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A Retrospective Analysis of Common Method Variance in Communication Research

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Abstract

There have been no systematic research efforts evaluating the effects of using self-report measures to collect data at a single point in time on research within the field of communication. In the present study we apply the marker variable approach to retrospectively analyze the extent of method bias in past communication research. Our findings indicate a significant problem in the field, with close to one in every three relationships examined becoming nonsignificant after being adjusted for common method variance. It appears that method variance is a relatively bigger contaminant in measurement within communication research compared to most other social science fields. This is particularly troubling given the increased emphasis on socially relevant research within our field. The overall findings point to the need for greater a-priori evaluation and proper accounting for method bias in future communication research.

Keywords: common method bias, method variance, communication science, methodology, empirical research

A Retrospective Analysis of Common Method Variance in Communication Research

Empiricism is central to the scientific study of communication. Many communication scholars utilize self-report surveys to gather empirical observations and validate hypothesized relationships between theoretical constructs. More often than not such studies utilize cross sectional designs wherein the independent and dependent constructs are measured at a single point in time using the same measurement instrument. Observations collected using such designs can be confounded by measurement artifacts that are difficult to detect because of the single method used to collect the data.

Common Method Variance (CMV) refers to the amount of spurious correlations shared among variables in a study due to this common method used in collecting data (Buckley, Cote, & Comstock, 1990; Malhotra, Kim, & Patil, 2006). It stems from the systematic error variance shared among measured variables as a function of using the same method to collect all the data. While CMV can inflate or attenuate relationships, it is usually expected to cause inflation when the method variance components of the individual measures are more positively related than the underlying true relationships (Conway & Lance, 2010; Doty & Glick, 1998; Lance et al., 2010; Williams & Brown, 1994). There is some debate as to whether all the manifest items in a study are contaminated to the same degree by a single cause of CMV or whether its effects are congeneric and unequal among the measures in a study. A large body of research, however, supports the non-congeneric perspective and only three studies to-date supports the congeneric effects perspective (Podsakoff et al., 2003; Richardson et al., 2009).

Researchers in other social science disciples and reviewers routinely acknowledge the problem of CMV and many journals expect authors to provide an estimate of method bias in submitted research. For instance, among 163 empirical articles published in *Academy of*

Management Journal and *Journal of Applied Psychology* in 2007 alone, almost half mention CMV and related issues (Richardson, Simmering, & Sturman, 2009). In contrast, there appears little mention of it in the communication discipline. A keyword search across all empirical research published to-date in *Journal of Communication*, *Human Communication Research*, and *Communication Research* netted only 11 articles that mentioned method bias, common method variance, or method variance. Typically authors devoted a single sentence to the issue and invoked it as a limitation of prior research when applying a novel methodology in their own research. Moreover, none of the articles provide a diagnosis or test for method related biases in their research. This absence of a diagnosis or testing of method bias in our field might be due to a lack of understanding of the issue and its potential impact.

There are three main facets of CMV that necessitates an evaluation of its affects in communication research. First, CMV inflates the observed correlations among variables thereby obscuring their true relationships. It makes it difficult to differentiate between the actual phenomena under investigation from measurement artifacts (Hufnagel & Conca, 1994). Conclusions based on such spurious observations could be dangerous especially given the increased emphasis on socially relevant research in the field of communication. Second, there are a number of sources of CMV in a study. These include construct characteristics, social desirability, ambiguous item wording, and scale length (Podsakoff et al., 2003 provide an extensive overview of all the sources of CMV). From these, the types of constructs that are measured in a study are a particularly important source (Cote & Buckley, 1987). Measures for abstract or difficult to interpret constructs such as attitudes and beliefs are more prone to CMV effects because the respondents' own tendencies and biases are more likely to systematically conflate with their interpretation and responses to these measures (Podsakoff et al., 2003). In contrast, concrete concepts such as the perceived attributes of innovations and satisfaction are less prone to the effects of such biases (Malhotra et al., 2006). Scholarship in communication focuses on a broad array of constructs ranging from abstract concepts such as perceived communication competence and message resonance to more concrete concepts such as media use, interactivity, and behavioral intent. Hence, we would expect significant variances in the affects of CMV in communication research. Finally, CMV effects vary by discipline and therefore, understanding its affects requires a discipline specific investigation (Podsakoff et al., 2003). CMV effects range from 15.8% in marketing, 18.6% in management information systems (MIS), 23.8% in management, 28.9% in psychology and sociology, to 30.5% in education research (Crampton & Wagner, 1994; Malhotra et al., 2006). CMV effects within the communication discipline have, however, never been systematically evaluated and the magnitude of this problem in communication research remains unclear.

The lack of research in the communication discipline stems, in part, from the extant methodological techniques for evaluating CMV effects. Most of these techniques are tedious or statistically intensive, require multiple waves of measurement, and are best applied prospectively by researchers suspecting method bias effects on the measures of a study. Recent methodological advances, specifically the marker variable approach proposed by Lindell and Whitney (2001), make it possible to study CMV on a posteriori basis and evaluate its affects across multiple studies. In the present study we undertake a retrospective evaluation of CMV effects in communication research using this approach. In doing so, the paper hopes to bring an increased awareness about the issue and provide guidance to researchers on how to detect and correct for CMV in their own research. The overall goal then is to improve the quality of empirical research in our field.

We begin the next section by briefly describing the extant methodological approaches to evaluating CMV followed by a detailed explanation of the marker variable technique.

Methodological approaches to detecting CMV

There are four approaches to estimating CMV. Two from these are methodological approaches while the others are statistical techniques. All the approaches have their inherent strengths and weaknesses; a detailed assessment of each approach is provided by Bagozzi (2011), Brannick et al. (2010), Lance et al. (2010), and Malhotra et al. (2006). Briefly, the first methodological approach, the Multi Trait Multi Method (MTMM) procedure (Campell & Fiske, 1959), requires the measurement of multiple constructs using multiple methods in order to detect method bias. The observed correlations for each construct's measures across the different methods are arrayed in a MTMM correlation matrix. CMV is assumed to exist if the average of the correlations for all the constructs measured using the same method is greater than the average of the correlations for all the constructs measured using different methods.

A second approach to detecting CMV is an analytic procedure that utilizes confirmatory factor analysis (CFA) to explicate the amount of influence the different methods in the traditional MTMM procedure have on the constructs being measured. In this CFA-MTMM approach, the observations for each construct are modeled as a function of the latent construct and its measures, some random error, and the methodology used to collect the data. This approach makes it possible to pinpoint the amount of influence each method factor has on the overall observations and estimate the true relationships between the latent constructs free from measurement error.

Another analytic approach to detecting CMV is Harman's Single Factor Test. It is by far the most widely known and applied approaches for detecting method bias because of its simplicity and because it can be applied in a study that utilizes a single method to collect the data. In this approach, all the items in a study are subjected to an exploratory factor analysis and CMV is assumed to exist if the unrotated factor solution nets a single factor, or if a single factor accounts for the majority of variance among the variables (Podsakoff & Organ, 1986). A CFA could alternatively be used in this approach, wherein all the items are modeled as indicators of a single latent factor and CMV is evidenced if that one factor were to best fit the data.

The newest approach to detecting CMV is the marker variable technique (Lindell & Whitney, 2001). This technique is a methodological as well as an analytical framework built on the assumption that a method factor is noncongeneric and has a constant correlation with all the measures in a study (Richardson et al., 2009). In this approach, a criterion variable that is theoretically unrelated to at least one variable in the study is included in the data collection. This criterion variable serves as a marker of CMV because it is expected to have no relationship with one or more variables in the study. Hence, any correlation between the marker variable and the theoretically unrelated variables serves as an estimate of CMV. While Lindell and Whitney (2001) advocate a correlational approach for testing and then partialling out the method effect, some scholars have incorporated the marker approach into the CFA framework by modeling the marker variable as a latent construct with paths to the substantive constructs in a study. The correlational marker approach, however, remains the dominant application of the marker variable technique and only a handful of studies have applied the CFA marker approach (Richardson et al., 2009).

The correlational marker variable technique has a number of inherent advantages over the other approaches to detecting CMV and is applied in this study. First, unlike the MTMM approach that requires multiple methods of measurement and at least twice the number of items measured (Lindell & Whitney 2001), the marker variable approach in general can be applied within a single methodology. This makes it easier for researchers to utilize the approach and reduces the chance of respondent fatigue and related restrictions that forces researchers to limit the scope of multi-method studies. Second, unlike the CFA based approaches that involves complex statistical modeling which often results in a highly parameterized, under identified model (Podsakoff et al., 2003) consequently requiring large samples with large degrees of freedom (Brannick et al., 2010), the correlational marker variable technique relies on mostly elementary statistical techniques. Third, the correlational marker variable analysis is not dependent on the number of latent factors measured and is capable of detecting very small CMV effects. In contrast, an approach like Harman's Single Factor Test is insufficiently sensitive to detect moderate or small CMV effects (Podsakoff et al., 2003) because as the number of latent factors being measured increases, the likelihood of netting a single factor solution decreases. Moreover, the level of sensitivity of the correlational marker variable analysis can be adjusted to account for varying degrees of CMV.

Fourth, an empirical comparison of marker variable approach against the traditional MTMM, CFA based MTMM, and Harman's single factors test by Malhotra et al. (2006) found that the correlational marker variable approach was quite robust against the violation of its major assumption, that the measures in a study are non-congeneric and equally influenced by the method factor. Furthermore, they found the technique provided reliable parameter estimates and the results based on the marker variable approach were consistent with the CFA based MTMM approach. In a subsequent study, Richardson et al. (2009) used simulated datasets to compare the CFA marker, CFA-MTMM and correlational marker variable approaches and found that the correlational marker approach was by far the most accurate at detecting method bias when an appropriate marker variable was employed, regardless of whether the true method bias was congeneric or noncongeneric. The technique had a bias detection rate of close to 97% but seemed to overestimate bias when a non-ideal marker variable that was not theoretically unrelated to the manifest construct was employed.

Finally, except for the correlational marker approach, all the other techniques to detect and correct method bias are best applied on a prospective basis by a researcher suspecting CMV in a study or by researchers attempting to develop construct measures that are free from measurement issues. The correlational marker variable approach, however, can be adapted to estimate CMV in prior research within a discipline. In a recent study, Malhotra et al. (2006) applied the technique to retrospectively assess CMV effects in Information Systems (IS) research. To the extent that the two fields share some overlapping domains of research, their study provides a benchmark for contrasting our results. Overall, our study attempts to answer the following research question: What is the extent of common method variance (CMV) in communication research?

Marker variable analysis to assess CMV in prior communication research

A researcher applying the marker variable framework in a single study design needs to identify a marker variable, r_M, before the start of the data collection. Partialling out r_M from the uncorrected correlations (denoted as r_u) and testing the significance of the CMV corrected correlation (denoted as r_A) provides an estimate of the magnitude and significance of method variance on the observed correlations (Lindell & Whitney, 2001). This computation focuses on variables that are positively correlated. Variables that have a preponderance of negative correlations with other variables are represented as positive by reverse coding them or if the negative correlation is because of a linear constant, such variables are excluded in the analysis.

For a sample size of n, r_A is computed by the formula:

$$r_A = (r_u - r_m) / (1- r_m)$$

The t-statistic to test the significance of r_A for α of 0.05 is computed as follows:

$$t_{(\alpha/2,\ n\text{-}3)} = r_A / \sqrt{}(1- r^2_A)/(n-3)$$

CMV can also be estimated in a post hoc fashion by selecting the smallest positive value in the correlation matrix as a proxy for CMV (Lindell & Whitney, 2001). In fact, close to half of all studies applying the marker variable technique tend to choose a marker variable on a post hoc basis (Williams, Hartman, & Cavazotte, 2003). In the present study, such a correlation is denoted as r_{M1}. Because the correlations among variables in a study reflect their true correlations, measurement error, as well as the affect of CMV, the criterion correlation r_{M1} would be a conservative estimate of CMV. Further, because the post-hoc approach has the potential to capitalize on chance factors, Lindell and Whitney (2001) recommend using the second smallest positive correlation r_{M2} as a better estimate of CMV.

In an extensive review of the applications of the marker variable approach in the field of organizational behavior, Williams et al. (2003) found that researchers have used CMV markers ranging from multi-item to single-item Likert-type scales, objective questions, and factual demographic questions. Williams et al. (2003) recommend against the use of demographic and other factual variables as markers because these measures might not suffer from the same types of biases (such as item ambiguity, transient mood states, demand effects, and such) that substantive study measures might suffer. Therefore, they advocate the selection of an ―ideal marker variable” that is in someway linked to the substantive variables in a study either in terms of measurement similarity or in terms of the types of underlying biases that might infect it.

Thus, in the present study, we also looked for the smallest reported correlation between a variable that was measured in a manner that was most similar to the substantive variables in a study; a substantive variable was one that was central to a hypothesis or a research question posed in the study. The smallest positive correlation between such variables (r_{M3}) and the second smallest such correlation (r_{M4}) were treated as ideal markers. CMV adjusted correlations (r_A) were computed using Lindell and Whitney's (2001) formula by replacing r_M with r_{M1}, $r_{M2,}$ $r_{M3,}$ r_{M4} consecutively. Using the t-test formula, the significance of r_A for each level of r_m (i.e., $r_{M1...4}$) was subsequently tested. Hence, any correlation that remained significant at the increasingly stringent r_M levels was least likely to be affected by method variance (Lindell & Whitney, 2001).

Furthermore, an important feature of the correlational marker technique is referred to as a sensitivity analysis. The need for a sensitivity analysis was primarily motivated by the recognition that the estimate of method variance associated with the marker variable is subject to sampling error (Williams et al., 2011). To deal with this concern, Lindell and Whitney (2001) recommend computing the point estimates for the marker correlations and using the larger values of r_m in the partial-correlation adjustment. Partial correlations that remained statistically significant at all these levels of the marker variable are least likely to be influenced by CMV.

Sample of research examined

To identify the studies for which the marker variable framework was applicable, the present research examined all past issues of the *Journal of Communication, Communication Research,* and *Human Communication Research* over a 10-year period from January 2000 – December 2009. Studies that were published in these journals were selected for our analysis if the data on the independent and dependent variables were collected using a single instrument, and the correlations between the variables were reported. A total of 27 articles met our criteria.

The list of articles used in the study is presented in the Appendix. To test whether CMV accounted for the observed relationship between variables, we focused our analysis only on the correlations between the independent and dependent variables that were positive and statistically significant at the 0.05 (two tailed) level. Based on this a total of 139 significant correlations were located and subsequently analyzed.

Results

Common method variance in communication research. Within each study, we selected the smallest reported correlation (r_{M1}) and the second smallest reported correlation (r_{M2}) as markers of r_M. We also selected as ideal markers the smallest (r_{M3}) and second smallest (r_{M4}) reported correlation between a variable that was measured in a manner similar to a substantive variable in a study. Next, in each study we computed the CMV adjusted correlations (r_A) from the respective marker variables ($r_{M1\ldots4}$) and tested the significance of the adjusted correlation.

Table 1 presents a summary of our analyses. The average sample size across 27 studies was 607 (*median* = 337, *s.d.* = 762.15). The average uncorrected correlation across these studies was 0.29. When r_{M1} was used as the estimate of CMV, the average size of r_M was 0.02 and the average CMV adjusted correlations (r_A) was 0.28. At this level of r_M only 5 percent of originally significant correlations became nonsignificant. When r_{M2} was used as the estimate of CMV, the average size of r_M was 0.04 and the average CMV adjusted correlations (r_A) was 0.26. At this level of r_M 12 percent of significant correlations became nonsignificant.

The average size of r_{M3} was 0.04, which although identical to $r_{M3,}$ had a higher standard deviation; the average CMV adjusted correlations (r_A) was 0.25. At this level of r_M only 17 percent of significant correlations became nonsignificant. When r_{M4} was used as the estimate of

CMV, the average size of r_M was 0.07 and the average CMV adjusted correlations (r_A) was 0.23. At this level of r_M 30 percent of significant correlations became nonsignificant.

We further expanded our analysis and examined the sensitivity of the reported correlations to increases in the marker variable. We conducted a sensitivity analysis by increasing r_M in small increments, 0.10, 0.15, 0.25, 0.35, and testing the CMV adjusted correlations at each increment. It is important to note that realistically r_M is expected to be around 0.10 or less in most social science measurement (Malhotra et al., 2006). When r_M was increased to 0.10, one in three (33%) of all correlations became nonsignificant; at r_M of 0.15, close to the half (45%) of all correlations became nonsignificant. Increases beyond 0.20 resulted in the vast majority of correlations (66% and 78%) becoming nonsignificant.

Furthermore, given the relatively large variance and positive skew (*skewness* = 2.58) in the distribution of sample sizes across the communication research articles examined, we estimated the influence of method bias within a more restricted range of sample sizes. Ten studies with sample sizes over 450 fell in the top quartile of the distribution and were excluded from the analysis. The remaining 17 articles had an average sample size of 230 (*median* = 213) and the distribution of sample sizes was less skewed (*skewness* = 0.25). The average sample size across these communication studies was fairly comparable to those in other social science research areas. Table 2 presents a summary of the subset analyses.

Within this subset of research articles, the average uncorrected correlation was 0.31. The method markers increased marginally (by 0.003) but for the most part remained the same. The average original correlation across the sample was 0.31. At the level of r_{M1} the average CMV adjusted correlations was 0.29 and 7 percent of significant correlations became nonsignificant. At r_{M2} the average CMV adjusted correlations was 0.29 and 15 percent of significant correlations became nonsignificant. At r_{M3} the average CMV adjusted correlations was 0.27 and 15 percent of significant correlations became nonsignificant. At r_{M4} the average CMV adjusted correlations was 0.23 and 32 percent of all significant correlations became nonsignificant.

When r_M was increased to 0.10, more than a third (37%) of all correlations became nonsignificant; at r_M of 0.15, 48 percent of all correlations became nonsignificant. At increases in the method factor beyond 0.20, the vast majority of correlations (72% and 81%) became nonsignificant.

Discussion

The research examined the influence of method variance in communication research. The overall analysis examined research published in the top journals in the field over the last ten years and examined the size of the method markers in each study. The average markers ranged from 0.01 – 0.07. In contrast, similar research in the MIS field found marker variables ranging from 0.08 - 0.11 (Malhotra et al., 2006). At these levels of the method factor 22 percent of all correlations within the MIS field became nonsignificant. In the communication field, a relatively lower size of the marker variables (0.07 for the ideal marker r_{M4}) resulted in 30 percent of all correlations becoming nonsignificant. Interestingly, the average sample size across the MIS studies was 214 compared to 608 across the communication field. When method bias was examined among communication research with a sample size comparable to the MIS studies, the use of the more conservative ideal marker (r_{M4}) resulted in 32 percent of all correlations becoming nonsignificant.

The research further conducted a sensitivity analysis by varying the size of the method marker. When the marker variable was increased to 0.10, a level that closely approximates the MIS levels of the marker, between 33 and 37 percent of all reported correlations became nonsignificant. At the 0.15 level, between 45-47 percent of all correlations became nonsignificant.

As reported earlier, the effects of CMV at its lowest is 15.8 percent in marketing science and 30.5 percent at its highest in education research (Crampton & Wagner, 1994). Compared to these, the extent of CMV in communication research, even after taking into account the higher than average sample sizes in our studies, is among the highest. In the field of communication, method effects potentially conflate more than one out of every three relationships that is reported as being significantly correlated.

The high method variance across the field of communication is perhaps because of the nature of research in our field. A large volume of research in the field remains exploratory, often amalgamating perspectives from other social science fields, and although many communication research studies use large representative samples, many continue to explore and test the relationships between weakly related variables. Moreover, when compared to constructs from other fields such as consumer behavior and MIS, many communication constructs are relatively abstract, making both operationalization and measurement difficult. Weakly operationalized constructs along with measures that are ad-hoc, study specific, poorly constructed, and at times poorly adapted from other fields, heighten the degree of error in measurement. Such issues are not easily corrected by enhancing the size of the sample or through the use of professional data collection enterprises. Only 11 of the studies we examined in this research actually used a student sample and almost all other studies used a professional survey organization for their data collection. Hence, if anything the use of general population samples in conjunction with poor measurement practices adds to the total amount of noise in the data. This problem seems to be endemic to the field of communication and is perhaps heightened is certain areas of study where the constructs are relatively abstract such as in health communication or interpersonal communication research compared to mass communication or communication and technology related research. Although the analysis evaluated over a hundred individual correlations, the relatively small number of studies from each cognate area restricted our ability to specifically examine whether research topics or certain types of constructs resulted in increased method bias. This remains a limitation of the current study and a topic ripe for future exploration.

Besides this, there are at least four other limitations mostly stemming from the marker variable approach applied in the study. First, the maker variable approach requires a correlation matrix, which limited our examination to the studies that presented correlation matrices. Researchers also vary in how they report the correlations in their study and there seems to be no best practice that everyone uniformly follows. Some provide a matrix of all variables that they collected data on while others report only the relationships that are central to a study. We are assuming that the relatively large number of articles reviewed and the large number of correlations examined by us to some extent diffuses any selection issues across the studies examined. Moreover, the number of correlations and studies we reviewed closely parallels the number of correlations reviewed in other fields (e.g., Malhotra et al.'s review of MIS research), pointing to the lack of a systematic problem with the way correlations are reported in our field, that is to say, there are no more or fewer correlations across studies being reported within our field.

Second, the marker variable approach is arguably a conservative approach because it assumes that the constructs are measured without measurement error. Measurement error would typically attenuate correlations (Lance et al., 2010; Williams et al., 2010) potentially underestimating the extent of method bias in a study. Recognizing this, Lindell and Whitney

(2001) provided a formula to correct for such attenuation based on sample estimates of the reliabilities of the involved variables. There is, however, no significance test for the attenuation-corrected partial correlations making the application of this correction difficult (Williams et al., 2010). Furthermore, this approach has been criticized because it is just as likely for the bias correction to result in an overestimation of the method effects (Lance et al., 2010). For these reasons, there appears to be few research studies that correct for attenuation using this approach (Williams et al., 2010). Further limiting us in the present study was that a number of reported correlations were among one or more single item variables and many studies we examined did not report the reliabilities for all the variables measured. To the extent that this issue is a limitation of all applications of this methodology, the results of our studies become comparable to all the studies applying the same methodology in other fields. It is, however, important to note that multi method approaches such as MTMM also suffer from this issue because mono method and hetero method correlations reflect the influence of correlated traits and correlated methods and measurement unreliability would attenuate these relationships as well (Lance et al., 2010).

A third limitation that is inherent to all applications of the marker variable approach is that it only assesses whether a significant zero order correlation between variables remains significant after partialling out a third variable—a proxy for the method factor. Thus the focus is on the difference between the significance levels rather than the statistical significance of the difference between the zero order and partialled correlation (Gelman & Stern, 2006). It is likely that some of the correlations that became nonsignificant after partialling out the method factor might not be significantly different from the zero order correlations, suggesting the lack of a substantive effect for the method factor. Again, the idea behind the marker variable approach is not to tax or reduce the zero order correlation by the method marker but to use a series of increasingly stringent tests as indicators of the likelihood of method variance contaminating a relationship. The more stringent the test criteria passed successfully, the greater the confidence in rejecting CMV as a plausible rival hypothesis (Lindell & Whitney, 2001). The final decision on whether method bias is a substantial problem in a study must be judged not only based on the significance of the partialled correlations but also based on whether the differences between the original and corrected correlations are substantial enough to warrant a reexamination of the measurement approach of the study.

Finally, the marker variable approach is based on the assumption that all the items in a study are affected to the same extent by method variance. Lindell and Whitney (2001) provide theoretical arguments in support of this assumption stemming from Wilk’s (1938) theorem and the vast literature on equal versus differential weights in regression analysis. Subsequent empirical comparisons of the CMV approach against other approaches that make the opposite assumption (congeneric method effects) has shown that the marker variable technique was quite robust and this assumption did not distort the results significantly enough to alter conclusions (Malhotra et al., 2006; Richardson et al., 2009). The non-congeneric effect of method variance on the measures within a study is, however, an assumption and thus a limitation worth noting.

Although these assumptions appear somewhat strict, such limitations are common to all analytic methodologies. For instance, researchers routinely assume that their ordinal measures have interval qualities with homoscedastic variances; techniques such as exploratory factor analysis rely on orthogonal rotations even when the scale items are expected to be interconnected and the factor weights are considered equal even when their factor loadings vary (Lindell & Whitney, 2001). Likewise, popular analytic techniques such as SEM require multivariate normality among observed variables, a situation that is hardly met in practice (Malhotra et al., 2006), while techniques such as social network analysis, that is very common in the field of communication, almost always violate the independence of observation assumption required for multivariate analysis. In all such cases, the question has been not whether the assumptions are correct, but rather whether the limitations are apparent, and the extent to which the methodology approximates reality and provides reasonably reliable estimates with some known deviations.

Finally, as we examine the limitations of the marker variable approach, it is important to note that none of the extant approaches to measuring method variance is without its detractors. Even the MTMM approach that many consider to be a robust technique for assessing method bias in a study (Bagozzi, 2011) has been criticized because different (hetero) methods are subject to covariance distortion because methods also tend to be correlated with each other, and depending on the direction of these correlations and the unreliability in measurement, this could attenuate or distort the method effects (Lance et al., 2010). Likewise, the CFA-MTMM and Harman's Single Factor test have also been criticized (Podsakoff et al., 2003, Williams & Anderson, 1994) even as newer approaches such as the comprehensive CFA based marker technique (Williams et al., 2010) and newer remedies for simultaneously correcting for attenuations and method effects in the MTMM approach (Lance et al., 2010) have been introduced.

The many different approaches with their respective advocates and critics, and the lack of a gold standard that dominates all (Bagozzi, 2011), have resulted in some scholars suggesting that the concept of method variance itself might need to be retired from the scientific vocabulary (Brannick et al., 2010). While it might be apt to throw up our hands and conclude that no approach is viable, "~~it~~ would be misleading and self-defeating [to do so]… drawbacks of approaches should not be taken as absolute stigmas and lead one to categorically avoid them."

(Bagozzi, 2011, pp. 288). Instead, each approach has its distinct advantages and the optimality of each approach is dictated by the study, the types of data, and the statistical procedures planned. Hence, similar to the SEM approach of using different, sometimes conflicting, indicators for the goodness of fit of a model, the different approaches for assessing method variance provide reasonable estimates of the likely issues related to measurement within a study or among studies within a field (Bagozzi, 2011), and its is left to the individual researcher's judgment about the appropriateness of a method in a context.

We find the marker variable approach particularly appealing because of the simplicity and the ease of its interpretation and use. Marker variables can be designed on a priori basis or selected on a post hoc basis and the computations can be easily accomplished by anyone with a basic understanding of statistics. In a field where methodological training is still not top priority and where a journal dedicated to methods and measures was only recently introduced, having a simple, ease to use mechanism to assess measurement validity makes it far more likely that that at marker variable approach would be adopted and applied. Moreover, among the extant methods to assess method bias in a field, the marker variable approach remains the only one that can be adapted to retrospectively assess the amount of method variance in mono method studies across a field of research.

The current study is the first to examine the issue of method variance within the field of communication. The results are noteworthy and point to a relatively high level of method variance in research in our field compared to the other social sciences. Given the increased emphasis on socially relevant research in the field of communication, it is especially troubling if a third of all our conclusions were untenable. The results therefore suggest the need for better methodological training and measurement practices. The availability of a new journal for methods and measures is a first step in that direction because it provides an outlet for scholars to highlight, present, and learn about methodological issues. We are further hopeful that our research draws attention to such measurement issues and spurs scholarly interest in the assessment of measurement validity within the field of communication. We also believe scholars should test for method bias in their research and reviewers and journal editors should routinely expect some clarification as to how the possibility of this contaminant was examined in a research. This clarification can be easily provided by selecting a marker variable, partialling out its effects, and conducting a sensitivity analysis, or by the application of another mechanism available for testing for such bias. Together, the use of such approaches would vastly improve the quality of the research within the field of communication.

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Appendix

List of Articles Analyzed

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Table 1.

Summary of Results

					Sensitivity analysis			
	r_{M1}	r_{M2}	r_{M3}	r_{M4}				
	0.02 ($s.d.$=0.01)	0.04 ($s.d.$=0.03)	0.04 ($s.d.$=0.05)	0.07 ($s.d.$=0.06)	0.10	0.15	0.25	0.35
Original studies								
Average (n)	607.93	607.93	607.93	607.93	607.93	607.93	607.93	607.93
Average (r_u)	0.29	0.29	0.29	0.29	0.29	0.29	0.29	0.29
CMV adjusted								
Average r_A	0.28	0.26	0.25	0.23	0.21	0.16	0.05	-0.09

% of correlations becoming non-significant	5%	12%	17.27%	29.5%	33%	45%	66%	78%

Note. s.d. = standard deviation

Table 2.

Summary of Results with Reduced Sample Size

					Sensitivity analysis			
	r_{M1}	r_{M2}	r_{M3}	r_{M4}				
	0.02	0.04	0.04	0.07	0.10	0.15	0.25	0.35
	($s.d.$=0.01)	($s.d.$=0.04)	($s.d.$=0.04)	($s.d.$=0.07)				
Original studies								
Average (n)	236.33	236.33	236.33	236.33	236.33	236.33	236.33	236.33
Average (r_u)	0.31	0.31	0.31	0.31	0.31	0.31	0.31	0.31
CMV adjusted								
Average r_A	0.29	0.29	0.27	0.23	0.23	0.18	.08	-0.06
% of	6.8%	14.77%	14.94%	32.22%	36.36%	47.72%	71.59%	80.68%

correlation

s becoming

non-

significant

Note. s.d. = standard deviation