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ABSTRACT

The issue of common method variance (CMV) has become almost legendary among today's business researchers. In this manuscript, a literature review shows many business researchers take steps to assess potential problems with CMV, or common method bias (CMB), but almost no one reports problematic findings. One widely-criticized procedure assessing CMV levels involves a one-factor test that examines how much common variance might exist in a single dimension. This paper presents a data simulation demonstrating that a relatively high level of CMV must be present to bias true relationships among substantive variables at typically reported reliability levels. The simulation data overall suggests that at levels of CMV typical of multiple item measures with typical reliabilities reporting typical effect sizes, CMV does not represent a grave threat to the validity of research findings.

1. Introduction

Academic business researchers currently pay tremendous attention to the potential influences of common method variance (CMV) and common method bias (CMB) (Bagozzi, 2011; Lance, Dawson, Birkelbach, & Hoffman, 2010; Malhotra, Kim, & Patil, 2006; Richardson, Simmering, & Sturman, 2009; Sharma, Yetton, Crawford, 2010; Sharma, Yetton, Crawford, 2009; Williams, Hartman, & Cavazotte, 2010). A search of the *Journal of Business Research* (*JBR*) database reveals CMB as the most conventionally used term with 239 articles in the *JBR* referring to "common method bias," dating back to 1985 (Oliver and Bearden, 1985), with mentions increasing dramatically in the past 3 years. A total of 203 articles to date (many overlapping with the 239), refer to "common method(s) variance." In addition to these reports appearing in print, many others potentially address reviewer queries related to CMV in earlier manuscript versions or directly in notes to reviewers or reviewer appendices. The hundreds of papers represent considerable attention, particularly in comparison to other typically reported and absolutely critical issues such as "construct validity," which appears 288 times. Today's survey researchers seem to face a presumption of guilt with respect to CMB.

Business researchers report post-hoc statistical tests for CMV or CMB with increasing frequency in recent years (Richardson et al., 2009; Simmering, Fuller, Richardson, Ocal, & Atinc, 2015). As more reviewers receive exposure to the concepts during review processes or doctoral training, they begin to ask potential authors more questions about CMV. Despite increased reports of tests for CMV and CMB (as demonstrated by the numerous mentions in the *JBR*), however, the vast majority of the diagnostic checks conclude that no concern due to CMB exists. Therefore, as a way of examining whether the presumption of guilt makes sense, the article addresses two research questions. First, just how much common method variance must be present to create bias sufficient to distort interpretations materially? Second, is the so-called Harman's one-factor test, which is fast and easy to apply, capable of detecting CMV at biasing levels? Given the increasingly common view that authors must report on common methods variance in self-report surveys in today's academic business research, this study addresses more widely whether the issue merits such attention, particularly in light of other potential sources of response error.

1.1. CMV and CMB in business research

CMV occurs when responses systematically vary because of the use of a common scaling approach on measures derived from a single data source. CMV biases result when the so-called method, as a causal factor, meaningfully distorts substantively-driven causal effects. However,

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CMV, should it even exist, may not produce changes in effect sizes and significance levels, may change them trivially, or may change them in an amount that is practically meaningless. Therefore, any report only addressing CMV is of limited utility. CMV biases data when it produces significant and nontrivial divergence between true and observed relationships (Ostroff, Kinicki, & Clark, 2002) and CMV itself is just one of the many sources of error that potentially lead to attenuated trustworthiness of reported results (Babin & Zikmund, 2016).

CMV may either artificially inflate or deflate correlations (Conway & Lance, 2010; Williams & Brown, 1994). Researchers place most concern in the possibility that CMV may falsely inflate observed relationships among measures. If so, biased results could cause a researcher to falsely conclude that a relationship exists (enhancing type I error). Researchers debate the nature and influence of CMV, ranging from those who argue that if CMV exists, the degree of CMV does not generally rise to biasing levels, to those who believe that distortion due to common methods is pervasive and rampant (see Brannick, Chan, Conway, Lance, & Spector, 2010; Podsakoff, MacKenzie, Lee, & Podsakoff, 2003; Richardson et al., 2009; Spector, 2006). Further, reviewers and editors may express greater skepticism regarding research that makes use of same-source, self-reported data because they believe that common methods drive effects more than the hypothesized cause (Brannick et al., 2010; Conway & Lance, 2010; Pace, 2010). Interestingly, response error sources that may drive common variance or otherwise distort results, such as low response involvement, acquiescence, or respondent dishonesty, receive relatively little notice.

1.1.1. Post-hoc tests

Business researchers typically apply one of four post-hoc statistical techniques to check for CMV and/or CMB. Traditionally, *Harman's One-Factor Test* indicates problematic CMV if an exploratory factor analysis (EFA) with all study variables produces eigenvalues suggesting the first factor accounts for more than 50% of the variance among variables (Podsakoff & Organ, 1986). The *Correlational Marker Technique* (Lindell & Whitney, 2001) provides a correction factor through use of a marker variable (one theoretically unrelated to other items in the survey) of the same scale type. The *Confirmatory Factor Analysis* (*CFA*) *Marker Technique* (Williams et al., 2010) uses a marker variable in a CFA model to detect CMV. Finally, the *Unmeasured Latent Method Construct* (*ULMC*) *test* specifies a latent construct with no uniquely observed indicators to represent shared variance between a method and the substantive constructs (Williams, Cote and Buckley, 1989).

1.1.2. Results of a review

The current review examines how recent survey-based business research addresses CMV and CMB across all articles published in *JBR* during 2011 and 2012. Of the 445 total articles in these issues, 137 articles are single-source, cross-sectional survey-based studies, which are believed to be most susceptible to bias from CMV. The first and second author independently coded whether or not each of 137 papers addressed CMV or CMB and in what way (i.e., mentioned, addressed procedurally, or addressed with a post-hoc technique). The post-hoc statistical techniques involved a consistent set of codes ("0" if the test was not used, "1" if the test was used and that study's authors concluded that CMV did not bias the data, and "2" if the test was used and that study's authors concluded that CMV biased the data). The mean inter-rater agreement between the coders across all coding was 95% (range: 86.9–98.5%). Discrepancies in coding were resolved through discussion.

Results indicate that 54 of the 137 (39.4%) papers mention CMV or CMB and that 42 of 137 (30.7%) same-source survey articles use some post-hoc statistical CMV detection technique. In these 42 papers, authors inconsistently indicate searching for CMV versus CMB. Most articles (59.5%) refer to any diagnosis or conclusion made with the term "common method bias," and fewer (35.7%) describe "common method variance."

This review suggests that researchers employ Harman's one-factor test most frequently (32 times; 76.2%) in these 42 papers, followed by the ULMC (7 times; 16.7%), the correlational marker technique (5 times; 11.9%) and the CFA marker technique (1 time; 2.4%). Two papers state no evidence of CMV without specifying a specific test. Most notably, *none* of these 42 (0.0%) studies draws a conclusion that CMV biases the data. This finding could have several explanations:

(1) CMV may be present, but CMB is not present;
(2) CMB is present, but the tests used do not detect the bias;
(3) A perceived publication bias prevents authors who do find evidence of CMB from submitting papers or when submitted, reviewers vote to reject these papers (Simmering, et al., 2015).

Both options 1 and 2 present possible challenges to the conventional thinking that CMV presents a grave and present danger perhaps over and above other potential sources of response error. That is, researchers use common methods analysis because the use appeases reviewers more than as a way of presenting results in a straightforward manner.

1.2. Use of Harman's one-factor test in prior research

Empirical studies address the efficacy of other post-hoc tests (see Richardson et al., 2009), yet Harman's one-factor test, although widely applied, remains understudied. Harman's one-factor test (also called Harman's single-factor test) uses concepts from Harman's (1967; 1976) texts on factor analysis and researchers apply the test to detect CMV. While this test bears Harman's name, whose work is often cited as the primary source of the test, the application of exploratory factor analysis (EFA) specifically to the detection of common method variance does not appear in Harman's texts (1967, 1976), and thus, the test's name originates from other sources. Researchers apply concepts regarding EFA from Harman (1967) to determine whether a third variable problem or a sizable method factor exists. Schriesheim (1979) illustrates such an early application of Harman's text to the common method issue (Schriesheim, personal communication, Feb. 21, 2011) and Podsakoff and Organ (1986) give the application the label "Harman's single-factor test."

As argued above, while CMB is truly more meaningful in terms of research findings, the earliest descriptions of Harman's one-factor test position the test as appropriate to identify common method *variance* (Podsakoff & Organ, 1986). Yet, articles summarizing techniques such as Harman's assume that any detection of CMV with the test is equivalent to the detection of bias (see Podsakoff & Organ, 1986 and Podsakoff et al., 2003). Such authors give little attention to the notion that post-hoc statistical tests may identify CMV that is not at biasing levels, and this lack of distinction continues in research. While no empirical evidence exists regarding the efficacy of Harman's one-factor test, numerous authors have warned against the use of the test. Podsakoff et al. (2003), who are frequently cited in support of the use of this technique, actually comment that for the technique to be effective, "… common method variance would have to completely account for the covariances among the items for it to be regarded as a problem in a particular study" (p. 889). Authors generally believe Harman's one-factor test to be not sensitive enough to detect CMB (Podsakoff et al., 2003).

2. Simulation

The first question in the current paper aims at determining whether or not the increased attention to common methods effects in business research creates a heresy. More specifically, does CMV equal CMB in data, or at what level does the presence of CMV create bias? Some authors have produced compelling evidence that CMV does not often occur at biasing levels (e.g., Crampton & Wagner, 1994; Lance et al.,

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2010; Malhotra et al., 2006; Spector, 2006), while others have argued the opposite (e.g., Cote & Buckley, 1987; Podsakoff et al., 2003; Sharma et al., 2009). However, the primary limitation of many of these studies is that levels of CMV were determined using real data. Actual data contains various sources of error, for which not all can be accounted; therefore, no researcher can draw accurate conclusions regarding the accuracy of CMV rates in real data. Even a comparison of self-ratings versus other-ratings of the same phenomenon potentially captures other sources of measurement error, random error, or perhaps even actual perceptual differences not attributable to error. Thus, simulated data provide a better alternative in assessing how much CMV exists in a sample, the precise point at which bias occurs, and the point at which tests can detect bias (Richardson et al., 2009).

Data simulation allows researchers to specify an amount of common variance present in data, then determine whether or not statistical methods can detect that variance (Harrison et al., 1996). By mimicking the level of CMV in simulated data along with other dataset characteristics (e.g., sample size), any mismatch between the point where CMV begins to bias data and where a given test detects CMV can be determined. If such a gap exists in simulated data, presumably this gap will also appear in actual data. However, actual data exacerbates the problem such that researchers do not see the difference between the point of bias and the point of detection. Further, simulation allows evaluation of the strengths and weaknesses of Harman's one-factor test across different levels of relationship strength (e.g., Chin, Marcolin, & Newstead, 2003).

Prior papers addressing post-hoc tests to detect CMV either ignore Harman's one-factor test (e.g., Bagozzi, 2011; Richardson et al., 2009) or present only conceptual arguments regarding the test's lack of accuracy (e.g., Podsakoff & Organ, 1986; Podsakoff, et al., 2003). With this gap in the research and the heavy use of Harman's one-factor test, this study focuses on Harman's one-factor test from this point forward. Before examining whether Harman's one-factor test can detect biasing levels of CMV, an important prerequisite is to first determine at what level CMV biases substantive relationships. If CMV does not bias data in certain cases, then there is no need to laboriously report a test to detect CMV in those cases. After surmising what level of CMV may cause bias, this research addresses whether Harman's one-factor test can detect CMV at biasing levels.

Monte Carlo simulation provides data for this study (using a Visual Basic-based program called DataSim, Sturman, 2004). This program allows a researcher to establish a pseudo-population resembling real-world data (Mooney, 1997). The researcher specifies the number of constructs, the correlations among the constructs, the characteristics of the constructs (e.g., mean) and a specified amount of common variance to represent CMV. DataSim generates random data from the pseudo-populations that fall within the specified parameters to create observed data that is comparable to actual data. Actual values of CMV cannot be determined in real data. Thus, the simulated common variance originating from various sources exists and allows determination of the efficacy of Harman's one-factor test.

A seven-variable model of satisfaction with complaint handling (or service recovery) provides a cover for this simulation. Published data provide estimates of true correlations and measurement and distributional characteristics (Maxham & Netemeyer, 2003). The simulation utilizes the meta-analytically corrected correlations and average scale reliabilities for the latent constructs (Orsingher et al., 2010), as meta-analytically corrected correlations offer a stronger approximation of true correlations than those that might come from a single study. The data model the following constructs: Distributive Justice (DJ), Procedural Justice (PJ), Interactional Justice (IJ), Satisfaction (SAT), Word of Mouth (WOM), Return Intention (RI), and Satisfaction with Service Recovery, also known as Satisfaction with Complaint Handling (SSR) (Orsingher, Valentini, & De Angelis, 2010). Table 1 displays the correlations and the average reported coefficient alpha for the study variables.

Using the measurement and distributional characteristics specified above as a guide, the simulation constructs datasets that vary in simulated scale reliability and CMV amounts. The simulation varies scale reliability because Lance et al. (2010) argue that, at lower levels of scale reliability, CMV causes less bias because any low reliability mathematically attenuates correlation. Thus, scale reliability influences the degree to which CMV causes CMB. In the "typical reliability" datasets, the simulation sets the reliability of each scale as noted in Table 1. The typical coefficient alpha is .87 to .90 for the measures providing the cover. In the "low reliability" datasets, the simulation sets coefficient alpha at .10 below reported reliability (.77–.80), and in the "high reliability" datasets, the simulation sets coefficient alpha to .10 higher (near perfect) than typically reported reliability (.97–.99).

The simulation sets the amount of CMV shared at equal levels among the variables from a low of 0% to a high of 90% at 10% increments. Modeling CMV in this way is consistent with the idea of constant effects of a single measurement scale. Thus, the CMV modeled here simulates data derived from a single source (e.g., a single self-report survey) and tests the possibility that the use of any one method will inflate correlations among substantive variables (Williams & Brown, 1994). In summary, with 3 levels of reliability (typical, lower, and higher) and 10 levels of CMV (0–90%), this study employs 30 different sets of parameters. The study simulates 10 datasets of each combination to account for random error that may occur in each particular dataset for a total of 300 datasets analyzed. The generation of 10 datasets per cell provides proper sampling distribution from the pseudo-population created (Mooney, 1997).

Following Richardson et al. (2009), the simulation estimates 95% and 99% confidence intervals (CIs) around the observed correlations in each dataset to determine whether the true correlation (modeled as the corrected correlations obtained from meta-analytic findings) falls within the CI. If the CI contains the true correlation, then this result indicates no bias. If the CI exceeds the true correlation, CMV biases the relationship downward (i.e., deflated), and if the CI falls below the true correlation, CMV biases the relationship upward (i.e., inflated).

Next, the authors apply a Harman's test to each dataset and record the total number of dimensions extracted based on the initial eigenvalues (eigenvalues greater than or equal to 1) reported and record the amount of variance associated with that first eigenvalue. Researchers interpret Harman's one-factor test as adequately identifying CMB when only one factor results from factor analysis (one eigenvalue exceeding 1) or a first factor accounts for more than 50% of the variance among variables (Podsakoff & Organ, 1986). Typically, authors make no distinction between components based or factor based algorithms. The

Table 1
Distributional characteristics and correlations among variables established in simulated datasets.

Variables	Mean	SD	1	2	3	4	5	6	7
1. Satisfaction with complaint handling/Satisfaction with service recovery (SSR)	5.49	1.01	(.88)						
2. Return intent (RI)	3.25	1.03	.46	(.88)					
3. Word of mouth (WOM)	4.03	.92	.70	.48	(.88)				
4. Satisfaction (SAT)	4.27	1.45	.38	.65	.34	(.90)			
5. Distributive justice (DJ)	3.44	1.38	.64	.50	.53	.51	(.89)		
6. Interactional justice (IJ)	3.89	1.27	.55	.47	.57	.52	.57	(.89)	
7. Procedural justice (PJ)	3.93	1.17	.47	.44	.43	.59	.55	.55	(.87)

Scales were modeled to be 7-point Likert, with 1 = minimum and 7 = maximum. Coefficient alpha reliabilities appear in the diagonals.

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number of variables in a model influences the results of Harman's one-factor test (Podsakoff et al., 2003) because fewer variables present fewer true factors, increasing the likelihood that the variables collapse to one factor.

3. Results

Table 2 presents the results of tests for bias using true correlations and the CIs around the simulated correlations for three correlation levels: the lowest (associated with WOM-SAT, true $r = .34$), highest (WOM-SSR, true $r = .70$), and midpoint correlations (IJ-SAT, true $r = .52$). The full table of 21 correlations at 3 levels of reliability and 10 levels of CMV is available from the authors. As shown in Table 2, at the typical level of reported scale reliabilities, correlations do not exhibit inflating CMB until a high amount of CMV exists – at least 60% common variance depending on measurement scale. At a typical level of reliability, CMV appears unlikely to inflate correlations. The results of the lower scale reliability datasets show even less inflation of correlations, with little upward bias in correlations until 70% CMV exists with no evidence at all for high construct correlations ($r_{wom\text{-}ssr} = .70$). Finally, the results of the test of bias in datasets with scale reliability set at .10 higher than typically observed reported reliabilities (at a range of $\alpha = .97–.99$) suggest that CMV may inflate correlations with CMV of exceeding 40%.

Table 2 indicates that low levels of CMV are associated with deflated, rather than inflated correlations, in datasets with scale reliability set 0.10 lower than typically reported. From a measurement perspective, the absence of CMV does not guarantee true effects. Low reliability still attenuates effect sizes in a manner and serves to offset any exaggerated correlation caused by response bias (Lance et al., 2010). Decreasing scale reliability exacerbates attenuation (Dunlap & Cureton, 1929). Conversely, as the reliability of measures increases, the amount of variance extracted in factors increases as well (Harman, 1976). CMB that inflates relationships only occurs when the CMV present is a sizable amount (60% or more). Between levels of 30% and 60% CMV, nearly all true correlations are within the specified 95% or 99% confidence intervals, suggesting little cause for CMB concerns in most typical data. Malhotra et al. (2006) suggest that typical levels of CMV in survey data are about 10% and in extreme cases perhaps 20%. At those levels, the possibility of inflating correlations appears nil.

Table 3 reports the findings regarding the level at which Harman's one-factor test can detect biasing levels of CMV. In both the full 7-variable model and the 4-variable partial model, and at all but the atypically high levels of scale reliability, Harman's one-factor test indicates bias when CMV levels reach problematic levels (70% or greater CMV). Referring back to Table 2, in only one instance does the possibility of inflated correlation arise with CMV less than 70%, and in that case the percentage of CMV is at 60.

Table 4 summarizes information from Tables 2 and 3 to indicate when Harman's one-factor test produces false negatives (i.e., indicates no CMB when CMB is present) or produces false positives (i.e., indicates upward bias from CMV when none is evident in data). False positive conclusions prove more likely than any other conclusion. When reliabilities are in the typical range, a false positive exists at the highest levels of CMV. At atypically low reliabilities, false positives occur at moderate and high correlation levels with 70% or more CMV. At atypically high reliability levels, false positives occur for each level of correlation. In only one instance is a false negative noted. For typical reliability levels, when correlations are in the low range and CMV is at 70%, Harman's one-factor standard does not signal bias when bias does exist. The predominance of false positive results increases the likelihood that researchers using Harman's one-factor test will conclude

Table 2
Results of test of CMV bias in three correlations in simulated datasets.

		Typical reliability levels				Atypically low reliability levels				Atypically high reliability levels			
	Simulated % of CMV	Mean obs. r	Range of obs. r	% of obs. rs inflated: 95%; 99% CI[a]	% of obs. rs deflated: 95%; 99% CI[b]	Mean obs. r	Range of obs. r	% of obs. rs inflated: 95%; 99% CI[a]	% of obs. rs deflated: 95%; 99% C[b]I	Mean obs. r	Range of obs. r	% of obs. rs inflated: 95%; 99% CI[a]	% of obs. rs deflated: 95%; 99% CI[b]
WOM-SAT corr. (true $r = .34$)	0%	.16	.11–.24	0%; 0%	40%; 0%	.17	.08–.27	0%; 0%	40%; 0%	.24	.16–.31	0%; 0%	0%; 0%
	10%	.21	.14–.28	0%; 0%	20%; 0%	.19	.13–.27	0%; 0%	20%; 0%	.30	.19–.38	0%; 0%	0%; 0%
	20%	.27	.21–.33	0%; 0%	0%; 0%	.22	.13–.28	0%; 0%	10%; 0%	.31	.24–.34	0%; 0%	0%; 0%
	30%	.26	.19–.40	0%; 0%	0%; 0%	.28	.21–.34	0%; 0%	0%; 0%	.40	.34–.54	10%; 0%	0%; 0%
	40%	.35	.31–.40	0%; 0%	0%; 0%	.31	.24–.38	0%; 0%	0%; 0%	.47	.42–.53	40%; 0%	0%; 0%
	50%	.38	.34–.43	0%; 0%	0%; 0%	.33	.27–.38	0%; 0%	0%; 0%	.52	.49–.59	70%; 20%	0%; 0%
	60%	.49	.40–.58	30%; 10%	0%; 0%	.42	.39–.47	0%; 0%	0%; 0%	.61	.53–.66	100%; 90%	0%; 0%
	70%	.55	.49–.62	80%; 40%	0%; 0%	.50	.45–.56	40%; 0%	0%; 0%	.70	.67–.74	100%; 100%	0%; 0%
	80%	.66	.59–.71	100%; 100%	0%; 0%	.58	.52–.64	100%; 70%	0%; 0%	.81	.77–.85	100%; 100%	0%; 0%
	90%	.77	.73–.81	100%; 100%	0%; 0%	.68	.64–.73	100%; 100%	0%; 0%	.83	.87–.92	100%; 100%	0%; 0%
IJ-SAT corr. (true $r = .52$)	0%	.22	.16–.29	0%; 0%	100%; 80%	.21	.13–.32	0%; 0%	100%; 90%	.33	.24–.43	0%; 0%	100%; 20%
	10%	.25	.20–.35	0%; 0%	100%; 70%	.23	.15–.34	0%; 0%	100%; 90%	.37	.31–.43	0%; 0%	100%; 0%
	20%	.31	.24–.41	0%; 0%	100%; 30%	.24	.15–.33	0%; 0%	100%; 70%	.41	.31–.51	0%; 0%	80%; 0%
	30%	.38	.27–.44	0%; 0%	100%; 10%	.29	.23–.41	0%; 0%	100%; 60%	.47	.41–.55	0%; 0%	50%; 0%
	40%	.44	.37–.49	0%; 0%	90%; 0%	.34	.24–.41	0%; 0%	100%; 10%	.54	.47–.60	0%; 0%	10%; 0%
	50%	.48	.45–.51	0%; 0%	40%; 0%	.38	.28–.45	0%; 0%	100%; 0%	.60	.53–.68	10%; 0%	0%; 0%
	60%	.56	.49–.63	0%; 0%	0%; 0%	.48	.39–.55	0%; 0%	50%; 0%	.68	.66–.73	100%; 20%	0%; 0%
	70%	.62	.60–.67	20%; 0%	0%; 0%	.54	.48–.58	0%; 0%	0%; 0%	.76	.72–.79	100%; 100%	0%; 0%
	80%	.71	.66–.75	100%; 40%	0%; 0%	.62	.57–.65	10%; 0%	0%; 0%	.85	.81–.88	100%; 100%	0%; 0%
	90%	.79	.77–.83	100%; 100%	0%; 0%	.69	.65–.73	80%; 30%	0%; 0%	.92	.91–.93	100%; 100%	0%; 0%
WOM-SSR corr. (true $r = .70$)	0%	.37	.28–.53	0%; 0%	100%; 100%	.33	.27–.38	0%; 0%	100%; 100%	.46	.37–.55	0%; 0%	100%; 90%
	10%	.39	.34–.46	0%; 0%	100%; 100%	.35	.25–.41	0%; 0%	100%; 100%	.48	.42–.56	0%; 0%	100%; 80%
	20%	.43	.36–.49	0%; 0%	100%; 100%	.36	.32–.41	0%; 0%	100%; 100%	.52	.46–.58	0%; 0%	100%; 50%
	30%	.45	.39–.55	0%; 0%	100%; 90%	.38	.30–.44	0%; 0%	100%; 100%	.56	.46–.62	0%; 0%	50%; 30%
	40%	.47	.43–.56	0%; 0%	100%; 90%	.43	.37–.47	0%; 0%	100%; 100%	.60	.46–.68	0%; 0%	20%; 10%
	50%	.53	.49–.56	0%; 0%	100%; 30%	.45	.41–.51	0%; 0%	100%; 100%	.65	.63–.68	0%; 0%	0%; 0%
	60%	.59	.52–.63	0%; 0%	50%; 0%	.50	.43–.53	0%; 0%	100%; 70%	.74	.68–.79	0%; 0%	0%; 0%
	70%	.63	.59–.69	0%; 0%	0%; 0%	.55	.50–.57	0%; 0%	100%; 10%	.77	.74–.83	30%; 10%	0%; 0%
	80%	.72	.68–.75	0%; 0%	0%; 0%	.61	.54–.65	0%; 0%	20%; 0%	.86	.82–.88	100%; 90%	0%; 0%
	90%	.79	.76–.83	30%; 10%	0%; 0%	.69	.66–.74	0%; 0%	0%; 0%	.91	.90–.92	100%; 100%	0%; 0%

[a] The percent of true correlations below the 95% and 99% confidence intervals around the observed correlations indicates that these correlations were inflated by CMV bias.
[b] The percent of true correlations above the 95% and 99% confidence intervals around the observed correlations indicates that these correlations were deflated (attenuated) by CMV bias.

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Table 3
Results of Harman's one-factor test on simulated datasets.

Full model with seven variables

% CMV in data	Typical reliability levels: Mean (SD) number of factors extracted	% Rate Harman's OFT found one factor	Mean % of variance extracted from first factor	Atypically low reliability levels: Mean (SD) number of factors extracted	% Rate Harman's OFT found one factor	Mean % of variance extracted from first factor	Atypically high reliability levels: Mean (SD) number of factors extracted	% Rate Harman's OFT found one factor	Mean % of variance extracted from first factor
0%	6.90 (.32)	0%	28.24%	6.90 (.32)	0%	21.17%	6.40 (.52)	0%	45.69%
10%	6.60 (.52)	0%	29.48%	6.90 (.32)	0%	22.08%	6.10 (.32)	0%	49.22%
20%	6.60 (.52)	0%	31.15%	6.70 (.67)	0%	22.62%	6.00 (.00)	0%	51.85%
30%	6.10 (.32)	0%	33.64%	6.70 (.48)	0%	24.50%	6.00 (.00)	0%	55.58%
40%	5.90 (.32)	0%	35.81%	6.10 (.32)	0%	25.95%	5.80 (.42)	0%	60.61%
50%	5.60 (.52)	0%	38.58%	5.70 (.48)	0%	28.25%	4.80 (.63)	0%	65.38%
60%	4.50 (.53)	0%	43.22%	5.30 (.67)	0%	30.64%	3.90 (.32)	0%	70.97%
70%	3.50 (.53)	0%	46.67%	4.10 (.74)	0%	34.01%	2.60 (.52)	10%	76.07%
80%	1.80 (.63)	30%	52.44%	3.20 (.92)	0%	37.31%	1.20 (.42)	70%	82.89%
90%	1.00 (.00)	100%	58.01%	1.20 (.42)	80%	42.48%	1.00 (.00)	100%	87.93%

Partial model with four variables

% CMV in data	Typical reliability levels: Mean (SD) number of factors extracted	% Rate Harman's OFT found one factor	Mean % of variance extracted from first factor	Atypically low reliability levels: Mean (SD) number of factors extracted	% Rate Harman's OFT found one factor	Mean % of variance extracted from first factor	Atypically high reliability levels: Mean (SD) number of factors extracted	% Rate Harman's OFT found one factor	Mean % of variance extracted from first factor
0%	4.00 (.00)	0%	33.69%	4.00 (.00)	0%	26.74%	4.00 (.00)	0%	48.69%
10%	4.00 (.00)	0%	34.80%	4.00 (.00)	0%	27.84%	4.00 (.00)	0%	51.30%
20%	4.00 (.00)	0%	36.64%	3.90 (.32)	0%	28.57%	4.00 (.00)	0%	53.92%
30%	4.00 (.00)	0%	38.33%	4.00 (.00)	0%	29.98%	4.00 (.00)	0%	57.16%
40%	3.90 (.32)	0%	40.71%	3.80 (.42)	0%	31.05%	3.80 (.42)	0%	61.57%
50%	3.40 (.52)	0%	43.00%	3.60 (.70)	0%	32.98%	2.90 (.74)	0%	66.47%
60%	2.60 (.52)	0%	48.31%	2.80 (.42)	0%	35.92%	2.10 (.32)	0%	71.74%
70%	2.20 (.42)	0%	50.63%	2.00 (.47)	10%	39.30%	1.90 (.32)	20%	76.88%
80%	1.30 (.48)	70%	57.20%	1.20 (.42)	80%	42.83%	1.10 (.32)	80%	83.41%
90%	1.00 (.00)	100%	62.40%	1.10 (.32)	90%	47.86%	1.00 (.00)	100%	88.57%

Cell values present the mean or standard deviation across the 10 datasets produced and analyzed for each sample size and amount of CMV.

falsely that bias exists, depending on the size of true correlation, the reliability of scales, and the number of variables analyzed. In simulated data, researchers can precisely identify these points of mismatch because of known amounts of simulated CMV and relationship strengths; such identification is impossible in actual data.

4. Discussion

In the presence of increased calls for attention to common methods effects in same-source self-reported data, the current study presents results of a different nature. CMV apparently can exist at relatively high levels before CMB occurs. Results from the simulation indicate that lower to moderate levels of CMV do not inflate correlations and in some cases may deflate correlations. Although other authors warn that CMV in same-source data biases correlations upward, the current study does not support this concern. Estimates of CMV in different types of data vary widely—10% (Malhotra et al., 2006), 18% (Lance et al., 2010), 26% (Williams, Cote, & Buckley, 1989), 35% (Podsakoff et al., 2003), and 23–41% (Cote & Buckley, 1987). Comparing this range of estimates to the findings in the current data simulation indicates that such levels of CMV are not likely to bias relationships sufficiently to alter substantive conclusions. CMV presents substantial potential for upward bias in relationships only when CMV is very high (approaching 70% or more). Reports of CMV in this range are the

Table 4
Conclusions drawn using Harman's one-factor test when detecting biasing levels of CMV[a].

	Typical reliability level: Lowest percent CMV at which inflating bias is observed	Lowest percent CMV at which Harman's detects bias[b] regarding accuracy[c]	Atypically low reliability level: Lowest percent CMV at which inflating bias is observed	Lowest percent CMV at which Harman's detects bias[b] regarding accuracy[c]	Atypically high reliability level: Lowest percent CMV at which inflating bias is observed	Lowest percent CMV at which Harman's detects bias[b] regarding accuracy[c]
WOM-SAT corr. (true $r = .34$)	60%	70% (false negative)	70%	70% (accurate)	30%	10% (false positive)
IJ-SAT corr. (true $r = .52$)	70%	70% (accurate)	80%	70% (false positive)	50%	10% (false positive)
WOM-SSR corr. (true $r = .70$)	90%	70% (false positive)	No bias at any level of CMV	70% (false positive)	70%	10% (false positive)

[a] Biasing levels of CMV occur when the observed correlation is inflated above the 95% confidence interval.
[b] Harman's one-factor test indicates bias when more than 50% variance is extracted in the first factor or when only one factor emerges in either the 7-variable or 4-variable model.
[c] A conclusion of "accurate" is indicated when the confidence interval indicates bias, and Harman's indicates bias. A false positive occurs when Harman's indicates CMB, but the confidence interval does not. A false negative occurs when the confidence interval indicates bias, but Harman's does not.

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exception rather than the rule (Sharma et al., 2009). In all other cases, the present simulation indicates that CMV would not overstate relationships. While authors cannot know the true amount of CMV, the likelihood is that such high levels of CMV are not present in most studies. Further, if researchers truly find more than 70% CMV across multiple constructs, the results signal likely fatal flaws in the research including potential problems with construct validity.

Additionally, the simulation indicates that typical levels of scale unreliability deflate observed relationships and may actually serve to balance out any CMB. This finding echoes the conclusion presented by Lance et al. (2010) suggesting that CMV may occur but attenuation due to unreliability of measures negates any problem. In the range of approximately 10–50% CMV, correlations do not show material indications of CMB. Conversely, very high (atypical and nearly perfect) levels of scale reliabilities suggest low levels of CMV are associated with bias in observed relationships. Thus, authors of research involving single-item measures, where perfect reliability is often implied, should indeed be particularly cautious about CMB.

Despite conceptual arguments against the use of Harman's one-factor test (e.g., Malhotra, et al., 2006; Podsakoff & Organ, 1986) and new information regarding more accurate post-hoc CMV detection techniques (Bagozzi, 2011; Richardson et al., 2009; Simmering et al., 2015; Williams et al., 2010), the current review indicates that scholars who employ such tests overwhelmingly use Harman's one-factor test, perhaps due to its simplicity. The current data simulation tests the efficacy of Harman's one factor test utilizing a typical marketing study model. Results from the simulation indicate that Harman's one-factor test fails to detect upward CMB only when CMV is 70%. While the true level of CMV in data can never be known, prior published estimates of CMV levels fall well below 70%.

Scholars acknowledge the differing perspectives on the nature and likelihood of CMV (e.g., Richardson, et al., 2009; Pace, 2010), and this debate has yet to be resolved. While this paper does not focus on this debate, this study lends support to the perspective argued by some scholars (e.g., Lance, et al., 2010; Spector, 2006) that CMV does not often occur at biasing levels. Specifically, a surprisingly high percentage of CMV is necessary to begin to bias relationships across all sample sizes tested in our data. Further, this study adds to the growing literature that warns against the reporting of many laborious post-hoc statistical CMV detection and correction techniques.

4.1. Limitations and future research

This study has several limitations, each of which provides an opportunity for other research ideas. One limitation is the focus of simulations related to Harman's one-factor test. While the literature review indicates that researchers also use other tests to detect CMV, the study does not address these tests here (see Richardson, et al., 2009). Researchers should remain cautious in the application of these other detection techniques (Bagozzi, 2011; Richardson, et al., 2009).

A second limitation is that, while this study demonstrates some weaknesses of Harman's one-factor test, the study does not offer an absolute assessment of this test because the simulated data only encompass a small range of conditions (e.g., magnitude of correlation). While variations in these pseudo-populations would no doubt produce some differences in results, the overall conclusions would likely still be supported. That is, Harman's one-factor test's inaccuracy lies more in suggesting the presence of CMB when none is present. Relatedly, the study offers no comparison of bias created by other response or administration errors. Future research should address and perhaps try to quantify the relative impact of other error sources so that researchers can better focus their attention in an effort to obtain the most truthful results. Third, the study provides limited scope in its reviews. A more exhaustive search across multiple disciplines may reveal different results. Realize that if CMV causes CMB, then correlation-based reliabilities like coefficient alpha, are biased too. If CMV artificially raises reliabilities, analytical procedures that correct for error attenuation may still present overly conservative effect sizes. Further research may address scale type and length. Fourth, the data algorithm simulates a common marketing model to the best of its ability. However, the correspondence between simulation and the intricacies of the real-world may not be entirely robust.

4.2. Recommendations and conclusion

This study presents three major conclusions. First, researchers need not automatically assume that CMV biases data just because that data originates from the same respondents. Although this simulation produced a limited range of observed correlations, these magnitudes of correlation are common in behavioral research. Recall from the simulation that CMV does not begin inflating observed correlations upward until simulated CMV is the primary source of data. Even the least forgiving estimates do not presume such high levels of CMV. Further, the data supports other researchers' findings (e.g., Lance et al., 2010), that attenuation from imperfect scale reliabilities offsets inflation due to CMV. Researchers should not automatically conclude that CMV biases data unless viable evidence suggests the presence of CMB. Survey research should not be presumed guilty of CMB. In fact, the results suggest the opposite. Only when researchers face specific situations should they present elaborate and lengthy reports of steps to assess CMV needed to allay fears of consequent misleading results. Further, the odds appear much more in favor of CMV understating relationships, and then mostly in situations with reliabilities beyond those typically reported in marketing research. Researchers should still consider including *a priori* procedural steps to minimize the risk of CMB (Podsakoff et al., 2003).

Second, Harman's one-factor test cannot consistently produce an accurate conclusion about biasing levels of CMV in data. Harman's produced both false positives and false negatives, and the potential for a false positive conclusion is particularly high when scale reliability is high. The finding of false positives contradicts the conceptual criticism that Harman's lacks the sensitivity to detect CMV in most data (Podsakoff et al., 2003).

Third, reviewers and editors should familiarize themselves with compelling empirical evidence that concerns about CMV are likely overstated (see Conway & Lance, 2010; Lance et al., 2010). Further, other sources of response error and other types of research bias deserve investigation. In particular, the simulation results here point to the need for the greatest caution when near-perfect reliabilities exist. As a consequence, single-item measures, where reliabilities are unknown, implicitly assumed perfect, or set at very high levels, present relatively high potential for CMB. Thus, when single items are used, manuscripts should provide attention to the potential of bias due to CMV.

In conclusion, this study indicates that the most commonly used post-hoc approach to managing CMV—Harman's one-factor test—can detect biasing levels of CMV under conditions commonly found in survey-based marketing research. For typical reliabilities, CMV would need to be on the order of 70% or more before substantial concern about inflated relationships would arise. At lower reliabilities, CMV would need to be even higher to bias data. In sum, today's reviewers may be asking more than is needed of authors in presenting evidence of a lack of CMB, and a review shows few authors presenting evidence of bias due to CMV. The evidence presented here should assist scholars in making informed choices regarding post-hoc approaches to dealing with CMV.

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