# A Tale of Three Perspectives: Examining Post Hoc Statistical Techniques for Detection and Correction of Common Method Variance

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Many researchers who use same-source data face concerns about common method variance (CMV). Although post hoc statistical detection and correction techniques for CMV have been proposed, there is a lack of empirical evidence regarding their efficacy. Because of disagreement among scholars regarding the likelihood and nature of CMV in self-report data, the current study evaluates three post hoc strategies and the strategy of doing nothing within three sets of assumptions about CMV: that CMV does not exist, that CMV exists and has equal effects across constructs, and that CMV exists and has unequal effects across constructs. The implications of using each strategy within each of the three assumptions are examined empirically using 691,200 simulated data sets varying factors such as the amount of true variance and the amount and nature of CMV modeled. Based on analyses of these data, potential benefits and likely risks of using the different techniques are detailed.

The use of self-reported data and the potential for measurement error because of common method variance (CMV) has been viewed as everything from a hobgoblin to a ghost. Although some suggest CMV ‘‘is often a problem and researchers need to do whatever they can to control for it’’ (Podsakoff, MacKenzie, Lee, & Podsakoff, 2003, p. 900), others call it an ‘‘urban legend’’ that is ‘‘both an exaggeration and oversimplification of the true state of affairs’’ (Spector, 2006, p. 230). Because of these differing underlying perspectives about CMV, researchers have little information about appropriately addressing its possibility in data. CMV is inherently unobservable, so evaluation of its effects (if any) can only be inferred methodologically, with results inevitably shaped by the 762 assumptions one makes about CMV's existence and pervasiveness. Yet, despite disagreement about the nature and likelihood of CMV, researchers are increasingly using post hoc statistical detection and correction techniques such as the correlational marker (Lindell & Whitney, 2001), confirmatory factor analysis (CFA) marker (Williams, Hartman, & Cavazotte, 2003), and unmeasured latent method construct (ULMC; Williams, Cote, & Buckley, 1989) approaches to allay concerns about its potential effects.

Therefore, the following questions arise: if CMV does not exist and, thus, is not biasing results, does applying various post hoc statistical detection and correction techniques accurately identify the absence of CMV such that researchers can confidently conclude correction is not necessary? Alternatively, if CMV is present in data, does applying a post hoc technique accurately identify the presence of CMV and produce ‘‘corrected’’ correlations that resemble true relationships? Unfortunately, even though multiple statistical detection and correction techniques have been proposed and used in published work, there is no systematic empirical evidence regarding their accuracy. Likewise, because of the multiple perspectives about CMV (e.g., that CMV exists and takes a certain form), the merits of competing post hoc statistical mechanisms for dealing with CMV tend to be proposed and used exclusively within the perspective that shaped the logic of the mechanism in the first place. That is, the techniques are based on and explicitly or implicitly proposed and used within the assumptions of a given CMV perspective—which may not be compatible with other CMV perspectives. Thus, the relative merits of these techniques can be determined only in terms of criteria that lie outside normal science (Kuhn, 1970). The purpose of this article is to provide an evaluation of statistical ‘‘solutions’’ to the CMV problem, but from a standpoint outside the debate regarding CMV’s existence and nature.

We define CMV as it is traditionally conceptualized: systematic error variance shared among variables measured with and introduced as a function of the same method and/or source. CMV can either inflate or attenuate relationships (Williams & Brown, 1994), but it is most commonly expected to cause inflation when ‘‘the method variance components of the individual measures are more positively related than an underlying true relationship’’ (Doty & Glick, 1998, p. 376). If CMV produces significant divergence between true and observed relationships, method bias is said to be in effect (Ostroff, Kinicki, & Clark, 2002). This conceptualization of CMV and bias has served as the basis for questioning research conclusions in a variety of organizational literatures, including leadership, participative decision making, organizational recruitment, team attitudes and behaviors, organizational justice, and work-family conflict.

Because of the multiple perspectives about CMV, researchers face a challenge in that peers and reviewers may hold differing beliefs about CMV, which affect the evaluation of research. For instance, given arguments and evidence supporting the notion that CMV does not exist or is overstated (Crampton & Wagner, 1994; Spector & Brannick, 1995), an author may believe there is justification for examining at least one (if not more) same-source relationship. Alternatively, given that evidence also exists to support the view that CMV may be extensive in such data (Cote & Buckley, 1987), a reviewer assigned to the article may ask the author to provide empirical evidence that CMV is not responsible for results. Given the disagreement about the nature and likelihood of CMV and lack of evidence regarding the effects of detection and correction techniques, it is not clear whether applying a post hoc statistical technique as a means of further justifying the findings and allaying the reviewer's concerns is appropriate.

Uncertainty among authors and reviewers about when and how CMV should be addressed also can be illustrated by examining its treatment in all empirical micromanagement and I/O psychology articles published in *Academy of Management Journal and Journal of Applied Psychology* in 2007. Of these 163 articles, almost half (67 articles, 41.1%) mention CMV. When a cross-sectional study design was used, researchers mentioned CMV as a possibility 44.6% of the time. When a single source was used for the data, CMV was mentioned in the article 33.8% of the time. Even when a longitudinal or multisource design was used, authors still mentioned CMV 36.7% and 47.8% of the time, respectively—albeit typically as an avoided limitation. It appears that, at least in this sample, that there is little consensus as to when data is or is not susceptible to CMV and when it should be addressed in published research.

The foregoing illustrations suggest that the decision to use statistical detection and correction (and, if so, which technique to use) is likely to be at least partially guided by one's perspective about CMV. Unfortunately, evaluating these techniques (or the use of no technique) solely from a theoretical perspective is not very helpful, as each set of assumptions ''will be shown to satisfy more or less the criteria that it dictates for itself and to fall short of a few of those dictated by its opponent'' (Kuhn, 1970, p. 110). Thus, the current article seeks to explicitly evaluate the potential usefulness of available analytical strategies relative to three sets of assumptions, or perspectives, about the existence and nature of CMV: (a) the No CMV Perspective is the belief that biasing levels of CMV do not exist in most, if not all, same-source/ method research; (b) the Noncongeneric Perspective is the notion that CMV likely exists at salient levels in same-source/method data and that it has equal effects on all variables within a given study; and (c) the Congeneric Perspective is that CMV exists, but its effects vary across substantive variables collected from the same data source and using one method.

As expected from normal science (Kuhn, 1970), there is no consensus as to which CMV perspective accurately describes same-source/method data. Proponents of each perspective present research supporting their view and/or interpret the same data in ways that support their conclusions (cf., Spector, 1987; Williams, Hartman, et al., 1989), resulting in no agreed on recommendations regarding the use and accuracy of statistical detection and correction. In this article, our aim is not to resolve the dispute regarding CMV's existence or to endorse a personally favored perspective. Rather, we examine the implications of using statistical detection and correction techniques (and of doing nothing) if each perspective is true and, as such, seek to determine the extent of risks and benefits associated with each statistical technique within the assumptions of all three perspectives. We accomplish this goal by applying the correlational marker, CFA marker, and ULMC approaches to 691,200 independent–dependent variable correlations simulated to have varying degrees of CMV contamination (including none), true correlations, and random error. By doing so, we hope to provide empirical evidence (i.e., as opposed to ideological speculation) regarding the usefulness of these techniques.

## Three CMV Perspectives

### The No CMV Perspective

The No CMV Perspective is the assumption CMV does not exist (or if it does, not as typically conceptualized) and, thus, is unlikely to affect observed same-source, same-method relationships. As a proponent of this perspective, Spector (2006, p. 228) argues, ''CMV is an urban legend, and the time has come to retire the idea and the term.'' Spector does not argue that method cannot influence measurement, but rather that common conceptualizations of CMV incorrectly assume (a) method alone is sufficient to produce bias and (b) all constructs measured with the same method share the same biases (for consistent, although not strictly identical, arguments see Bagozzi & Yi, 1990; Crampton & Wagner, 1994; Doty & Glick, 1998). Spector (2006, p. 223) further notes ''there are few scientific data to unequivocally support [the common view of CMV], and there are data to refute it.'' For example, in a meta-analysis of 581 articles, Crampton and Wagner (1994, p. 72) conclude CMV inflation ''may be more the exception than the rule.'' Spector (1987) himself finds evidence of CMV in only 1 of 10 studies examined using multi-trait multi-method (MTMM) procedures.

Despite evidence that CMV may not exist or that its pervasiveness may be overstated, the extent to which the research community subscribes to the No CMV Perspective is unclear. As one indication, a cited reference search (conducted June 2008) produced 260 unique published management and applied psychology articles citing the four publications, which arguably most clearly articulate the No CMV logic (i.e., Spector, 1987, 1994, 2006; Spector & Brannick, 1995). Review of the citing studies reveals that, most commonly, the No CMV Perspective is presented in discussion sections as a means of counterbalancing concerns that CMV provides an alternative explanation for reported findings (e.g., Avery, McKay, & Wilson, 2008). Nonetheless, authors also typically mention there is disagreement about the veracity of this perspective.

Noncongeneric Perspective

This perspective is the notion that CMV likely exists in same-source and -method data, and that it is noncongeneric. That is, manifest items are contaminated to the same degree by a single cause of CMV. This perspective assumes any CMV in a given data set is the function of a single method factor affecting all constructs nearly equally. As such, the method factor is expected to have ‘‘a constant correlation, $r$ (which may turn out to be zero but is not assumed a priori to be so), with all of the manifest variables’’ (Lindell & Whitney, 2001, p. 115).

As it is comprised of two key beliefs—that CMV (a) exists and (b) has equal effects— two types of support for this perspective exist. The first provides only partial support and includes studies finding evidence of CMV, but not examining whether it is noncongeneric. For instance, Cote and Buckley (1987) found measures in 70 studies to be comprised of about 26% method variance on average. Williams et al. (1989) used CFA to examine the same studies as Spector (1987), but concluded (contrary to Spector’s findings of almost no CMV) that about 25% of the variance accounted for in the sampled studies was due to method. More recently, Podsakoff et al. (2003, p. 880) summarized a large number of studies examining the prevalence of CMV by stating, ‘‘…. on average, the amount of variance accounted for when CMV was present was approximately 35% versus approximately 11% when it was not present.’’ The second category of research, which more fully supports this perspective, explicitly finds evidence of noncongeneric CMV. To date, there is at least found method effects associated with positive affectivity were noncongeneric within and across substantive construct items.

As was the case with the No CMV Perspective, it is difficult to determine the extent to which scholars subscribe to the Noncongeneric Perspective. On one hand, authors do not appear to explicitly consider whether CMV is likely to be noncongeneric; in the year’s worth of empirical articles from AMJ and JAP that we reviewed, most authors offered no more than one sentence addressing CMV. On the other hand, there are instances in which authors explicitly state they are invoking this perspective (e.g., Kelloway, Francis, Catano, & Teed, 2007). Unfortunately, failure to explicitly consider whether potential CMV is noncongeneric may be problematic when detecting and correcting CMV because the correlational marker technique (see below) is intended solely for use with data in which, if CMV exists, it is noncongeneric.

## Congeneric Perspective

This perspective assumes CMV exists, but method effects are not equal across all same-source, same-method measures in a data set. Rather, method effects are expected to vary based on the nature of the rater, item, construct, and/or context. As such, one or more method constructs will be differentially correlated with substantive items and constructs. This logic is inherent in studies conceptualizing method effects as the result of one or more method factors with unique effects (e.g., Williams & Brown, 1994), even if the authors do not test for congeneric CMV.

Support for congeneric CMV can be found in three studies. Williams and Anderson (1994) found evidence that the method effects associated with negative affectivity were not equal among items within or across substantive constructs. Williams, Hartman, et al. (2003) and Rafferty and Griffin (2004) also report evidence of unequal method effects. Despite limited empirical investigations of unequal effects, other results indirectly imply method effects may tend to be congeneric. For example, Cote and Buckley (1987) found the amount of CMV depended on the type of measure: about 41% for attitude measures, about 25% for personality and aptitude/achievement measures, and about 23% for performance and satisfaction measures.

As was the case with noncongeneric CMV, research articles give little explicit attention to whether potential CMV is congeneric. If CMV truly contaminates data, however, the issue of whether the contamination is congeneric or noncongeneric may have important implications for detecting and correcting CMV. Applying a technique that is based on the assumption of noncongeneric effects to data in which the method effects are actually congeneric may prevent researchers from accurately detecting CMV and, if it exists, accurately correcting for it.

# Three Post Hoc Statistical Strategies for Detecting and Correcting CMV

Below we describe three statistical strategies, highlighting their expected strengths and weaknesses, and their use in published work.[i] The strengths and weaknesses discussed are those suggested by the developers or advocates of the techniques based on the conceptual logic on which each technique is built. They are, therefore, a function of the single perspective on which assumptions about the given technique were based (Kuhn, 1970). To date, the veracity of the strengths and weaknesses has not been verified through systematic empirical research.

## Correlational Marker Technique

An approach developed by Lindell and Whitney (2001), which we call the correlational marker technique, is based on the notion of controlling for CMV by partialling out shared variance in bivariate correlations associated with a particular covariate. According to this technique, the best estimate of CMV in a data set is represented by the smallest observed positive correlation between a substantive variable and an a priori chosen ''marker'' variable that is believed to be theoretically unrelated to at least one substantive variable, but susceptible to the same causes of CMV (Lindell & Whitney, 2001). The logic behind the marker is that, because it should be theoretically unrelated to one of the substantive variables, any observed correlation between the two cannot be due to a true relationship and, thus, must be due to something else the variables have in common (i.e., CMV). This approach assumes observed shared variance between the marker and the substantive variable is a function of a single unmeasured method factor and, therefore, is the best representative of CMV in the data. The marker itself is not conceptualized as a method construct or other representation of CMV; it is simply a substantive variable that, like other such variables in a study, may be contaminated by CMV. It is the shared variance between the marker and another substantive variable (with which the marker is not expected otherwise to be related) that is believed to be representative of CMV.

Lindell and Whitney propose using the following equation to remove shared variance between the marker and other variables: $\mathrm{r_{Yi.M}} = (\mathrm{r_{Yi}} - \mathrm{r_S})/(1 - \mathrm{r_S})$, where $r_{Yi.M}$ is the partial correlation between Y and Xi controlling for CMV, $r_{Yi}$ is the observed correlation between Y and Xi suspected of being contaminated by CMV, and $r_S$ is the smallest observed correlation between the marker variable and one of the substantive variables with which it is expected to be theoretically unrelated. Thus, this approach assumes noncongeneric CMV by partialling out the same amount of method variance at the construct level from all relationships in a data set to which it is applied. The resulting ''corrected'' correlations should be closer approximations to true relationships than are the uncorrected correlations. Although this strategy does not include a formal mechanism for detecting CMV, if the controlling procedure alters observed correlations, it is assumed that CMV is, indeed, present (Lindell & Whitney, 2001)—which means this technique may be likely to identify CMV in most data (Williams, Hartman, et al., 2003). If a correlation becomes nonsignificant after correction, bias is assumed to have been in effect.

Lindell and Whitney (2001) also argue that, if an a priori marker variable is not included, one may be selected post hoc by using the variable with the smallest positive correlation in the data set. Because researchers generally measure only variables they expect to be related, a post hoc marker is less likely to be theoretically unrelated, which may increase the likelihood of removing substantive, as well as method, variance from correlations. We refer to marker variables with no expected theoretical relationship with substantive variables as ‘‘ideal markers,’’ and those with expected theoretical relations to substantive variables as ‘‘nonideal markers.’’

Although this technique only recently was introduced, its use appears to be steadily growing. A cited reference search indicates that, between the publication of Lindell and Whitney (2001) and June 2008, 48 published articles report using this technique. Furthermore, two articles recommend its future use (Grant & Campbell, 2007; Sendjaya, Sarros, & Santora, 2008). Although the specific use and results of the strategy often are ambiguously reported, many authors appear to use post hoc markers, and the majority use the technique to conclude CMV is not present at biasing levels in the data (e.g., Arvey, Rotundo, Johnson, Zhang, & McGue, 2006). It is not clear whether this technique so rarely finds evidence of bias because it truly is not present in most data, because studies using the technique are less likely to be published if bias is detected, or because the technique is ineffective at detection. Indeed, the latter may be true because of the coarse guidelines for determining bias (a point also raised by Williams, Hartman, et al., 2003).

CFA Marker Technique

For the CFA marker approach, Williams and colleagues (Williams, Edwards, Vandenberg, 2003; Williams, Hartman, et al., 2003) propose that the Williams and Anderson (1994) procedure can be adapted for use with a theoretically irrelevant marker such as that described by Lindell and Whitney (2001). Shared variance between a marker and other variables that is believed to be a function of CMV is represented by modeling the latent marker construct with paths to each of its own unique manifest indicators as well as with paths to the manifest indicators of all the substantive constructs believed to be contaminated by CMV. Again, the latent marker construct is a substantive variable and is not intended to represent CMV; rather, the variance shared between the marker and the other substantive constructs is believed to represent CMV.

Comparing the change in fit between a model in which the marker construct-substantive item loadings are freely estimated to one in which they are constrained to zero is posited as a statistical test for detecting CMV. Comparing the marker construct model to an identical one in which substantive construct correlations have been constrained to their values from the model with no marker construct-substantive item paths is posited as a statistical test for detecting method bias. If CMV and bias are detected, the correlations from the marker construct model represent the ‘‘corrected’’ correlations.

Williams, Hartman, et al. point out several possible advantages the CFA marker approach may have over the correlational marker approach, including the ability to model random error in the marker and substantive constructs, the ability to model CMV at the item level, and thus the ability to account for noncongeneric and congeneric CMV. Williams et al. (2003) also describe the statistical tests to detect CMV presence and bias as advantages over the correlational marker approach because these should prevent researchers for relying on ‘‘corrected’’ correlations when CMV is not present or does not significantly alter the magnitude of observed relationships.

Despite the potential advantages of this technique, we identified only four published studies using this approach—(i.e., Agustin & Singh, 2005; Alge, Ballinger, Tangirala, & Oakley, 2006; Rafferty & Griffin, 2004; Ye, Marinova, & Singh, 2007). Finding studies using this technique, however, was much more difficult than it was for the correlational marker approach because the CFA marker approach was not introduced in a single published study. As was the case with the correlational marker approach, how this approach was used and its ultimate results tended to be ambiguously reported. As such, it is not always clear whether model comparison was explicitly used to detect CMV presence and bias. Yet, in all but one study (Alge et al., 2006) it appears that the authors ultimately included the marker construct in structural models as a means of controlling or correcting method effects. Interestingly, three of the studies mention an assumption of noncongeneric effects, although they do not necessarily test for them.

ULMC Technique

Authors have built on latent variable MTMM approaches (Widaman, 1985; Williams et al., 1989) to specify an ULMC in CFA as a means of detecting and partialling out variance shared among substantive indicators that are due neither to their substantive constructs nor to random error. Rather than a marker that is measured with multiple manifest indicators, a latent construct with no unique observed indicators represents the shared variance. Although the marker construct described for the two previous approaches is simply a substantive variable comprised of both substantive and method variance, the ULMC is believed to be method variance only. CMV is modeled by specifying factor loadings from the ULMC (which has no unique indicators of its own) to all of the substantive items suspected of CMV contamination.

As with the CFA marker approach, nested models are compared to formally detect CMV. Specifically, the fit of the model with both substantive construct-substantive item and method construct-substantive item loadings can be compared to the fit of a model with only substantive construct-substantive item loadings to determine whether observed relationships can be attributed to both method and substantive variance, thereby indicating the presence of CMV. If CMV is detected,

‘’corrected’’ correlations are produced by the model including both substantive and method components. Although not formally proposed in any existing work, it also may be possible to statistically test for bias by adapting the test from the CFA marker approach. That is, the model with both method and substantive components could be compared to an identical model except with construct correlations constrained to the values obtained in the substantive-only model. If the two models are significantly different, there is evidence of method bias.

Because of its operational similarity with the CFA marker approach, it has many of the same expected advantages. Notably, the ULMC technique allows researchers to model random error and item-level method effects, and it can be used regardless of whether method effects are noncongeneric or congeneric across items and constructs. Additionally, it is efficient to use because it does not require measuring additional variables such as a marker. Yet, this also is a potential drawback because, just as the marker approaches remove variance shared between the marker and substantive variables and assume the shared variance is CMV, the ULMC may remove all unaccounted for variance shared between the unmeasured and the substantive constructs, also assuming the shared variance represents CMV. With the marker techniques, researchers cannot know without question whether the variance is biased or substantive in nature, but they do know it is at least partially a function of the measured marker construct. With an unmeasured latent construct, it is possible the shared variance is substantive and due to unmeasured variables, but because the method construct has no unique indicators, there are no potential mechanisms for ascertaining a substantive role, and any number of unmeasured variables (including method and other substantive constructs) could be responsible for the shared variance (Kenny & Kashy, 1992).

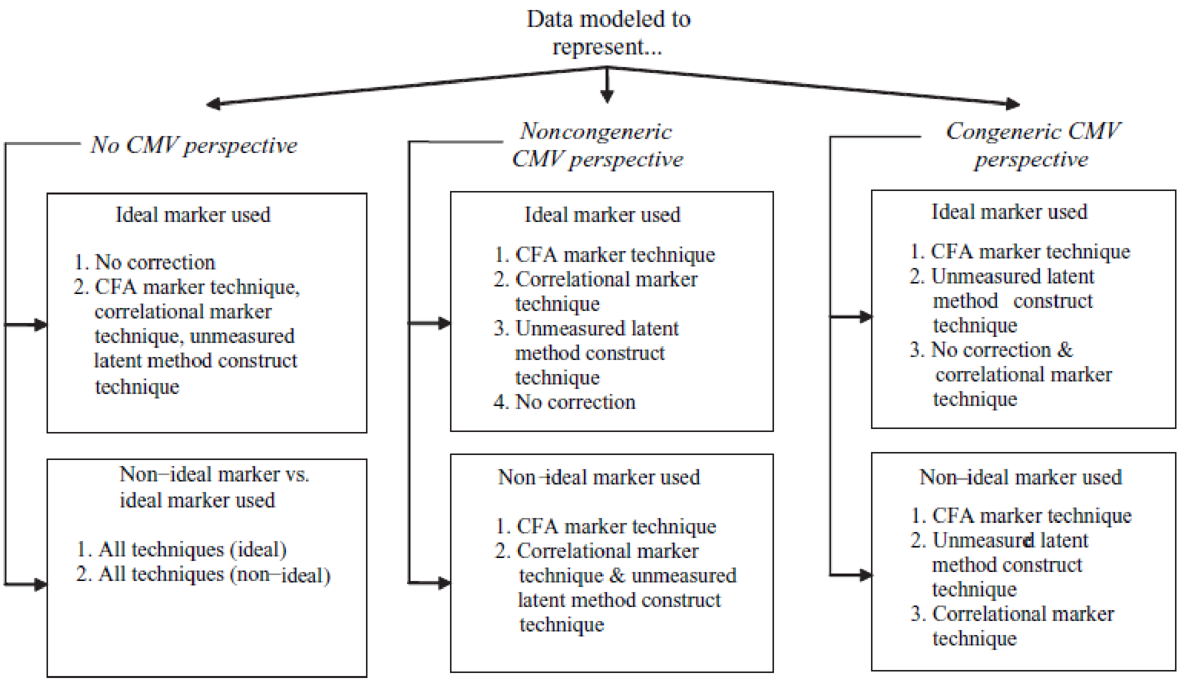
The ULMC approach appears to be used frequently in published work—perhaps in part because of the recommendation by Podsakoff et al. (2003). They (see p. 894) identify 11 studies using this procedure, and we found an additional 38. Because of inconsistent terminology used by authors, however, it is possible there are other studies using this technique that we failed to identify. Interestingly, almost without exception, studies using this technique report detecting evidence of CMV, but do not choose to rely on or report the resulting ‘’corrected’’ correlations (e.g., see Diefendorff & Mehta, 2007). Rather, because, the proportion of variance attributed to method is generally smaller than 25% (the median amount of method variance found across the studies examined by Williams et al., 1989), authors conclude that the CMV present in their data is not sufficient to bias results (e.g., see Choi& Chen, 2007). As was the case with the CFA marker technique, it is not clear whether the consistent absence of biasing levels of CMV reported by authors using this approach is a function of true absence in typical data, difficulty in publishing work in which bias is found, or ineffectiveness of the technique. Finally, although multiple method factors can be modeled using this technique, all the studies we identified appear to specify only a single unmeasured method construct.

## Hypotheses

Each of the detection and correction techniques is based on assumed mechanisms through which CMV (if it exists) affects measured variables. As such, the accuracy of the techniques depends, at a minimum, on whether these assumptions reflect given data. For present purposes, an accurate technique correctly identifies the presence of CMV and bias when they truly are present and, assuming they are present, brings observed correlations into range of true correlations. Additionally, an accurate technique correctly identifies the absence of CMV and bias when they truly are not present and, assuming they are absent, does not (or negligibly) alter observed correlations. We define accuracy in terms of both detection and correction because the two are interrelated. For all three techniques, the mechanisms for detecting CMV and bias are at least partially a function of the extent to which correction alters observed correlations.

Because one cannot truly know the likelihood and nature of CMV in real data, we consider three different conceptualizations of self-reported, same-source data, based on the three CMV perspectives: one in which no CMV is present, one in which noncongeneric CMV affects variables, and one in which congeneric CMV affects variables. Ideally, a technique would be accurate regardless of the nature of the data for any given study. We do not, however, anticipate that any technique will perform equally well in data representing all three perspectives. We now consider the ramifications of applying the techniques described above to the different representations of CMV, proposing where the differing assumptions about CMV might make the techniques more or less accurate. The hypotheses are summarized in Figure 1.

**Figure 1**
**Summary of *Hypotheses* by Perspective**




Note: For each marker condition in each perspective, techniques are listed in order of hypothesized accuracy. CMV = common method variance; CFA = confirmatory factor analysis.

Data Without CMV

In the real world, researchers cannot know a priori whether the No CMV Perspective accurately represents their data. Thus, applying one of the three correction and detection techniques may be an important means of allaying concerns about the presence of CMV or of convincingly justifying a given perspective and/or study design. Lindell and Whitney (2001) suggest the correlational marker technique be used with a marker that is theoretically unrelated to at least one of the substantive variables of interest. If CMV is not present, the logic of this approach indicates the $r_S$ value used in equation (1) will be very small or nonexistent because there is no true relationship with the marker and no CMV to bias observed relationships upward. Using a $r_S$ of .00 will produce no change in the observed correlation, and using a very small $r_S$ will produce very little change. Using an equivalent marker with the CFA marker approach or using the ULMC approach also should produce little change in observed correlations in data with no CMV because the marker construct, the ULMC, and other substantive constructs should share negligible or no variance. As such, accounting for any shared variance between substantive constructs and either a marker or ULMC will be unlikely to significantly improve model fit.

Nonetheless, in data that truly contain no CMV, application of a statistical detection and correction technique will be, on average, more likely than doing nothing to change the measured correlation and may cause its estimate to deviate from the most likely approximation of the true value as established by statistical estimation. Not only might such deviation indicate the presence of CMV and/or eliminate correlation significance (especially among variables with a small true correlation and in data derived from a small sample) but it also may increase the likelihood that model fit will significantly improve if some other form of spurious variance (e.g., from an unmeasured variable) is inadvertently captured via the procedure. As such, applying any of the techniques may be less accurate than applying no technique.

> **Hypothesis 1:** If no CMV exists and the best available marker is ideal, applying no correction will result in more accurate conclusions than will applying (a) the correlational, (b) the CFA, and (c) the ULMC strategies.

If a chosen marker is not theoretically unrelated to substantive variables (i.e., is nonideal), it is likely to exhibit correlations with those variables that are significantly different from .00. Although a nonideal marker should not knowingly be used, it may be difficult in real data to determine the extent to which a marker is or is not ideal. For example, observed relationships between a marker and substantive variables should become increasingly greater than .00 as the amount of CMV in the data also increases, if indeed CMV upwardly biases relationships and even if the marker truly is ideal (Spector, 2006). Thus, researchers cannot be certain whether nonzero observed marker-substantive variable relationships are a function of shared substantive variance (e.g., because of an unmeasured variable or use of a nonideal marker) or method variance.

In the uncontaminated data modeled for this study, any marker-substantive variable correlation that is significantly greater than .00 is a function of substantive variance and, thus, indicative that the marker is not truly ideal. As such, partialling out variance associated with such a marker will inappropriately remove substantive variance from the relationship, regardless of whether the correlational or CFA marker approach is used. The latter means that observed correlations are more likely to exhibit significant change and, in the case of the CFA marker technique, model fit may be subject to significant change as well. Thus, overall accuracy may be reduced for the correlational and CFA marker approaches when used with nonideal markers.

Given the potential results of the marker-based approaches when using a nonideal marker, the ULMC approach might appear more attractive because it does not require use of a marker. Again, the ULMC strategy may remove variance shared among substantive construct indicators that is not accounted for by the constructs themselves or by error terms. Thus, if any specification error exists in the model of the dependent variable where an unspecified variable covaries with the independent variable—such as is the case when a nonideal marker exists in the data—this covariance incorrectly may be captured as method variance.

In almost any social science research, researchers predict a relatively small portion of total variance. It is thus likely that, for any dependent variable, there exists specification error that covaries with the independent variables. If an independent and dependent variable are both truly related to some other construct (such as a variable initially intended as a marker or any other substantive variable, measured or unmeasured), the ULMC technique may capture this variance plus any other shared variance (theoretically appropriate or spurious) and attribute it to the unmeasured construct. As a result, even though it does not require the use of a marker, the ULMC approach also is expected to be less accurate overall when other theoretically related variables exist (e.g., when a nonideal marker is present in the simulated data).

> **Hypothesis 2:** If no CMV exists, applying (a) the correlational, (b) the CFA, and (c) the ULMC strategies when the best available marker is ideal will produce more accurate conclusions than will applying these strategies when the best available marker is nonideal.

Data with NonCongeneric CMV

CMV exists and affects all observed items equally in noncongeneric CMV data. Both the CFA marker and ULMC techniques are intended to detect and remove CMV and bias from observed relationships regardless of whether the CMV is noncongeneric or congeneric. The correlational marker technique, however, is designed for use only with noncongeneric effects because it removes the same amount of variance from all constructs. Thus, assuming noncongeneric CMV exists in the data, applying any of the three approaches should bring observed correlations closer into range of true correlations and increase the likelihood that CMV and bias (when it exists) are detected—thereby making use of a technique more desirable than not.

> **Hypothesis 3:** If noncongeneric CMV exists and the best available marker is ideal, applying (a) the correlational, (b) the CFA, and (c) the ULMC strategies will produce more accurate conclusions than will applying no correction.

Although using any of the techniques may generally bring observed correlations closer into range of true correlations and although the resulting change in observed correlations may make all the techniques likely to identify CMV in the noncongeneric data, it seems unlikely that all three will produce identical corrections. As such, conclusions about detection of bias may vary across the techniques as well. Although the correlational marker approach is likely to identify CMV in most, if not all, contaminated correlations to which it is applied (i.e., because CMV is identified any time $r_S$ is greater than .00), the CFA technique may produce slightly more accurate corrected correlations than the correlational marker technique because it has the ability to account for substantive, error, and method variance. The correlational approach does not account for error variance. Additionally, detection of bias is crudest when using the correlational marker approach because bias is indicated only if observed correlations lose significance. Alternatively, the CFA marker strategy indicates bias if corrected and uncorrected correlations are significantly different from one another, even if the corrected correlation maintains significance. As such, the CFA should perform better than the correlational marker approach on two of the three accuracy criteria (i.e., bias detection and correction accuracy, but not necessarily CMV detection).

Although the ULMC and CFA strategies share potential benefits, using an ULMC may produce less accurate conclusions overall than the two marker approaches. Although the marker-based approaches remove variance shared with the marker, the ULMC strategy may remove all shared variance not accounted for by substantive constructs or random error. This variance may be a function of CMV, spurious relationships, or unmeasured constructs. Thus, the ULMC approach may be more likely to produce misleading corrections, which also may result in false conclusions that bias is present (keeping in mind that bias may not be present even if CMV is).

**Hypothesis 4:** If noncongeneric CMV exists and the best available marker is ideal, applying (a) the correlational and (b) the CFA strategies will produce more accurate conclusions than will the ULMC strategy.

**Hypothesis 5:** If noncongeneric CMV exists and the best available marker is ideal, the CFA strategy will produce more accurate conclusions than will the correlational strategy.

When a marker-substantive variable relationship is nonideal, accounting for that variance by partialling out an $r_S$ value or specifying a latent marker construct will inappropriately reduce the magnitude of observed substantive relationships and may lead researchers to draw inaccurate conclusions regarding the magnitude of true relationships. Doing so also may increase the likelihood of concluding bias is present in instances when it is not. As was the case when using an ideal marker, however, the CFA marker approach may perform slightly better than the correlational marker approach because the former has the ability to account for random error, whereas the latter does not. At the same time, although, the mere existence of a nonideal marker means using the ULMC approach does not solve the potential accuracy problem associated with nonideal markers and the two marker-based approaches. As noted above, the ULMC approach will still capture this theoretically related variance, plus any other theoretically or spuriously related variance, and attribute it to the latent construct intended to connote the common method.[1ii]

**Hypothesis 6:** If noncongeneric CMV exists and the best available marker is nonideal, the CFA strategy will produce more accurate conclusions than will the correlational strategy.

**Hypothesis 7:** If noncongeneric CMV exists and the best available marker is nonideal, the CFA strategy will produce more accurate conclusions than will the ULMC strategy.

Data with Congeneric CMV

When a dataset contains congeneric CMV, we expect using the CFA marker or ULMC approaches may be more desirable than applying no technique, provided that any marker variable existing in the data is ideal. Because CMV affects at least some observed items and the two approaches can model unequal effects across items, removing some of the variance associated with unequal method effects should produce a more accurate representation of relationships. Doing so also will increase the likelihood of detecting CMV and bias when they are present.

**Hypothesis 8:** If congeneric CMV exists and the best available marker is ideal, applying (a) the CFA and (b) the ULMC strategies will produce more accurate conclusions than will applying no correction.

Using the two structural equations-based approaches also may be more desirable than applying the correlational marker approach. Although the correlational marker approach still may be highly likely to identify CMV even in congeneric data (i.e., again because any change after applying the technique suggests CMV is present), this approach is intended for use only under the assumption of noncongeneric CMV and will remove the same amount of construct-level variance from every substantive relationship to which it is applied. If the CMV affecting a set of variables varies across the variables and their constituent items, the correlational marker strategy necessarily will inaccurately adjust at least some of the relationships between variables. In other words, this strategy may be susceptible to both overcorrection (i.e., in situations where there is less CMV present than is captured by $r_s$) and undercorrection (i.e., in situations where there is more CMV present than is captured by $r_s$). Thus, the correlational marker technique also may be more likely than the other two techniques to falsely identify bias when it is not present as well as fail to identify bias when it is present. Because the correlational marker approach has the potential to simultaneously overcorrect and undercorrect relationships inflated by congeneric CMV, we do not hypothesize it will be more accurate than using no correction or vice versa.

> **Hypothesis 9:** If congeneric CMV exists and the best available marker is ideal, applying (a) the CFA and (b) the ULMC strategies will produce more accurate conclusions than will applying the correlational strategy.

For reasons stated for the Noncongeneric Perspective, the CFA approach also should be more accurate than the ULMC approach when an ideal marker is available.

> **Hypothesis 10:** If congeneric CMV exists and the best available marker is ideal, applying the CFA strategy will produce more accurate conclusions than will applying the ULMC strategy.

Again, the presence of a nonideal marker creates problems for all techniques. Applying the two marker-based approaches when using a nonideal marker may inappropriately reduce the magnitude of observed substantive relationships, thereby increasing the likelihood of falsely detecting bias. Yet, the CFA marker technique may perform slightly better than the correlational marker technique because the former also accounts for error variance and, in this case, is designed for use with congeneric data. Using the ULMC approach when an inappropriate marker exists may result in capturing this theoretically related variance plus any other theoretically and spuriously related variance, and wrongly attributing it to the latent method construct.

> **Hypothesis 11:** If congeneric CMV exists and the best available marker is nonideal, applying (a) the CFA and (b) the ULMC strategies will produce more accurate conclusions than will applying the correlational strategy.

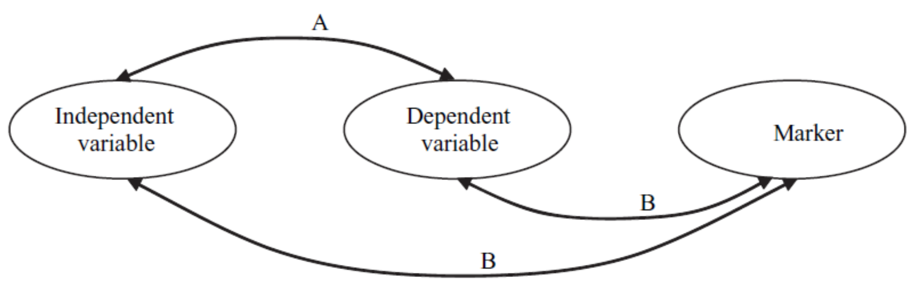
> **Hypothesis 12:** If congeneric CMV exists and the best available marker is nonideal, applying the CFA strategy will produce more accurate conclusions than will applying the ULMC strategy.

# Methods

## Conceptual Model

Our unit of analysis is the bivariate correlation, and each uncorrected bivariate correlation that we simulated was based on the conceptual model presented in Figure 2. This model is a partial replication and extension of that used by Williams and Brown (1994). Each correlation was comprised of a variable conceptualized as an exogenous (or independent) variable and one conceptualized as an endogenous (or dependent) variable. Because of the requirements for the two marker variable approaches, a marker variable was modeled in relation to each simulated independent–dependent variable pair. For corrections using the ULMC technique, the marker variable existed in the data but was not included in the analyses of each independent–dependent pair. All variables were modeled as measured by four continuous items each. To operationalize the correlational marker technique, we created constructs by taking the mean of the four items associated with each variable. For the two CFA-based approaches, we modeled the four items associated with each variable as manifest indicators for the relevant latent construct.

**Figure 2**
**Conceptual Model for Simulating Independent-Dependent-Marker Sets**




Note: "A" represents the bivariate correlation between the independent and dependent variables. It was modeled to have a true value of .00, .20, .40, or .60. "B" represents the correlations between the marker and the independent/dependent variables. This correlation was modeled to have a true value of .00, .20, or .40. Each of the independent, dependent, and marker variables was measured with four unique items that were averaged to create a scale score when used with the correlational marker technique and that were treated as manifest indicators when used with the two CFA-based approaches. The correlations described above were modeled as based on constructs with alpha reliabilities of .70, .80, or .90 and as based on a sample size of 100, 300, or 1000. Finally, the ratio of true variance to method variance was modeled to be 100:0, 80:20, 60:40, or 40:60. The latter three ratios of true to method variance also were each modeled in two ways: as noncongeneric and as congeneric. Thus, there were 108 cells of conditions for data modeled to have no CMV, 324 cells of conditions for data modeled to have noncongeneric CMV, and 6,480 cells of conditions for the data modeled to have congeneric CMV. Each of these total 6,912 cells of conditions was replicated 100 times, producing 691,200 analyzable independent-dependent-marker sets.

Our conceptual model also assumed that CMV effects (if modeled) were a function of a single method, representing data collected from a single source (e.g., as from one paper-and-pencil, self-report survey). We believe this conceptualization exemplifies the situation in organizational research most likely to generate concerns about CMV (i.e., data collected from a single source, at a single time, using a single method). There is also evidence that authors who operationalize method generally do so as a single method construct (e.g., see the ULMC approach above). Furthermore, by modeling method variance from a single source, we can assume the presence of method variance in the simulated data will inflate, rather than deflate, relationships (Williams & Brown, 1994). Although CMV may result in deflation under certain conditions, the detection and correction techniques we examine are intended for use only in cases of inflation.

We created a simulation program in Visual Basic specifically for the purposes of investigating data that conform to the three CMV perspectives. The program generated multiple independent-dependent-marker data sets for which, at a minimum, the following characteristics were manipulated: the strength of the true substantive relationship between the independent and dependent constructs, the strength of the true substantive relationship between these constructs and a marker construct, coefficient alpha reliability for all three constructs, and sample size. We created simulated data sets of three sample sizes (i.e., 100, 300, and 1,000) to represent a broad range of sample sizes likely found in micro-oriented organizational research. Each independent–dependent construct pair was modeled to correspond to one of the four possible true correlations (i.e., no, a weak, a moderate, and a moderately strong relationship—represented by true correlations of .00, .20, .40, and .60, respectively). We used a correlation of .20 to represent a weak relationship, as that is the minimum required (rounded to two decimal places) to detect significance when N ¼ 100. To represent stronger relationships, we simulated additional correlations in increments of .20 to represent a broad range of correlations likely to be observed in microlevel organizational research. The marker construct created for each independent–dependent pair was modeled to have a true correlation with both substantive constructs of either .00 (i.e., ideal), .20, or .40 (i.e., the latter two, nonideal). Note that we did not simulate a marker variable with a correlation of .60, as we felt it highly unlikely that one would mistakenly think a construct has no theoretical relationship with another construct when the true correlation is actually very strong—.60—for organizational research. We varied all the above within three levels of alpha reliability (i.e., .70, .80, and .90), to represent constructs with what is often seen as the minimally acceptable level of reliability for the early stages of research (Jaccard &Wan, 1995; Lance, Butts, & Michels, 2006; Nunnally & Bernstein, 1994) to higher levels typically found in micro-oriented research (i.e., .80 and .90). The levels of reliability are also those used in a key prior simulation on CMV (Williams & Brown, 1994) and are values typical of those in other simulations of hypothetical psychological constructs when the level of item reliability is manipulated (e.g., Aguinis, Sturman, & Pierce, 2008; Cheung & Lau, 2008; McDonald, Seifert, Lorenzet, Givens, & Jaccard, 2002). Finally, the program performed the analyses for no correction and the correlational marker technique and created the necessary text files so that the CFA and the ULMC techniques could be implemented in batch mode using LISREL 8.50.

Simulations that created data with no CMV included no further manipulations. Thus, for tests using this data, there were a total of 108 cells of conditions (i.e., 4 true variance conditions x 3 marker conditions x 3 alpha levels x3 sample sizes). For the noncongeneric simulations, we manipulated the amount of CMV present in the independent, dependent, and marker variables. CMV was defined as a percentage of the total variance in each construct. Following Williams and Brown (1994), we examined three ratios of true variance to method variance where CMV was present: 80:20, 60:40, and 40:60. Because this simulated CMV is shared variance, the random variable was added to all the relevant observed scores (i.e., for data with noncongeneric CMV, it was added equally to the items of each construct to help yield each observed score). The remaining variance represented true variance and random error (as determined by the internal consistency reliability of .70, .80, or .90 set for all constructs). By definition of noncongeneric, the effect of CMV in this perspective was equal for all observed simulated constructs (and, more specifically, across all items) within each independent-dependent-marker set. Based on these manipulations, there were a total of 324 cells of conditions (i.e., 4 true variance conditions x 3 CMV conditions x 3 marker conditions x 3 reliability levels x 3 sample sizes) for the data with noncongeneric CMV.

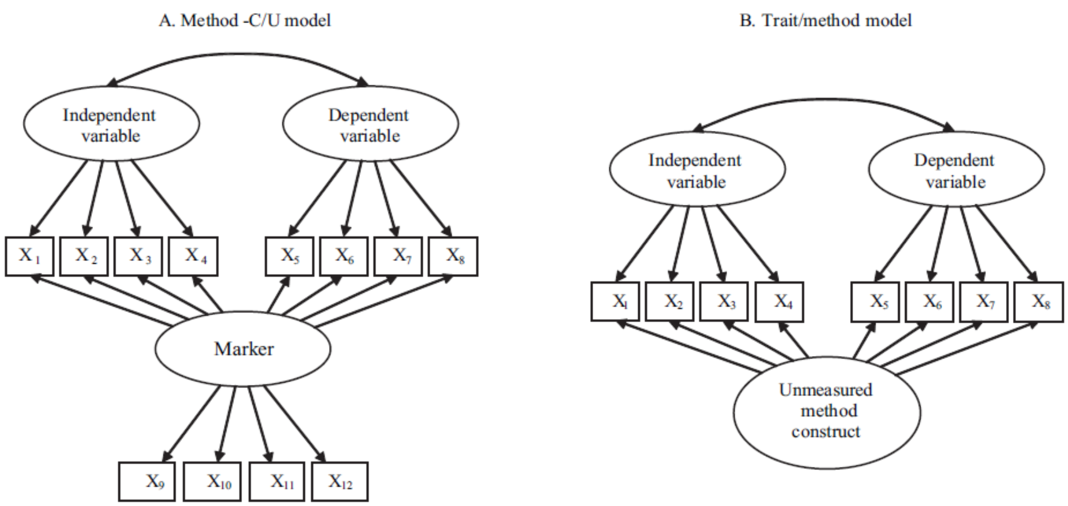
Finally, data simulated to have congeneric CMV contained CMV that was not equal across the variables in each independent-dependent-marker set. For a given set of constructs, any one variable could be represented by any of the four ratios of true-to-method variance described for the two previous perspectives (100:0, 80:20, 60:40, or 40:60), but excluded all situations where the level of CMV was the same for all three variables in the set. Hence, for the three constructs within each set, CMV equally contaminated the items within each construct, but differentially contaminated the items across constructs. For data with congeneric CMV, error was added to each true score (to help yield the observed score) in the appropriate proportion for each specific construct (with none being added if the appropriate proportion was 0%). Given the four possible levels of CMV and the three variables it could affect (i.e., 4 x4 x 4 conditions, minus the conditions where CMV was equal across all three variables, i.e., four conditions), there were a total of 60 possible congeneric CMV scenarios. Adding to this, the multiple conditions for independent–dependent true relationships (four conditions), independent/dependent-marker true relationships (three conditions), reliability (three conditions), and sample size (three conditions), there were a total of 6,480 cells of conditions. Across data sets representing all three perspectives, we considered 6,912 cells of data, with each cell corresponding to a set of independent, dependent, and marker variables characterized by one of the sets of conditions described above. To reduce concerns about sampling error in the data generation, each of the 6,912 cells was simulated 100 times, yielding a total of 691,200 independent-dependent-marker sets. Uncorrected observed independent–dependent correlations were calculated for each of the 691,200 variable sets. The three techniques were applied to each observed correlation using the procedures below.

Analytical Procedures

Below, we briefly describe the analytical procedures intended to detect and correct CMV and bias in the simulated data via each of the techniques. In each case, we analytically perform the technique precisely as described by the authors initially proposing it (with the exception of the added bias test used for the ULMC approach). For detailed descriptions of how to apply these techniques, please see Lindell and Whitney (2001) and Williams and colleagues (Williams & Anderson, 1994; Williams et al., 1989; Williams, Hartman, et al., 2003).

**Correlational marker technique.** Equation (1) was used to partial out variance shared between a marker and a substantive variable. The smallest observed positive correlation between a relevant marker and either the independent or dependent construct in its set was used for rs.

**Figure 3**
**The Method-C/U Model and the Trait/Method Model**




Note: In both models, (a) the paths from the independent construct to $X_1$ through $X_4$ and from the dependent construct to $X_5$ through $X_8$ were allowed to freely estimate (except one item for each construct that was set to a value of 1.0 to establish the construct metric), (b) error terms (not shown) for manifest items were allowed to freely estimate unless otherwise noted, and (c) the independent and dependent constructs were allowed to freely correlate, but the marker and method constructs were not allowed to correlate with either of the other two constructs. For the method-C/U model, paths from the marker construct to $X_9$ through $X_{12}$ were set to the values obtained from the initial CFA model, as were the error terms for $X_9$ through $X_{12}$ (not shown). For the method-C model, all paths from the marker construct to manifest items $X_1$ to $X_8$ were set to be equal; they were allowed to freely estimate in the case of method-U.

**CFA marker technique.** For the CFA marker analyses, item-level covariance matrices generated from the raw simulated data were used as input. We specifically implemented this approach by estimating and comparing a series of nested models for each independent– dependent construct set and its associated marker, as described by Williams and Anderson (1994) and Williams, Hartman, et al.

(2003). Four models were estimated for each simulated independent–dependent construct pair: a baseline model, method-C model, method- U model, and method-R model.

Briefly, the baseline model forced the correlations between the marker construct and both the independent and dependent constructs in the given set to zero (i.e., in the phi matrix), and fixed marker construct-marker item loadings to the unstandardized values obtained from a basic CFA model of the substantive and marker constructs. The method- C model was identical to the baseline model but with the addition of factor loadings from the marker construct to each independent/dependent construct item. These loadings were constrained to be equal (i.e., noncongeneric). The method-U model was identical to the method-C model, but the marker construct-independent/dependent item loadings were freely estimated (i.e., were congeneric). The method-C and -U models are visually depicted in Figure 3A. Finally, the method-R model was identical to either the method-C/U model; however, the independent–dependent construct correlation was constrained to its unstandardized value from the baseline model.

Chi-square differences between the baseline and method-C models, method-C and method-U models, and the method-C or -U and method-R models were then compared for statistical significance. If method-C fits significantly better than the baseline model, there is evidence of CMV in the data. If method-U fits significantly better than method-C, there is evidence of unequal (i.e., congeneric) method effects. If method-R fits significantly worse than either method-C or -U (depending on which fit better), there is evidence of bias because of CMV. If the latter is true, then the independent–dependent construct correlation (i.e., from the completely standardized phi matrix) in the method-C or -U model (again, depending on which fit better) reflects the corrected substantive relationship when method variance is partialled out.

**ULMC technique.** The procedure outlined by Williams et al. (1989) was used for the ULMC technique. Again, item-level covariance matrices generated from the raw simulated data were used as input for the analyses. Because it does not require the use of a marker variable, the markers were simply omitted from all models estimated in this approach (i.e., they functioned as unmeasured variables). The first model estimated—the trait-only model—was a measurement model of a given independent–dependent construct pair that included a null method construct. That is, the method construct was specified to be uncorrelated with the independent and dependent constructs, and no paths to or from the method construct were free to be estimated. In the second, or method-only, model the independent and dependent constructs were null, but paths from the method construct to all manifest indicators of the independent and dependent constructs were allowed to be estimated. The third, or trait/method, model was identical to the trait-only model, but paths from the method construct to all the independent and dependent construct manifest indicators were added (see Figure 3B). Finally, the trait/method-R model was identical to the trait/method model, but the independent–dependent construct correlation was constrained to the value obtained from the trait-only model. If the trait-only model fits the data better than the method-only model, there is evidence that observed variance in the independent and dependent constructs is not because of method alone. If the trait/method model fits better than the trait-only model, there is evidence that trait-based and method variance are present in the data. If the trait/method-R model fits significantly worse than the trait/method model, there is evidence of bias because of CMV. The independent–dependent correlation (i.e., from the completely standardized phi matrix) in the trait/method model reflects the corrected correlation.

### Hypothesis Testing

For the purposes of testing hypotheses, accuracy was conceptualized in terms of three categories: accuracy at detecting CMV, accuracy at detecting the presence or absence of bias, and accuracy of correction. Because all data analyzed was explicitly modeled to be either free from or contaminated by CMV, accuracy at detecting CMV simply refers to the average rate for which a given technique correctly identifies the absence of CMV in the data representing the No CMV Perspective and correctly identifies the presence of CMV in the data representing the other two perspectives. Operationalizing bias detection accuracy was slightly more complex, however, because data contaminated by CMV is not necessarily  biased. Rather, bias only exists if CMV produces significant divergence between true and observed relationships (Ostroff et al., 2002). As such, 95% confidence intervals were constructed around each of the observed, uncorrected independent–dependent correlations in the noncongeneric and congeneric CMV data. They were coded as biased if their confidence intervals did not include their true correlations. In the data modeled with no CMV, it is impossible to have bias as a result of CMV; thus, these correlations were all coded as unbiased. In all data, accuracy at detecting bias refers to the average rate for which a given technique correctly identifies the presence of bias for those correlations coded as biased and correctly identifies absence of bias in those coded as unbiased. Finally, correction accuracy refers to the extent to which corrected correlations are similar to true correlations. Correction accuracy was operationalized in two ways. First, average correction accuracy was calculated by constructing 95% confidence intervals around approximately 2,764,800 corrected and uncorrected independent–dependent observed correlations (i.e., 691,200 simulated correlations _ 4—that is, 3 strategies and doing nothing). A given correlation was coded as accurate if its confidence interval included the true correlation. In the remainder of the article, we refer to this aspect of accuracy as ''95% confidence interval accuracy.'' Second, correction accuracy was operationalized in terms of absolute error, which is the magnitude of the absolute difference between the corrected or uncorrected correlation (depending on whether a technique or no technique was being considered) and the true correlation.

Most hypotheses were tested via two separate analyses; for descriptive purposes, we began by considering the average accuracy of each correction technique within the data sets modeled to fit each CMV perspective by marker condition (i.e., ideal vs. nonideal). Tables 1, 2, and 3 depict summary statistics for the CMV detection, bias detection, and 95% confidence interval dummy variables and absolute error. In the second set of analyses, we used the CMV detection, bias detection, and 95% confidence interval dummy variables and absolute error as the dependent variables in separate regression equations calculated for the subset of correlations associated with each of the three CMV perspectives. In all cases, the independent variables were dummy variables representing the three CMV correction techniques and no correction. The results of these regression equations allowed us to statistically rank the correction techniques and no correction in order of accuracy by each of the four accuracy criteria. Furthermore, we were able to determine whether each strategy was statistically less accurate than the next most accurate strategy for each of the accuracy criteria. For the CMV detection, bias detection, and 95% confidence interval dummy variables, we ran logistic regression analyses separately for correlations modeled with an ideal marker (true marker r ¼ .00) and correlations modeled with a nonideal marker (true marker r > .00; i.e., either .20 or .40). These same analyses also were performed using ordinary least squares regression, specifying the absolute error of the correction as the dependent variable. These additional analyses allowed us to determine whether a given correction technique or no correction produced significantly larger errors than the technique performing just better than it in the ranking of corrections determined through the logistic regression.[iii]

In all analyses, we examine results separately for true r values equal to .00 and true r values greater than .00. The importance of delineating the size of true correlations relative to zero can be thought of in terms similar to Type I and Type II error. When the true r equals .00 and CMV is present in the data, the primary danger facing researchers is falsely concluding that a true relationship exists if no detection and correction technique is used. When true r is greater than .00, the danger is falsely concluding a true relationship does not exist after using a detection or correction technique. In cases where the true correlation is greater than zero, CMV may affect the magnitude of the observed correlation but will not necessarily alter its significance. As implied by the hypotheses, some techniques or no correction may be more prone to one type of error than the other. Because of the complexity of the study, however, we do not explicitly hypothesize about the implications of true correlation size.

**Table 1**
**Summary of Average CMV Detection Rate, Bias Detection Rate, 95% Confidence Interval (CI) Accuracy Rate, and Absolute Error in Data Modeled With No CMV[a]**

| | | Incorrectly Detected CMV | | Correctly Detected Absence of Bias | | 95% CI of Uncorrected Includes True | | \|Error\| | |
|---|---|---|---|---|---|---|---|---|---|
| | | True $r = .00$ | True $r > .00$ | True $r = .00$ | True $r > .00$ | True $r = .00$ | True $r > .00$ | True $r = .00$ | True $r > .00$ |
| No correction technique | Mean (*SD*) | Note that use of no correction technique does not allow for tests of these types | | | | 0.94 (0.23) | 0.59 (0.49) | 0.05 (0.05) | 0.09 (0.06) |
| | *N* | | | | | 2,700 | 8,100 | 2,700 | 8,100 |
| All correction techniques | Mean (*SD*) | 0.63 (0.48) | 0.61 (0.49) | 0.82 (0.38) | 0.53 (0.50) | 0.68 (0.47) | 0.47 (0.50) | 0.12 (0.13) | 0.16 (0.17) |
| | *N* | 7,555 | 21,995 | 7,555 | 21,988 | 7,539 | 21,879 | 7,539 | 21,879 |
| Correlational marker (all) | Mean (*SD*) | 0.89 (0.31) | 0.86 (0.35) | 0.99 (0.10) | 0.46 (0.50) | 0.54 (0.50) | 0.24 (0.43) | 0.17 (0.16) | 0.22 (0.14) |
| | *N* | 2,700 | 8,100 | 2,700 | 8,100 | 2,700 | 8,100 | 2,700 | 8,100 |
| Correlational marker [$m = .00$] | Mean (*SD*) | 0.70 (0.46) | 0.60 (0.49) | 0.97 (0.16) | 0.56 (0.50) | 0.97 (0.17) | 0.49 (0.50) | 0.04 (0.04) | 0.11 (0.07) |
| | *N* | 900 | 2,700 | 900 | 2,700 | 900 | 2,700 | 900 | 2,700 |
| Correlational marker [$m > .00$] | Mean (*SD*) | 0.988 (0.11) | 0.988 (0.11) | 0.998 (0.04) | 0.41 (0.49) | 0.33 (0.47) | 0.12 (0.32) | 0.23 (0.16) | 0.28 (0.13) |
| | *N* | 1,800 | 5,400 | 1,800 | 5,400 | 1,800 | 5,400 | 1,800 | 5,400 |
| CFA marker (all) | Mean (*SD*) | 0.64 (0.48) | 0.61 (0.49) | 0.75 (0.43) | 0.57 (0.49) | 0.72 (0.45) | 0.73 (0.44) | 0.09 (0.09) | 0.07 (0.07) |
| | *N* | 2,700 | 8,100 | 2,700 | 8,100 | 2,700 | 8,100 | 2,700 | 8,100 |
| CFA marker [$m = .00$] | Mean (*SD*) | 0.06 (0.23) | 0.04 (0.21) | 0.91 (0.29) | 0.58 (0.49) | 0.86 (0.34) | 0.85 (0.36) | 0.07 (0.07) | 0.06 (0.05) |
| | *N* | 900 | 2,700 | 900 | 2,700 | 900 | 2,700 | 900 | 2,700 |
| CFA marker [$m > .00$] | Mean (*SD*) | 0.93 (0.25) | 0.90 (0.30) | 0.68 (0.47) | 0.57 (0.49) | 0.65 (0.48) | 0.67 (0.47) | 0.11 (0.09) | 0.08 (0.07) |
| | *N* | 1,800 | 5,400 | 1,800 | 5,400 | 1,800 | 5,400 | 1,800 | 5,400 |
| ULMC (all)[b] | Mean (*SD*) | 0.19 (0.40) | 0.20 (0.40) | 0.90 (0.31) | 0.59 (0.49) | 0.70 (0.45) | 0.56 (0.50) | 0.11 (0.13) | 0.17 (0.23) |
| | *N*[c] | 1,594 | 4,539 | 1,404 | 3,664 | 1,578 | 4,423 | 1,578 | 4,423 |
| ULMC [$m = .00$][b] | Mean (*SD*) | 0.18 (0.39) | 0.20 (0.40) | 0.88 (0.32) | 0.58 (0.49) | 0.71 (0.45) | 0.56 (0.50) | 0.11 (0.12) | 0.17 (0.23) |
| | *N*[c] | 509 | 1,522 | 444 | 1,230 | 506 | 1,482 | 506 | 1,482 |
| ULMC [$m > .00$][b] | Mean (*SD*) | 0.20 (0.40) | 0.20 (0.40) | 0.90 (0.30) | 0.60 (0.49) | 0.71 (0.46) | 0.56 (0.50) | 0.11 (0.12) | 0.17 (0.23) |
| | *N*[c] | 1,085 | 3,017 | 1,072 | 2,434 | 1,072 | 2,941 | 1,072 | 2,941 |

Note: CMV = common method variance; CFA = confirmatory factor analysis; ULMC = unmeasured latent method construct.

a. Means for the CMV detection rates are the average proportion of cases in which a technique identified the presence of CMV in observed simulated independent–dependent correlations. Means for the bias detection rates are the average proportion of cases in which a technique identified the absence of bias in observed simulated independent–dependent correlations. Means in the 95% CI columns represent the average proportion of cases in which 95% CIs constructed around the corrected correlations (or uncorrected correlations in the case of no correction) contain the true correlations. |Error| is defined as |observed value of correlation−true value of correlation|, with the mean representing the average |Error| found among the correlation sample in each cell. In all cases, *SD* is the standard deviation of the mean reported in that cell, whereas *m* refers to the true value of the marker-independent/dependent variable correlation. *N* is the correlation sample size for each cell.

b. Although a marker is not used for the ULMC technique, to evaluate the same sample of correlations when comparing this technique with the marker-based techniques and because the presence of an unaccounted for variable may affect the results from this approach (e.g., see *hypotheses 2, 7, 11, 12*), we separate the correlations modeled with true marker-substantive relationships of .00 from those modeled with true marker-substantive relationships greater than .00. When using the ULMC technique, only the substantive correlations are analyzed. The markers are disregarded statistically.

c. Frequent difficulty in obtaining convergence is a well-recognized issue when estimating the trait-method model of the ULMC technique (Kenny & Kashy, 1992). When convergence could not be achieved for a given independent–dependent pair, the corrected correlation was treated as missing for the purposes of the present analyses. As such, the sample sizes for the ULMC cells differ somewhat from those in the other techniques.

## Table 2
**Summary of Average CMV Detection Rate, Bias Detection Rate, 95% Confidence Interval (CI) Accuracy Rate, and Absolute Error in Data Modeled With Noncongeneric CMV[a]**

| | | Correctly Detected CMV | | Correctly Detected Presence/Absence of Bias | | 95% CI of Uncorrected Includes True | | \|Error\| | |
|---|---|---|---|---|---|---|---|---|---|
| | | True $r = .00$ | True $r > .00$ | True $r = .00$ | True $r > .00$ | True $r = .00$ | True $r > .00$ | True $r = .00$ | True $r > .00$ |
| No correction technique | Mean (*SD*) | Note that use of no correction technique does not allow for tests of these types | | | | 0.11 (0.31) | 0.42 (0.49) | 0.32 (0.15) | 0.14 (0.11) |
| | *N* | | | | | 8,100 | 24,300 | 8,100 | 24,300 |
| All correction techniques | Mean (*SD*) | 0.80 (0.40) | 0.80 (0.40) | 0.72 (0.45) | 0.56 (0.50) | 0.38 (0.48) | 0.27 (0.45) | 0.21 (0.17) | 0.22 (0.17) |
| | *N* | 21,907 | 64,660 | 21,892 | 64,571 | 21,801 | 64,291 | 21,801 | 64,291 |
| Correlational marker (all) | Mean (*SD*) | 0.997 (0.06) | 0.997 (0.06) | 0.95 (0.21) | 0.51 (0.50) | 0.46 (0.50) | 0.24 (0.43) | 0.18 (0.15) | 0.23 (0.14) |
| | *N* | 8,100 | 24,300 | 8,100 | 24,300 | 8,100 | 24,300 | 8,100 | 24,300 |
| Correlational marker [$m = .00$] | Mean (*SD*) | 0.991 (0.09) | 0.991 (0.10) | 0.87 (0.34) | 0.42 (0.49) | 0.83 (0.38) | 0.49 (0.50) | 0.07 (0.06) | 0.12 (0.09) |
| | *N* | 2,700 | 8,100 | 2,700 | 8,100 | 2,700 | 8,100 | 2,700 | 8,100 |
| Correlational marker [$m > .00$] | Mean (*SD*) | 0.9998 (0.01) | 0.9998 (0.01) | 0.998 (0.05) | 0.55 (0.50) | 0.28 (0.45) | 0.12 (0.32) | 0.23 (0.15) | 0.29 (0.13) |
| | *N* | 5,400 | 16,200 | 5,400 | 16,200 | 5,400 | 16,200 | 5,400 | 16,200 |
| CFA marker (all)[c] | Mean (*SD*) | 0.98 (0.14) | 0.97 (0.17) | 0.77 (0.42) | 0.69 (0.46) | 0.31 (0.46) | 0.37 (0.48) | 0.21 (0.15) | 0.14 (0.11) |
| | *N*[c] | 8,071 | 24,125 | 8,056 | 24,036 | 8,093 | 24,273 | 8,093 | 24,273 |
| CFA marker [$m = .00$] | Mean (*SD*) | 0.94 (0.24) | 0.93 (0.26) | 0.59 (0.49) | 0.70 (0.46) | 0.10 (0.30) | 0.16 (0.36) | 0.31 (0.13) | 0.19 (0.10) |
| | *N*[c] | 2,695 | 8,069 | 2,695 | 8,041 | 2,700 | 8,093 | 2,700 | 8,093 |
| CFA marker [$m > .00$] | Mean (*SD*) | 0.9990 (0.03) | 0.995 (0.07) | 0.87 (0.34) | 0.68 (0.47) | 0.41 (0.49) | 0.48 (0.50) | 0.17 (0.13) | 0.12 (0.10) |
| | *N*[c] | 5,376 | 16,056 | 5,361 | 15,995 | 5,393 | 16,180 | 5,393 | 16,180 |
| ULMC (all)[b] | Mean (*SD*) | 0.21 (0.41) | 0.21 (0.41) | 0.25 (.43) | 0.45 (.50) | 0.17 (0.38) | 0.21 (0.41) | 0.33 (0.19) | 0.29 (0.25) |
| | *N*[c] | 4,476 | 12,895 | 3,647 | 10,642 | 4,348 | 12,378 | 4,347 | 12,378 |
| ULMC [$m = .00$][b] | Mean (*SD*) | 0.21 (0.41) | 0.21 (0.41) | 0.25 (0.43) | 0.45 (0.50) | 0.17 (0.38) | 0.21 (0.41) | 0.33 (0.19) | 0.28 (0.25) |
| | *N*[c] | 1,473 | 4,207 | 1,207 | 3,477 | 1,435 | 4,032 | 1,435 | 4,032 |
| ULMC [$m > .00$][b] | Mean (*SD*) | 0.21 (0.41) | 0.21 (0.40) | 0.25 (0.43) | 0.45 (0.50) | 0.17 (0.38) | 0.22 (0.41) | 0.33 (0.19) | 0.29 (0.26) |
| | *N*[c] | 3,003 | 8,688 | 2,440 | 7,165 | 2,913 | 8,346 | 2,913 | 8,346 |

Note: CMV = common method variance; CFA = confirmatory factor analysis; ULMC = unmeasured latent method construct.

a. Means for the CMV detection rates are the average proportion of cases in which a technique identified the presence of CMV in observed simulated independent–dependent correlations. Means for the bias detection rates are the average proportion of cases in which a technique correctly identified the presence of bias in observed simulated independent–dependent correlations that actually were biased and correctly identified the absence of bias in cases where there truly was no bias. Means in the 95% CI columns represent the average proportion of cases in which 95% CIs constructed around the corrected correlations (or uncorrected correlations in the case of no correction) contain the true correlations. |Error| is defined as |observed value of correlation−true value of correlation|, with the mean representing the average |Error| found among the correlation sample in each cell. In all cases, *SD* is the standard deviation of the mean reported in that cell, whereas *m* refers to the true value of the marker-independent/dependent variable correlation. *N* is the correlation sample size for each cell.

b. Although a marker is not used for the ULMC technique, to evaluate the same sample of correlations when comparing this technique with the marker-based techniques and because the presence of an unaccounted for variable may affect the results from this approach (e.g., see *hypotheses 2, 7, 11, 12*), we separate the correlations modeled with true marker-substantive relationships of .00 from those modeled with true marker-substantive relationships greater than .00. When using the ULMC technique, only the substantive correlations are analyzed. The markers are disregarded statistically.

c. Frequent difficulty in obtaining convergence is a well-recognized issue when estimating the trait-method model of the ULMC technique (Kenny & Kashy, 1992). When convergence could not be achieved for a given independent–dependent pair, the corrected correlation was treated as missing for the purposes of the present analyses. As such, the sample sizes for the ULMC cells differ somewhat from those for the other techniques. In a very small number of cases, convergence also was not achieved in some of the CFA marker models.

**Table 3**
**Summary of Average CMV Detection Rate, Bias Detection Rate, 95% Confidence Interval (CI) Accuracy Rate, and Absolute Error in Data Modeled With Congeneric CMV[a]**

| | | Correctly Detected CMV | | Correctly Detected Presence/Absence of Bias | | 95% CI of Uncorrected Includes True | | \|Error\| | |
|---|---|---|---|---|---|---|---|---|---|
| | | True $r = .00$ | True $r > .00$ | True $r = .00$ | True $r > .00$ | True $r = .00$ | True $r > .00$ | True $r = .00$ | True $r > .00$ |
| No correction technique | Mean (*SD*) | Note that use of no correction technique does not allow for tests of these types | | | | 0.47 (0.50) | 0.41 (0.49) | 0.19 (0.16) | 0.14 (0.10) |
| | *N* | | | | | 162,000 | 486,000 | 162,000 | 486,000 |
| All correction techniques | Mean (*SD*) | 0.73 (0.44) | 0.72 (0.45) | 0.65 (0.48) | 0.48 (0.50) | 0.47 (0.50) | 0.29 (0.45) | 0.18 (0.16) | 0.21 (0.17) |
| | *N* | 445,590 | 1,310,892 | 445,501 | 1,309,880 | 443,944 | 1,303,626 | 443,944 | 1,303,626 |
| Correlational marker (all) | Mean (*SD*) | 0.94 (0.23) | 0.93 (0.26) | 0.83 (0.38) | 0.43 (0.50) | 0.46 (0.50) | 0.24 (0.43) | 0.17 (0.14) | 0.23 (0.14) |
| | *N* | 162,000 | 486,000 | 162,000 | 486,000 | 162,000 | 486,000 | 162,000 | 486,000 |
| Correlational marker [$m = .00$] | Mean (*SD*) | 0.85 (0.36) | 0.81 (0.39) | 0.72 (0.45) | 0.39 (0.49) | 0.67 (0.47) | 0.37 (0.48) | 0.11 (0.11) | 0.15 (0.10) |
| | *N* | 54,000 | 162,000 | 54,000 | 162,000 | 54,000 | 162,000 | 54,000 | 162,000 |
| Correlational marker [$m > .00$] | Mean (*SD*) | 0.990 (0.10) | 0.987 (0.11) | 0.88 (0.32) | 0.45 (0.50) | 0.35 (0.48) | 0.17 (0.38) | 0.20 (0.15) | 0.27 (0.15) |
| | *N* | 108,000 | 324,000 | 108,000 | 324,000 | 108,000 | 324,000 | 108,000 | 324,000 |
| CFA marker (all)[b] | Mean (*SD*) | 0.85 (0.35) | 0.84 (0.37) | 0.59 (0.49) | 0.55 (0.50) | 0.43 (0.49) | 0.38 (0.48) | 0.20 (0.17) | 0.15 (0.11) |
| | *N*[c] | 161,910 | 485,018 | 161,821 | 484,006 | 161,969 | 485,869 | 161,969 | 485,869 |
| CFA marker [$m = .00$][b] | Mean (*SD*) | 0.65 (0.48) | 0.64 (0.48) | 0.55 (0.50) | 0.54 (0.50) | 0.44 (0.50) | 0.37 (0.48) | 0.21 (0.18) | 0.15 (0.11) |
| | *N*[c] | 53,991 | 161,857 | 53,996 | 161,532 | 54,000 | 161,968 | 54,000 | 161,968 |
| CFA marker [$m > .00$][b] | Mean (*SD*) | 0.95 (0.21) | 0.94 (0.23) | 0.61 (0.49) | 0.56 (0.50) | 0.42 (0.49) | 0.38 (0.49) | 0.19 (0.16) | 0.15 (0.12) |
| | *N*[c] | 107,919 | 323,161 | 107,855 | 322,474 | 107,969 | 323,901 | 107,969 | 323,901 |
| ULMC (all)[b] | Mean (*SD*) | 0.21 (0.40) | 0.21 (0.40) | 0.55 (0.50) | 0.45 (0.50) | 0.42 (0.49) | 0.30 (0.46) | 0.22 (0.18) | 0.24 (0.24) |
| | *N*[c] | 92,526 | 267,752 | 77,736 | 219,114 | 90,821 | 259,635 | 90,821 | 259,635 |

*(continued)*

| | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| ULMC [$m = .00$][b] | Mean (*SD*) | 0.21 (0.40) | 0.21 (0.40) | 0.54 (0.50) | 0.45 (0.50) | 0.42 (0.49) | 0.30 (0.46) | 0.22 (0.18) | 0.24 (0.24) |
| | $N^{c}$ | 30,880 | 89,438 | 25,976 | 73,033 | 30,285 | 86,714 | 30,285 | 86,714 |
| ULMC [$m > .00$][b] | Mean (*SD*) | 0.20 (0.40) | 0.21 (0.40) | 0.55 (0.50) | 0.44 (0.50) | 0.42 (0.49) | 0.30 (0.46) | 0.22 (0.18) | 0.24 (0.24) |
| | $N^{c}$ | 61,646 | 178,314 | 51,760 | 146,081 | 60,536 | 172,921 | 60,538 | 172,921 |

Note: CMV = common method variance; CFA = confirmatory factor analysis; ULMC = unmeasured latent method construct.

a. Means for the CMV detection rates are the average proportion of cases in which a technique identified the presence of CMV in observed simulated independent–dependent correlations. Means for the bias detection rates are the average proportion of cases in which a technique correctly identified the presence of bias in observed simulated independent–dependent correlations that actually were biased and correctly identified the absence of bias in cases where there truly was no bias. Means in the 95% CI columns represent the average proportion of cases in which 95% CIs constructed around the corrected correlations (or uncorrected correlations in the case of no correction) contain the true correlations. |Error| is defined as |observed value of correlation − true value of correlation|, with the mean representing the average |Error| found among the correlation sample in each cell. In all cases, *SD* is the standard deviation of the mean reported in that cell.

b. Although a marker is not used for the ULMC technique, to evaluate the same sample of correlations when comparing this technique with the marker-based techniques and because the presence of an unaccounted for variable may affect the results from this approach (e.g., see *hypotheses 2, 7, 11, 12*), we separate the correlations modeled with true marker-substantive relationships of .00 from those modeled with true marker-substantive relationships greater than .00. When using the ULMC technique, only the substantive correlations are analyzed. The markers are disregarded statistically.

c. Frequent difficulty in obtaining convergence is a well-recognized issue when estimating the trait-method model of the ULMC technique (Kenny & Kashy, 1992). When convergence could not be achieved for a given independent–dependent pair, the corrected correlation was treated as missing for the purposes of the present analyses. As such, the sample sizes for the ULMC cells differ somewhat from those for the other techniques. In a very small number of cases, convergence also was not achieved in some of the CFA marker models.

# Results

Before testing hypotheses, we statistically checked the accuracy of the simulation. For each level of true correlation, we looked at the distribution of errors between the observed and the ‘‘expected’’ correlation derived mathematically (based on the level of alpha and the amount of CMV). We then tested whether the means of these distributions were significantly different from zero. For all comparisons (looking at the overall sample, testing the distributions for each CMV condition, and testing the distributions for each level of true r), the 95% confidence interval around the mean error score always included zero. Comparing observed correlation variances to the values expected because of the level of the observed correlation and the sample size indicated 95% confidence intervals around the observed correlations’ variances all contained the expected levels. These tests help confirm that the simulated data conforms to the characteristics we intended to simulate.

## Data With No CMV

Hypothesis 1 predicts that when CMV is not contaminating data, using no correction will result in more accurate estimations of substantive relationships than will applying a correction technique when an ideal marker is used or present in the data. Because there is no way to examine CMV and bias detection when using no correction, this hypothesis was tested only in terms of 95% confidence interval accuracy and absolute error. As shown in Table 1, when no correction was applied to the observed correlations, the 95% confidence intervals included the true correlation 94% and 59% of the time (in the current article, whenever two accuracy values are given in succession, they represent the values for true r ¼ .00 and true r > .00, respectively, unless otherwise noted). The average error for no correction was .05 and .09. The regression results presented in Table 4 show that the ULMC approach was significantly less accurate than no correction. When used with an ideal marker, the correlational marker approach was significantly more accurate than no correction when the true correlation was equal to .00 (95% confidence interval accuracy: 97%, error: .04), and the CFA marker approach was significantly more accurate than no correction when the true correlation was greater than .00 (95% confidence interval accuracy: 85%, error: .06). As such, hypothesis 1 was only partially supported. One explanation for this result is that the CFA marker approach accounts for measurement error, thereby enabling it to correct for the unreliability modeled in the data. Likewise, by partialling out variance associated with the marker, the correlational approach may inadvertently correct for measurement error as well (i.e., it is reaching the right conclusion, but for the wrong reasons).

**Table 4**
**Results of Regression Equations to Determine Relative Accuracy of the Correction Techniques and No Correction in Data Modeled With No CMV**

| Relative Performance | Incorrectly Detected CMV | | Correctly Detected Absence of Bias | | In CI | | \|Error\| | |
|---|---|---|---|---|---|---|---|---|
| Ideal marker variable | | | | | | | | |
| *N* | 1,909 | 6,136 | 1,844 | 5,843 | 2,606 | 8,403 | 2,606 | 8,043 |
| | True $r = .00$ | True $r > .00$ | True $r = .00$ | True $r > .00$ | True $r = .00$ | True $r > .00$ | True $r = .00$ | True $r > .00$ |
| 1 | CFA (.03–.09) | CFA (.03–.06) | Corr (.96–.99) | CFA (.56–.60) | Corr (.95–.99) | CFA (.83–.87) | Corr (.04–.05) | CFA (.05–.06) |
| 2 | ULMC[a] (.14–.21) | ULMC[a] (.18–.22) | CFA[a] (.89–.93) | ULMC (.55–.61) | None[a] (.92–.96) | None[a] (.57–.61) | None[a] (.05–.06) | None[a] (.09–.10) |
| 3 | Corr[a] (.66–.72) | Corr[a] (.59–.62) | ULMC (.86–.91) | Corr (.54–.58) | CFA[a] (.84–.89) | ULMC (.54–.59) | CFA[a] (.06–.07) | Corr[a] (.10–.11) |
| 4 | Note that use of no correction technique does not allow for tests of these types. | | | | ULMC[a] (.68–.74) | Corr[a] (.47–.51) | ULMC[a] (.10–.11) | ULMC[a] (.16–.18) |
| Nonideal marker variable | | | | | | | | |
| *N* | 3,963 | 12,091 | 3,838 | 11,504 | 5,389 | 16,552 | 5,389 | 16,552 |
| | True $r = .00$ | True $r > .00$ | True $r = .00$ | True $r > .00$ | True $r = .00$ | True $r > .00$ | True $r = .00$ | True $r > .00$ |
| 1 | ULMC (.18–.22) | ULMC (.19–.21) | Corr (.98–1.0) | ULMC (.58–.61) | None (.93–.97) | CFA (.66–.69) | None (.05–.06) | CFA (.08–.08) |
| 2 | CFA[a] (.91–.94) | CFA[a] (.89–.91) | ULMC[a] (.88–.92) | CFA (.55–.58) | ULMC[a] (.68–.73) | None[a] (.58–.61) | CFA[a] (.10–.11) | None[a] (.09–.09) |
| 3 | Corr[a] (.98–1.0) | Corr[a] (.98–1.0) | CFA[a] (.66–.69) | Corr[a] (.39–.42) | CFA[a] (.62–.67) | ULMC[a] (.54–.58) | ULMC (.10–.12) | ULMC[a] (.17–.18) |
| 4 | Note that use of no-correction technique does not allow for tests of these types | | | | Corr[a] (.31–.36) | Corr[a] (.11–.13) | Corr[a] (.22–.23) | Corr[a] (.27–.28) |

Note: None = no correction; Corr = correlational marker technique; CFA = confirmatory factor analysis marker technique; ULMC = unmeasured latent method construct technique; CMV = common method variance; CI = confidence interval.

a. The technique (or no correction) is significantly less accurate (at $p < .001$) than the technique (or no correction) listed above it in the table. Significance tests are from regression analyses, each with a different dependent variable. The first dependent variable is based on whether the technique incorrectly identified the presence of CMV (0 = no, 1 = yes). The second dependent variable is based on whether the technique correctly identified the absence of bias (0 = no, 1 = yes). The third dependent variable is based on whether the 95% CI around the corrected correlation included the true correlation and is referred to as "In CI" (0 = no, 1 = yes). The fourth dependent variable represented correction error as defined by the absolute difference in magnitude between the observed corrected/uncorrected correlation and true correlation and is referred to as "|Error|" (|observed value of correlation—true value of correlation|). For the first three dependent variables, analyses used logistic regression; for the fourth dependent variable OLS regression was used. Independent variables were dummy variables representing the three CMV detection and correction techniques and no correction. Results are presented in rank performance order, beginning with the approach which was most accurate. Numbers in parentheses represent 95% CIs constructed around the average value within each cell for each dependent variable.

To test hypothesis 2, we determined whether each technique was significantly more accurate in terms of all four criteria when the marker was ideal, versus when the marker was nonideal, in the no CMV data. The hypothesis was largely confirmed for the correlational and the CFA marker techniques. Regardless of true r size, both techniques were significantly more accurate with an ideal marker than with a nonideal marker. The one exception to this finding was for identifying bias when the true r equaled .00 and when using the correlational marker technique. The correlational approach correctly identified the absence of bias 97% of the time when the marker was ideal and 99% of the time when it was nonideal. Although this difference is statistically significant, it is not practically significant. Keep in mind that the correlational marker technique detects bias only when a correlation loses significance after correction. In data with no CMV and a true r equal to .00, very few correlations will be significant in the first place. Counter to our expectations, the ULMC technique did not perform significantly differently based on the marker present in the data. It is worth noting, however, that when a nonideal marker was present, all three techniques were generally significantly less accurate than no correction (see Table 4). It also is worth noting that, as shown in Table 1, both the CFA (93% and 90%) and correlational marker (99%) techniques were highly likely to identify CMV in the no CMV data when used with nonideal markers.

Data With Noncongeneric CMV

Hypothesis 3, which argues that applying any correction is preferable to doing nothing when noncongeneric CMV exists and when the best available marker is ideal, was partially supported. Consistent with expectations, Table 5 indicates that, when true r was equal to .00, doing nothing produced significantly lower 95% confidence interval accuracy and significantly larger absolute error than the correlational marker and ULMC techniques. Doing nothing also performed worse than the CFA marker technique on 95% confidence interval accuracy and worse than the ULMC technique on error, but not significantly so. Contrary to expectations, when true r was greater than .00, doing nothing was only significantly less accurate than the correlational technique. As shown in Table 2, the confidence interval rate for the correlational technique used with an ideal marker and when true r was greater than .00 was 49%, whereas it was 42%for no correction. Average error for the correlational technique under the same conditions was .12, and it was .14 for no correction. Both the CFA marker and ULMC approaches were significantly less accurate than no correction when true r was greater than .00.

Examination of error direction indicated the CFA marker approach tended to remove too little variance, whereas the ULMC approach tended to remove too much variance.

Hypothesis 4 suggests when noncongeneric CMV is present and when using an ideal marker, the correlational and CFA marker approaches will be more accurate than the ULMC approach. As shown in the top part of Table 5, hypothesis 4 was partially supported. The correlational marker technique performed significantly better than the ULMC approach on all four accuracy criteria except bias detection when the true correlation was greater than .00. The latter result is not surprising, given the coarseness with which the correlational approach detects bias. That is, it only detects bias when the observed correlation loses significance after correction. As the true correlation becomes increasingly different from .00, it also becomes increasingly less likely that the correlational marker technique will detect bias. The CFA marker technique was significantly better than the ULMC approach at detecting CMV and bias regardless of true $r$ size. In terms of 95% confidence interval accuracy and absolute error, the CFA marker technique only outperformed the ULMC approach for absolute error.

**Table 5**

**Results of Regression Equations to Determine Relative Accuracy of the Correction Techniques and No Correction in Data Modeled With Noncongeneric CMV**

| Relative Performance | Correctly Detected CMV | | Correctly Detected Presence/ Absence of Bias | | In CI | | \|Error\| | |
|---|---|---|---|---|---|---|---|---|
| Ideal marker variable | | | | | | | | |
| $N$ | 6,042 | 18,080 | 5,776 | 17,324 | 8,296 | 24,872 | 8,296 | 24,872 |
| | True $r = .00$ | True $r > .00$ | True $r = .00$ | True $r > .00$ | True $r = .00$ | True $r > .00$ | True $r = .00$ | True $r > .00$ |
| 1 | Corr (.98–1.0) | Corr (.98–1.0) | Corr (.85–.89) | CFA (.69–.71) | Corr (.82–.85) | Corr (.49–.51) | Corr (.07–.08) | Corr (.11–.12) |
| 2 | CFA[a] (.93–.95) | CFA[a] (.92–.93) | CFA[a] (.57–.61) | ULMC[a] (.44–.47) | ULMC[a] (.15–.19) | None[a] (.41–.43) | CFA[a] (.30–.31) | None[a] (.14–.14) |
| 3 | ULMC[a] (.21–.24) | ULMC[a] (.21–.22) | ULMC[a] (.22–.27) | Corr[a] (.41–.43) | CFA[a] (.08–.11) | ULMC[a] (.20–.22) | ULMC[a] (.32–.34) | CFA[a] (.19–.19) |
| 4 | Note that use of no-correction technique does not allow for tests of these types | | | | None (.09–.12) | CFA[a] (.15–.17) | None (.32–.32) | ULMC[a] (.28–.29) |
| Nonideal marker variable | | | | | | | | |
| $N$ | 12,086 | 36,586 | 11,510 | 35,006 | 16,566 | 50,362 | 16,566 | 50,362 |
| | True $r = .00$ | True $r > .00$ | True $r = .00$ | True $r > .00$ | True $r = .00$ | True $r > .00$ | True $r = .00$ | True $r > .00$ |
| 1 | CFA (.99–1.0) | CFA (.99–1.0) | Corr (.99–1.0) | CFA (.68–.69) | CFA (.40–.43) | CFA (.48–.49) | CFA (.16–.17) | CFA (.11–.12) |
| 2 | Corr (.99–1.0) | Corr (.99–1.0) | CFA[a] (.86–.88) | Corr[a] (.55–.56) | Corr[a] (.27–.29) | None[a] (.40–.42) | Corr[a] (.23–.24) | None[a] (.14–.14) |
| 3 | ULMC[a] (.20–.22) | ULMC[a] (.20–.21) | ULMC[a] (.24–.26) | ULMC[a] (.44–.46) | ULMC[a] (.15–.18) | ULMC[a] (.21–.22) | None[a] (.32–.33) | Corr[a] (.28–.29) |
| 4 | Note that use of no correction technique does not allow for tests of these types. | | | | None[a] (.09–.11) | Corr[a] (.11–.13) | ULMC (.33–.34) | ULMC (.29–.29) |

Note: None = no correction; Corr = correlational marker technique; CFA = confirmatory factor analysis marker technique; ULMC = unmeasured latent method construct technique; CMV = common method variance; CI = confidence interval.

a. The technique (or no correction) is significantly less accurate (at $p < .001$) than the technique (or no correction) listed above it in the table. Significance tests are from regression analyses, each with a different dependent variable. The first dependent variable is based on whether the technique correctly identified the presence of CMV (0 = no, 1 = yes). The second dependent variable is based on whether the technique correctly identified the presence or absence of bias (0 = no, 1 = yes). The third dependent variable is based on whether the 95% CI around the corrected correlation included the true correlation and is referred to as "In CI" (0 = no, 1 = yes). The fourth dependent variable represented correction error as defined by the absolute difference in magnitude between the observed corrected/uncorrected correlation and true correlation and is referred to as "|Error|" (|observed value of correlation—true value of correlation|). For the first three dependent variables, analyses used logistic regression; for the fourth dependent variable OLS regression was used. Independent variables were dummy variables representing the three CMV detection and correction techniques and no correction. Results are presented in rank performance order, beginning with the approach which was most accurate. Numbers in parentheses represent 95% CIs constructed around the average value within each cell for each dependent variable.

These results also indicate hypothesis 5, which predicts the CFA marker technique will be more accurate than the correlational marker technique, was largely unsupported. The correlational marker approach performed significantly better than the CFA marker approach on all criteria except bias detection among correlations based on true r values greater than .00. The particularly high CMV detection rate (nearly 100%) for the correlational marker approach in data modeled with noncongeneric CMV is unsurprising, given that this technique will detect CMV any time there is an observed marker correlation (rS) that differs from zero. Of course, this characteristic also means the approach will be highly inaccurate when CMV is truly not present in the data, as illustrated by the no CMV data results shown in Table 1.

Hypothesis 6 suggests when noncongeneric CMV is present and the best available marker is nonideal, the CFA approach will perform better than the correlational approach. This hypothesis was supported for all dependent variables except bias detection when true r equals .00 and CMV detection (regardless of true r size). For CMV detection, the performance of the two marker variable approaches was not significantly different. As shown in Table 2, both marker-based approaches identified CMV in nearly 100% of the cases. Again, the nature of CMV detection when using the correlational technique is such that CMV is likely to be identified in most data, making this technique highly accurate in terms of this criterion when used with an ideal or, especially, a nonideal marker and in data modeled with CMV (but highly inaccurate in data modeled without CMV). For the CFA approach, the accurate CMV identification results when using a nonideal marker are a by-product of removing substantive variance from data that happens to be contaminated by CMV. To the extent a marker shares true variance with substantive variables that is of similar magnitude to the CMV present, the tests of CMV are more likely to find evidence of it. As such, conclusions about the presence of CMV based on results obtained with a nonideal marker may be highly misleading—even if inadvertently accurate. Hypothesis 7 proposes that when noncongeneric CMV is present and a nonideal marker is available, the CFA marker approach will outperform the ULMC approach. As shown in Table 5, the CFA approach was significantly better than the ULMC approach on all four indicators.

Data With Congeneric CMV

Hypothesis 8 suggests the CFA and the ULMC approaches (when an ideal marker is available in the data) will be more accurate than no correction in data modeled with congeneric CMV. Results reported in Table 6 indicate that neither the CFA marker nor the ULMC approach was significantly more likely than no correction to produce correlations with confidence intervals containing the true correlation or smaller error, regardless of true r size. As shown in Table 3, average 95% confidence interval accuracy for no correction was 47% and 41%, and it was 44% and 37% for the CFA marker strategy and 42% and 30% for the ULMC strategy. Error rates for no correction were .19 and .14. They were .21 and .15 for the CFA approach, and they were .22 and .24 for the ULMC approach. These results indicate that hypothesis 8 was unsupported.

Hypothesis 9 suggests the CFA (used with an ideal marker) and the ULMC approaches will be more accurate than the correlational marker approach. The correlational marker approach performed better than the other two approaches in terms of CMV detection (regardless of true r size) and in terms of bias detection, 95% confidence interval accuracy, and absolute error when the true correlation was equal to .00. The CMV and bias detection results for the correlational marker technique are unsurprising and consistent with those found in the noncongeneric data. Both the CFA marker and ULMC techniques detected bias more accurately than the correlational technique when the true correlation was greater than .00. Only the CFA marker approach had better 95% confidence interval accuracy and less absolute error than the correlational marker approach when true r was greater than .00, but the difference between the two for 95% confidence interval accuracy was not significant. The ULMC approach did not perform better than the correlational marker approach on any criteria. Thus, hypothesis 9 was partially supported. Hypothesis 10 suggests the CFA approach will be more accurate than the ULMC strategy. Table 6 indicates that this hypothesis was supported for all criteria except 95% confidence interval accuracy and absolute error (when the true correlation is equal to .00).

Hypothesis 11 proposes that the CFA and ULMC strategies will be more accurate than the correlational marker strategy in congeneric data modeled with a nonideal marker. Results in Table 6 indicate that this hypothesis was supported for all criteria except CMV detection (regardless of true r size) and bias detection when true r equaled .00. Again, these results are not surprising, given that the nature of the correlational approach makes it particularly likely to detect CMV in most data. It should be noted that the correlational approach also produced significantly less error than the ULMC approach when true r was equal to .00. Hypothesis 12, which proposes the CFA marker technique will produce more accurate conclusions than the ULMC technique in congeneric data and when the best available marker is nonideal, was supported for CMV and bias detection, and absolute error (regardless of true r size). It also was supported for 95% confidence interval accuracy when true r was greater than .00. The CFA marker and ULMC strategies were not significantly different in terms of 95% confidence interval accuracy when true r was equal to .00. Again, although, the highly accurate CMV detection rates for the CFA approach when used with a nonideal marker are likely accurate for the wrong reasons.

**Table 6**
**Results of Regression Equations to Determine Relative Accuracy of the Correction Techniques and No Correction in Data Modeled With Congeneric CMV**

| Relative Performance | Correctly Detected CMV | | Correctly Detected Presence/ Absence of Bias | | In CI | | \|Error\| | |
|---|---|---|---|---|---|---|---|---|
| Ideal marker variable | | | | | | | | |
| *N* | 119,480 | 365,494 | 114,555 | 348,816 | 163,197 | 500,943 | 163,197 | 500,943 |
| | True $r = .00$ | True $r > .00$ | True $r = .00$ | True $r > .00$ | True $r = .00$ | True $r > .00$ | True $r = .00$ | True $r > .00$ |
| 1 | Corr (.85–.86) | Corr (.81–.81) | Corr (.70–.71) | CFA (.54–.54) | Corr (.66–.67) | None (.41–.41) | Corr (.11–.12) | None (.14–.14) |
| 2 | CFA[a] (.65–.65) | CFA[a] (.63–.64) | CFA[a] (.54–.54) | ULMC[a] (.45–.46) | None[a] (.45–.46) | CFA[a] (.36–.37) | None[a] (.20–.20) | CFA[a] (.15–.15) |
| 3 | ULMC[a] (.20–.21) | ULMC[a] (.20–.21) | ULMC (.54–.55) | Corr[a] (.39–.40) | CFA[a] (.42–.43) | Corr (.37–.38) | CFA[a] (.22–.22) | Corr[a] (.15–.15) |
| 4 | Note that use of no correction technique does not allow for tests of these types. | | | | ULMC (.41–.42) | ULMC[a] (.30–.30) | ULMC (.22–.22) | ULMC[a] (.24–.24) |
| Nonideal marker variable | | | | | | | | |
| *N* | 238,658 | 729,170 | 228,721 | 696,342 | 326,137 | 1,000,210 | 326,138 | 1,000,210 |
| | True $r = .00$ | True $r > .00$ | True $r = .00$ | True $r > .00$ | True $r = .00$ | True $r > .00$ | True $r = .00$ | True $r > .00$ |
| 1 | Corr (.99–.99) | Corr (.99–.99) | Corr (.87–.88) | CFA (.56–.56) | None (.45–.46) | None (.41–.41) | CFA (.20–.20) | None (.14–.14) |
| 2 | CFA[a] (.95–.96) | CFA[a] (.94–.94) | CFA[a] (.61–.62) | ULMC[a] (.45–.46) | CFA[a] (.41–.42) | CFA[a] (.38–.38) | None (.20–.20) | CFA[a] (.15–.15) |
| 3 | ULMC[a] (.20–.21) | ULMC[a] (.20–.21) | ULMC[a] (.54–.55) | Corr (.45–.45) | ULMC (.41–.42) | ULMC[a] (.30–.30) | Corr[a] (.20–.20) | ULMC[a] (.24–.24) |
| 4 | Note that use of no correction technique does not allow for tests of these types. | | | | Corr[a] (.35–.36) | Corr[a] (.17–.18) | ULMC[a] (.22–.22) | Corr[a] (.27–.27) |

Note: None = no correction; Corr = correlational marker technique; CFA = confirmatory factor analysis marker technique; ULMC = unmeasured latent method construct technique; CMV = common method variance; CI = confidence interval.

a. The technique (or no correction) is significantly less accurate (at $p < .001$) than the technique (or no correction) listed above it in the table. Significance tests are from regression analyses, each with a different dependent variable. The first dependent variable is based on whether the technique correctly identified the presence of CMV (0 = no, 1 = yes). The second dependent variable is based on whether the technique correctly identified the presence or absence of bias (0 = no, 1 = yes). The third dependent variable is based on whether the 95% CI around the corrected correlation included the true correlation and is referred to as "In CI" (0 = no, 1 = yes). The fourth dependent variable represented correction error as defined by the absolute difference in magnitude between the observed corrected/uncorrected correlation and true correlation and is referred to as "|Error|" (|observed value of correlation—true value of correlation|). For the first three dependent variables, analyses used logistic regression; for the fourth dependent variable OLS regression was used. Independent variables were dummy variables representing the three CMV detection and correction techniques and no correction. Results are presented in rank performance order, beginning with the approach which was most accurate. Numbers in parentheses represent 95% CIs constructed around the average value within each cell for each dependent variable.

## Discussion

Scholars disagree about the likelihood and nature of CMV in same-source, same-method data, yet researchers often find themselves in positions where they have no choice but to use such data. Despite a priori procedural precautions they may take to avoid concerns about CMV, researchers may be asked to offer post hoc evidence that observed relationships are not a function of CMV. In such instances, they may turn to the use of post hoc statistical detection and correction techniques, or they may argue such techniques are inappropriate and choose to do nothing. The difficulty, however, is that one's perspective regarding the nature and likelihood of CMV will affect the strategy chosen to identify and deal with its potential existence, and to date there has been no real understanding of the empirical implications of using (or not using) detection and correction techniques—neither in general nor within any given perspective.

To summarize the results from data modeled without CMV, in most cases across all conditions and techniques, applying statistical correction when CMV is absent can produce less accurate estimates of relationships than applying no statistical correction. Perhaps more importantly, the correlational marker and the ULMC approaches (both regardless of marker size) and the CFA marker approach used with a nonideal marker tend to identify CMV when it is not present. In contrast, the CFA marker approach used with an ideal marker rarely identifies CMV when it is not present. All four approaches tend to incorrectly identify the presence of bias in no CMV data, regardless of marker size. The latter finding was especially noticeable when true $r$ equaled zero. Even when true $r$ was greater than zero, all three techniques falsely identified bias about 50% of the time, again regardless of marker size.

Interestingly, for data with noncongeneric and congeneric CMV, applying a statistical correction does not necessarily produce more accurate estimations of relationships than doing nothing. Overall, results suggest, when any kind of CMV was present in the data, the absolute correction accuracy of all techniques tended to be low. Yet, both the correlational and CFA marker approaches can be highly accurate at detecting CMV and, to a lesser extent, detecting bias—particularly in data with noncongeneric CMV. Again, it is important to highlight that when used with nonideal markers, these approaches produce accurate results for the wrong reasons. For example, they remove variance as a function of substantive relationships rather than variance as a function of CMV. The resulting changes in observed correlations indicate CMV and bias are present, but not because variance truly associated with CMV was identified.

Given that many of the best results across techniques were for CMV detection (i.e., as opposed to bias detection or correction) and given that researchers cannot know the true nature of their data, it also is worthwhile to consider the average CMV detection accuracy rates for the three techniques across all possible conditions simulated in this study (i.e., the three perspectives, four true $r$ conditions, three marker conditions, three alpha levels, and three samples sizes). Overall, the ULMC approach correctly identified the presence or absence of CMV about 41% of the time, and the correlational marker approach was correct about 69% of the time. Based on these average rates, it is reasonable to assume that at least some—possibly many—of the 97 studies we found that use one of these two techniques falsely concluded CMV was absent from their data. It also is possible that some studies never were published because use of these two techniques falsely indicated CMV was present. The CFA marker technique, which has been used less frequently than the others, accurately identified the presence or absence of CMV 73% of the time on average across all conditions. Interestingly, this technique was accurate about 84% of the time on average when only ideal markers were considered (the ideal-only averages for the correlational and ULMC approaches were .72 and .41, respectively). Of note, the CFA marker technique was the only one highly unlikely to detect CMV when it truly was not present.

Based on these results, we can provide cautious advice to authors who are faced with criticisms related to CMV that are derived from a given perspective. Similarly, our results have implications for reviewers trying to provide constructive criticism to authors who may be writing an article from a perspective that differs from that of their reviewers. Thus, it is  our hope that the current study can inform research by drawing from empirical evidence to suggest the extent to which detection and correction strategies can help address both author and reviewer concerns, even when scholars consider a single article from multiple CMV perspectives.

## Advice to Authors

Given that (a) the perspective debate continues, (b) the perspective that best represents any given real-world study cannot be determined unequivocally from research to date, and (c) those concerned about CMV as an alternative explanation will not necessarily share perspectives, a detection and correction technique ideally should function well in all three perspectives. Thus, when used in truly uncontaminated data, a useful technique will not identify CMV and bias, and it will remove negligible or no variance from observed relationships (i.e., exhibit accuracy levels similar to no correction). Likewise, when either noncongeneric or congeneric CMV is present, the technique will accurately identify the presence of CMV and of CMV-derived bias, when the latter truly exists. Additionally, it will remove at least some of the method-related variance, while also removing negligible amounts of true variance. Across perspectives, identification and removal of method variance (or lack thereof) should be accurate regardless of whether the true relationship between the corrected variables is or is not greater than .00. Finally, a useful correction technique must have applied utility—researchers should be able to have reasonable confidence that they can apply the technique to their data as it is conceptually intended to be applied. Results suggest the correlational marker and ULMC approaches rarely meet the criteria for usefulness, whereas the CFA marker approach may be slightly more likely to do so.

Thus, perhaps our most obvious advice is that we do not recommend using the correlational marker or the ULMC approaches. When used in data with CMV, the ULMC technique was almost always the least accurate at detecting CMV and bias. Although occasionally the ULMC approach produced accurate corrected correlations in data modeled with CMV, it was consistently one of the worst performing techniques in data modeled with no CMV and an ideal marker. As such, it is highly risky to use the ULMC approach for detection and to improve the accuracy of conclusions drawn about hypothesized relationships. This recommendation is in contrast with Podsakoff et al. (2003), who imply the ULMC approach is a useful technique.

Although the correlational marker approach sometimes performed better than any of the alternatives, we still recommend it not be used. We support this claim by considering the use of this technique under a best case scenario (e.g., when it is used, as intended, with an ideal marker in noncongeneric contaminated data). Under these conditions, this technique produced an accurate corrected correlation only about 66% of the time. Average bias detection accuracy was about 65%. Despite the fact that these results are equivalent to, if not better than, those reported for no correction and the other two techniques, they still represent accuracy rates that are only slightly greater than 50%. Although the average CMV detection accuracy rate of 99% is impressive, when used with real data, researchers do not know for certain whether noncongeneric CMV truly is contaminating their data—one reason why the perspective debate continues. In the event that CMV, noncongeneric or otherwise, is not actually contaminating data, the current study indicates there is almost an equally high chance that using this technique will cause researchers to falsely conclude CMV and/or bias are present—especially if a nonideal marker is inadvertently used.

In contrast to the correlational marker and ULMC approaches, the CFA marker approach appears to have some, albeit limited, practical value. As described in the summary of results and as shown in Tables 4 through 6, the CFA approach does not necessarily produce accurate corrected estimates of relationships and sometimes performs significantly worse than no correction on this accuracy criterion. Thus, it is highly risky to draw conclusions about the magnitude of true relationships based on corrected correlations derived from this approach. Therefore, as was the case with the other two correction techniques, we do not recommend using the CFA marker technique for the purpose of producing ‘‘corrected’’ correlations. Because of its generally low accuracy at detecting the presence or absence of bias, on average across all conditions, we also do not recommend using the CFA marker technique for detecting bias.

Despite the CFA marker approach’s lack of utility for correcting correlations, it may have practical value for alleviating concerns about the presence of CMV in data. When noncongeneric CMV was present in the data, the CFA marker approach correctly identified it about 93% of the time when used with an ideal marker. The approach correctly identified the absence of CMV about 94% of the time in data modeled with no CMV, again when used with an ideal marker. The technique has the most difficulty detecting CMV in data modeled with congeneric CMV. In this case, it accurately detected CMV about 64% of the time when used with an ideal marker, but its overall CMV detection accuracy was nonetheless about 84%. These results suggest, rather than simply guessing whether (or assuming) data is contaminated by CMV, the CFA marker approach can contribute to making more informed judgments when it is used as intended (i.e., with an ideal marker). According to the findings of the current study, if results suggest CMV is present, authors can be reasonably confident CMV really is present, regardless of which perspective actually represents their data.

From a practical standpoint, the key to confidently and appropriately testing for the presence of CMV is dependent on availability of an ideal marker. As such, we recommend the CFA marker technique be used only as a means for providing evidence about the presence of CMV and only when researchers can be reasonably confident they have used an ideal marker. As suggested regarding the correlational approach, identifying an ideal marker for use in real data may be difficult in practice. Thus, if authors are to use the CFA marker approach to identify CMV, they must include in their study items measuring an a priori identified and thoughtfully chosen marker. This recommendation represents a departure from what we observed among published studies using a marker approach. Almost none indicated whether the marker was chosen a priori or provided any conceptual rationale for the marker used. The marker chosen often was identified only as ‘‘marker variable,’’ with no indication of its content or measurement properties. In the rare cases where the marker was identified fully, it often was a demographic characteristic (e.g., tenure; Krishnan, Martin, & Noorderhaven, 2006). As both Lindell and Whitney (2001) and Williams, Hartman, et al. (2003) point out, although factual demographic variables may have a high likelihood of being theoretically unrelated to other study variables, they are less likely to share characteristics expected to produce CMV in the first place (e.g., measuring perceptions). Authors should be able to make convincing and conceptually appropriate arguments regarding the likely true relationships between their marker and other study variables. Authors also should take care that the marker shares characteristics with the other study variables that may make it similarly susceptible to potential causes of CMV (e.g., substantive and marker items use the same response scale and anchors; Harrison, McLaughlin, & Coalter, 1996). Authors can more credibly support their findings regarding CMV if they combine cogent arguments regarding the appropriateness of their chosen marker with equally cogent arguments regarding why a given perspective may or may not represent their data.

In sum, based on our results, we cannot recommend any post hoc CMV technique as a means for correcting CMV's potential effects in a given data set, nor can we recommend any technique as means of detecting bias. We do, however, suggest the CFA marker technique can be applied with an appropriate marker variable to test for the presence of CMV. We emphasize, however, that we do not recommend the CFA marker technique as a definitive mechanism for identifying CMV. Rather, we simply suggest the technique as one means of providing some (as opposed to no) evidence about its presence or absence.

Advice to Reviewers

So far, our advice has been mostly statistical and aimed at authors attempting to address CMV based on their preferred perspective, while also addressing reviewer concerns about CMV that may be from a different perspective. We believe that our results can be of benefit to reviewers who are evaluating how or whether authors address CMV in their data, and in particular when the approach used by the authors is from a perspective with which the reviewers do not agree. We approach this section based on the logic that one role of reviewers is to provide constructive comments to authors for the purpose of improving an article.

First, if reviewers advise authors about CMV, we believe they should be clear about their own perspective. Reviewers need to do more than simply criticize an article for potential CMV effects; if they think CMV may cause problems, they should specifically explain why it may exist and in what form they believe it takes. It may even be appropriate for reviewers to present evidence from existing research that CMV is (or is not) likely among the relevant constructs and measures. This information can aid authors in constructing arguments and presenting evidence intended to address CMV concerns. Second, when applicable, reviewers need to consider the suitability of any marker used in a given study. In particular, the authors' arguments regarding the theoretical relevance of their chosen marker need to be evaluated carefully, and reviewers should encourage authors to use best practices regarding markers (as described above) when applicable. Finally, we argue reviewers must understand there are multiple perspectives regarding CMV and, to some extent, accept there is no definitive evidence to date suggesting that one perspective is universally appropriate. Consequently, disagreement over perspective choice leads to reasonable but divergent approaches to study design and data analysis. This is not to say that authors should necessarily feel comfortable using all self-report data or that they can treat concerns about CMV superficially, thereby ignoring reviewer comments simply because their own perspective differs. Rather, both authors and reviewers need to recognize they may be wrong in how they conceptualize CMV and, thus, work with each other to help rule out alternative explanations that may result from different CMV perspectives. Using the CFA approach to provide evidence about CMV presence may be one way of doing so.

## Limitations and Future Research

Although we believe our results provide compelling evidence regarding the risks and potential benefits associated with the three statistical detection and correction techniques, they should be considered in light of the study's limitations. First, we designed the data to simulate the effects of variance stemming from a single method used with a single respondent because, arguably, this is the situation most likely to raise concerns about method bias (Spector, 1994). Second, we examined only a subset of the myriad conditions researchers may face when dealing with real data. With unlimited time and resources, we could have manipulated additional aspects of the data to increase the extent to which it represented the possible population of data in the real world. For example, we could have modeled multivariate relationships and multiple method factors. We also could have examined a broader range of marker true correlations and looked at CMV that was congeneric within constructs as well as across them. Nonetheless, our simulated data provide an important first step, and it allowed us to examine technique accuracy in ways that would not be possible had we used data from real respondents, which is characterized by unknowable conditions. It is possible that the correction techniques might perform even more poorly in real data contaminated by multiple causes of CMV.

The current study implies four distinct needs for future research. First, as this study is one of the first to empirically evaluate multiple detection and correction techniques, the results need to be replicated and extended. For example, examining the techniques—especially the CFA marker technique—in a multivariate context may prove worthwhile. Second, given the potential usefulness of the CFA marker approach for identifying CMV in data when used with an ideal marker and the potential difficulty of identifying an ideal marker a priori, research examining the ''idealness'' of a selection of generalized markers for use with measures commonly studied in the organizational sciences may be valuable. Third, more research clearly is needed to determine the likelihood and nature of CMV in typical data, because disagreements about this issue abound. Fourth, new detection and correction techniques should be proposed and evaluated.

## Conclusion

In a recent commentary directed toward *Journal of Organizational Behavior* contributors, Editor Neal Ashkanasy (2008, p. 264) writes, ''…..authors need at a minimum to address potential threats to validity occasioned by common methods. While common methods issues are controversial in some respects (e.g., see Spector, 2006), they cannot be ignored.'' Review of the organizational literature suggests despite—or perhaps because of—the CMV debate, many others share this sentiment. It is, therefore, unsurprising that researchers appear to be increasingly relying on post hoc statistical detection and correction techniques to provide evidence regarding the likelihood and/or extent of CMV and bias in their data. Our study suggests doing so frequently may be no better than ''throwing darts in the dark,''[iv] leading researchers to falsely conclude CMV is not present and biasing their data or vice versa. Given this situation, it is possible that published work using these techniques has drawn misleading conclusions about the presence and extent of CMV in results. It also is possible that research not contaminated or biased by CMV has not been published because application of a correction or detection technique falsely indicated findings were a function of CMV. As such, a primary contribution of our article is to make authors and reviewers aware of the potential risks associated with using these techniques. Because there are so few instances where any of the techniques performed with a high degree of accuracy, an additional contribution is to suggest when and how one technique can be used with cautious confidence. That is, although all techniques produced highly inaccurate corrected correlations, the CFA approach demonstrated some promise at detecting CMV (but not bias), provided it was used with a truly ideal marker.

Our article also provides a useful perspective on the CMV debate by framing it as one of competing perspectives. If the CFA approach indeed proves to be accurate at detecting CMV, its future use can help settle this debate. As such, we hope the current study advances and inspires future research, addressing both what effects CMV may have (if any) and how authors should address CMV concerns when appropriate. Ultimately, organizational science scholars need to know if CMV is, indeed, a dreaded monster or a just a ghost story. Depending on the answer, they also need to know what must be done to control the beast or stop the nightmares.

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[i] Techniques reviewed by Podsakoff et al. (2003) but not addressed here are Harman's single factor test (which is subsumed in the unmeasured latent method construct [ULMC] approach), partial correlation, and multitrait-multimethod (MTMM).We do not consider partial correlation (Williams & Anderson, 1994) because it controls for common method variance (CMV) using a variable with a specific conceptual meaning (e.g., social desirability). Although CMV effects can be simulated across data, simulated variables have no inherent conceptual meaning. We do not consider the MTMM approach because it requires use of multiple methods—making it as much a procedural as statistical means of dealing with CMV. As we address statistical corrections, we deemed the MTMM technique as beyond our focus.

[ii] Note that we cannot hypothesize the performance of the correlational marker, confirmatory factor analysis (CFA) marker, and ULMC strategies relative to no correction in the nonideal condition, as the effects of overcorrecting

versus not correcting will be a function of the extent to which the marker has a true relationship with the study's focal variables compared with the degree of CMV contamination. Likewise, we cannot hypothesize the performance of the correlational and ULMC techniques relative to one another because this performance will depend on whether the measurement error present in data is greater than the spurious additional variance captured by the ULMC strategy.

[iii] Corrected correlations were not used in the analyses of the CFA marker and the ULMC approaches unless the statistical tests indicated CMV and bias were present. Researchers applying these approaches would use model comparison to test for bias or CMV before drawing conclusions based on the corrected correlation. If model comparison did not indicate bias or CMV, the corrected correlation would not be used. In these instances, we constructed confidence intervals around the uncorrected correlation and also used it to calculate error— thereby making these tests very conservative. The logic behind this approach is that it allowed us to compare the accuracy of conclusions about correlations based on the choices researchers are likely to take given the results of CMV and/or bias detection from the same technique, that is, as opposed to the accuracy of the techniques only in the subset of data for which CMV or bias is found.

[iv] We thank an anonymous reviewer for suggesting this apt description.