) meta-analysis.

The graph is partitioned into four domains, identifying the conditions under which the MV/L correlation (MV/L r) underestimates the method bias estimated by the MV/MMP correlation (MV/MMP r). The levels of the MV/L and MV/MMP correlations used to define domain A, r=0.15, are taken from Malhotra et al. (2006), who claim that, above this level, method bias could affect the conclusions drawn from published research studies.

In domain A, the MV/L and MV/MMP correlations are both less than 0.15 and, therefore, when selecting one or the other to control for method bias, differences in the conclusions that would be drawn would be small. In domain B, the difference between selecting the MV/L and MV/MMP correlations to control for method bias can be large. For example, in one case (Zmud 1984), MV/L correlation (r=0.05) is substantially lower than the corresponding MV/MMP correlation (r=0.40). In this study of software practice, the MV/L correlation occurs between a system-captured measure of project complexity and a Likert-based measure of management attitude. In contrast, the MV/MMP correlation is between software practice use (affect measure) and a Likert-based measure of the software development group's receptivity towards change. Podsakoff et al. (2003) argue that there is no reason to expect that the method bias in the two observed correlations should be the same. Their speculation is supported by the data.

In domain C, both the MV/L and MV/MMP correlations are high and would cause significant negative adjustments to the observed correlations. In addition, an inspection of Figure 2 shows that, for this sample, Malhotra et al.'s (2006) speculation that the MV correlation would rarely exceed 0.15 is not supported. Finally, domain D is an empty set as, by definition, the MV/MMP correlation is equal to or greater than the corresponding MV/L correlation.

Replicating the analysis presented in Table 1, the effects of controlling for the MV/L and MV/MMP correlations are different. As reported in Table 1, controlling for MV/L, the uncorrected average correlation between PU and U is r=0.37, the corrected value is r=0.29 and the proportion of significant published correlations that become non-significant is 24.6%. Controlling for the MV/MMP correlation, the average uncorrected PU-U is r=0.38, the corrected value is r=0.25 and 31.2% of significant published correlations become non-significant.

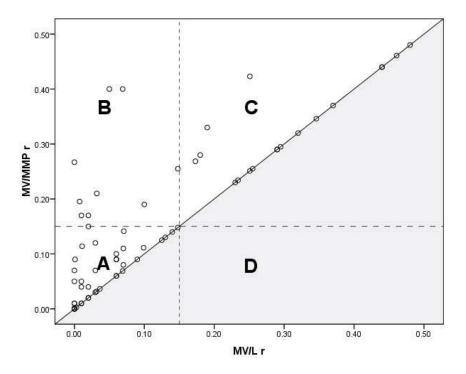


Figure 1. Relationship between the MV/L correlation and the MV/MMP correlation

ISSUE 3: DOES THE MV CORRELATION CAPTURE THE EFFECTS OF ALL SOURCES OF METHOD BIAS?

Podsakoff et al. (2003) identify 21 sources of method bias, which they classify into four categories: rater effects, item characteristics effects, item context effects and measurement context effects. In addition, there are interactions among those sources. For example, Le et al. (2009) identify interaction between persons and occasions, persons and scale items, and persons and scales, and three-way interactions between persons and other measurement facets as potential sources of method bias. Similarly, Hoyt (2000) and Podsakoff et al. (2003) discuss the method bias arising from the interaction between the subject and the trait being rated.

Podsakoff et al.'s (2003) review of the techniques to statistically correct for the effect of method bias concludes that neither the MV nor any CFA-based techniques accounts for the effect of interaction between sources of bias. While the interaction effects have not received as much attention as the main effects, Le et al. (2009) and Hoyt and colleagues (2000; 1999) report that these effects exert a significant bias.

Theoretical critiques of the MV technique also argue that while it may capture the main effects of some sources of method bias, it does not capture all the main effects and certainly does not capture important interaction effects such as the halo effect (Burton-Jones 2009; Podsakoff et al. 2003; Straub and Burton-Jones 2007). If, as argued above, the MV technique underestimates the method main effect and does not capture the interaction effects, researchers cannot be confident that the MV-corrected correlations are not still biased by method effects.

Illustration: How much of the method bias is corrected for by the MV/MMP correlation?

Sharma et al. (2009) estimate the method bias in the PU–U correlations reported in the TAM literature. They regress the published correlation in each study against the susceptibility to method bias of that study. The slope of the regression is an estimate of the method bias in the correlations being analyzed. The intercept is an estimate of the correlation controlling for method bias. The relationship is labeled in Figure 2 as the Observed Relationship. It explains 56.1% of the variance in the published correlations.

Figure 2 also graphs the relationship between MV/MMP r and the method-method pair used to estimate the focal correlation. The area between the MV/MMP r graph and the True Relationship horizontal graph (Area 1) is the method bias explained by the MV/MMP correlation. Similarly, the area between the MV/MMP r graph and the Observed Relationship graph is the method bias not explained by the MV/MMP correlation (Area 2). It includes method bias due to person and person x method interactions. A variable effects ANOVA shows that, controlling for the MV/MMP correlation, the method-method pair used to estimate the focal correlation still explains 29.1% (F=5.65, $p \le 0.05$) of the variance in the published correlations.

Controlling for the MV/MMP correlation does not fully partial out all the method effects. The MV technique systematically underestimates the magnitude of method bias. Inspecting Figure 2, the variance explained by the person and person x method interactions is greater than the variance explained by the MV/MMP correlation, which primarily captures the instrument-based main effects component of method bias, supporting the critiques by Podsakoff et al. (2003) and Straub and Burton-Jones' (2007) that the MV technique significantly underestimates the magnitude of method bias.

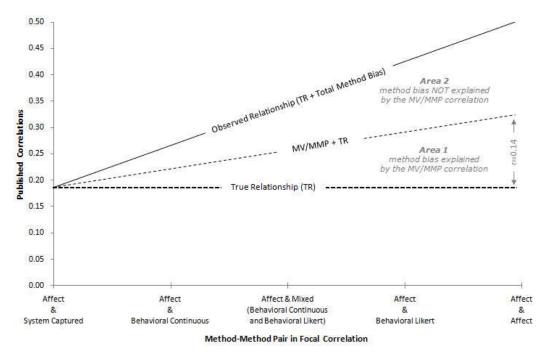


Figure 2. The Effect of method bias on the PU-U correlation

DISCUSSION

This study analyzes three critical issues concerning the validity of the MV technique. It finds that the MV technique is subject to major validity threats on each of the three issues. First, the multiple definitions of the MV correlation proposed by Lindell and Whitney (2001) lead to substantially different conclusions that could be drawn from a study. Second, the constant method effect assumption underpinning the MV technique results in the definition of the MV correlation proposed by Lindell and Whitney, the lowest observed correlation, systematically underestimating the magnitude of method bias. Third, MV-corrected correlations are subject to method bias. The MV technique cannot be relied upon to partial out the total effect of method bias.

To the best of our knowledge, this is the first study to empirically evaluate the validity of the MV technique. Earlier, Richardson et al. (2009) conducted a simulation-based evaluation of the MV technique and found it to be unreliable. The

results in Domain B in Figure 1 show that MV/L correlation is an unreliable estimate of the main effect of method bias as estimated by MV/MMP correlation.

Redefining the MV correlation, the MV/MMP correlation is an unbiased estimator of the method bias main effect. This effect is independent of the research domain. The next step is to identify a technique to estimate the interaction components of method bias.

The other important insight from the partitioning of the method bias effect into a method main effect, and the person and person x method effects, is that it begins to explain why the Harman single factor and CFA-based techniques fail to detect the presence of method bias in studies. From Figure 2, the highest estimate for the method main effect bias is approximately r=0.14 for a focal correlation estimated from two variables each of which is measured on perceptual-based Likert (Affect) scales.

This level of method bias would not be significant in the typical mono-method research study under either the Harman single factor or a CFA-based test. However, combined with an equal or stronger person-based effect, this would result in more than 50% of significant PU-U correlations to be reclassified as non-significant.

Inspecting six journals (MISQ, ISR, ISJ, JMIS, JAIS, EJIS) from 2007-2010, one hundred and five articles were found to utilize various techniques to address potential method-based validity threats. Of these, 76 (72.4%) test for the presence of a method effect using the Harman or CFA-based techniques and all (100.0%) conclude that their findings are not subject to a method-based validity threat.

While there is evidence of method-based validity threats to published correlations (See Sharma et al. 2009), tests for the effect of a method main effect would not typically be significant in an individual study. Therefore, the tests as reported in these 76 studies are not evidence for the absence of a major CMV-based validity threat to their findings. Instead, the tests are subject to a major Type II error.

Limitations of study

One limitation of this study is that the empirical illustrations are restricted to the TAM research domain. Therefore, the findings are subject to a potential generalizability validity threat. Against this, the definition of the MV/MMP correlation as an estimate of a method main effect is independent of the specific research domain. However, the person and person x method interaction effects would be domain specific.

Implications for research

While the MV technique offers a simple approach for addressing the effects of method bias in mono-method research, the preceding discussion illustrates why caution must be taken when employing the technique. Rather than rejecting the MV technique entirely, this research provides a systematic analysis of the errors and biases inherent in the technique and identifies a number of steps which can help enhance its reliability. First, we recommend that future studies planning to employ the MV technique ex- ante rather than ex-post should include at least two marker variables that are not expected to be correlated. These should be measured employing the identical method-method pair used to measure the focal correlation. Second, we propose that standard corrections for method main effects should replace the ad hoc corrections of the marker variable. The magnitudes of the main effects of method bias for commonly employed method-method pairs can be easily estimated. Sharma et al. (2009) present estimates of four such method-method pairs and present a technique for extending the estimation to other methods. Such estimates would be more reliable than estimates based on the correlations of the marker variable obtained within individual studies. By demonstrating ways in which one can strengthen the rigor and application of the MV technique, this paper contributes significantly to mono-method research that must address the effects of method bias.

Finally, the findings highlight that the MV technique, even with the enhancements identified here, cannot address all sources of method bias expected to exist in mono-method studies. By utilizing the MV technique to highlight both person and person x method sources of method bias, this research illustrates that commonly accepted tests for the effects of CMV (e.g., CFA-based techniques) systematically underestimate the magnitude of method bias. Future research can build on this knowledge to develop robust techniques to detect and control for the effects of method bias.

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