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USING META-ANALYTIC STRUCTURAL EQUATION MODELING TO ADVANCE STRATEGIC MANAGEMENT RESEARCH: GUIDELINES AND AN EMPIRICAL ILLUSTRATION VIA THE STRATEGIC LEADERSHIP-PERFORMANCE RELATIONSHIP

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This paper demonstrates how meta-analysis can be combined with structural equation modeling (MASEM) to address new questions in strategic management research. We review this integration, describe its implementation, and compare findings from bivariate meta-analyses, a direct-effect structural equations model, and two mediating frameworks using data on the strategic leadership and performance relationship. Results drawn from 208 articles that collectively included data on 495,638 observations demonstrate the new insights available from MASEM while also suggesting a revision to conventional thinking on strategic leadership. Whereas some theories posit that boards of directors influence firm performance through monitoring and disciplining the top management team, MASEM provides more support for the view that boards mediate the top management teams' decisions. Implications for applying MASEM in strategic management are offered. Copyright © 2014 John Wiley & Sons, Ltd.

INTRODUCTION

As the strategic management field matures, scholars are increasingly using meta-analysis to synthesize prior work on many topics, including the performance implications of strategic resources (Crook *et al.*, 2008), configuration membership (Ketchen *et al.*, 1997), and strategic leaders (Dalton *et al.*, 1998, 1999). However, meta-analysis assesses one element of a theoretical model at a time—typically through a bivariate correlation coefficient. Consequently, meta-analysis is unable to provide higher-level assessments, such as comparing competing models that might have multiple permutations of predictors, mediators, and outcomes.

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For example, the resource-based view, the knowledge-based view, the social capital perspective, and the strategic human resource view each offer competing frameworks that relate resources to firm performance. Meta-analysis can only be used to test the direction and significance of the bivariate relationships specified *within* each view, but cannot test the competing views against one another. Without being able to evaluate alternative or complementary theoretical models directly, meta-analysis leaves important questions unanswered.

Recently, a few pioneering strategy researchers have begun to address these concerns using MASEM—a combination of meta-analysis (MA) and structural equation modeling (SEM) (Carney, et al., 2011; Van Essen, Otten, and Carberry, 2012). By incorporating the advantages of both tools, MASEM allows researchers to draw on accumulated findings to test the explanatory value of a theoretized model against one or more competing models, thereby allowing researchers to conduct "horse races" between competing frameworks that cannot be carried out by meta-analysis alone. The insights derived from such analyses can help inform the boundaries, structure, and shortcomings of theoretical models while also enabling researchers to determine the explanatory and predictive adequacy of theories in advancing the field's knowledge. We seek to contribute to "the ongoing stream of methodological inquiry in strategy research" (Wiersema and Bowen, 2009: 688) by providing a framework for understanding MASEM's benefits and boundaries, specifying how researchers can implement the technique, and demonstrating possible methodological and conceptual implications by re-examining the strategic leadership-performance relationship. Drawing on findings from 208 articles, we compare the results from bivariate meta-analyses, a direct effects model, and two alternative mediating models. One model represents the conventional agency theoretical perspective where boards of directors monitor and discipline top managers, while an alternative view proposes that top managers work through boards of directors to approve the managers' suggestions.

Findings show that traditional bivariate meta-analyses produced results that were overly optimistic and represented too simplistic a view of the strategic leader-performance relationship. Our tests reveal that the agency theory model did receive some support for the relationships between boards and top management teams, but few links had any performance implications. In contrast, the view that boards mediate the top management team–performance relationship received stronger support. Collectively, the findings illustrate how MASEM provides the opportunity to test and compare the structure of theoretical models in ways unavailable in traditional meta-analysis. Implications for testing and improving strategic management theories via MASEM are discussed.

MASEM: STRENGTHS AND BOUNDARIES

Meta-analysis allows researchers to synthesize and cumulate research findings into a single effect size (Hunter and Schmidt, 2004). The effect size reflects the magnitude and directionality of the association between the two variables. MASEM goes further by providing effect sizes that control for other variables in the model, and providing information on the degree of fit of the entire model. In addition, MASEM can be used for testing intermediate mechanisms in a chain of relationships and pitting mediation hypotheses or models against one another in terms of the existence, ordering, directions, and magnitudes of mediation (i.e., underlying) mechanism(s). Because mediating effects involve three or more variables, a meta-analysis, which focuses on bivariate relationships, is ill-equipped to offer insights into important conceptual gaps in our field such as the microfoundations of strategy (Baer, Dirks, and Nickerson, 2013) and what concepts lie in the "black box" between strategic resources and performance (Sirmon, Hitt, and Ireland, 2007).

In addition, because it includes all the available data for a particular relationship, MASEM can maximize external validity (Shadish, Cook, and Campbell, 2002). MASEM can also integrate bivariate relationships from different primary-level studies. Finally, MASEM has a unique statistical power advantage (Cheung and Chan, 2005). Because the input for the SEM models are obtained via meta-analysis, which often pool thousands of firms (e.g., Crook *et al.*, 2008), the sample size in MASEM is much larger than in a typical SEM study. Thus, findings from entire fields of study can be synthesized and then tested using alternative model structures. In sum, MASEM provides a substantially more powerful and in-depth basis for quantitative synthesis of research findings than that which can be offered by traditional meta-analysis or by traditional SEM.

Recent studies in organizational behavior offer good examples of MASEM's advantages in action. Berry, Lelchook, and Clark (2011) specified a model involving three withdrawal behaviors—lateness, absenteeism, and turnover. The authors also specified an alternative mediation model in which lateness affects turnover only through absenteeism, and the authors made use of MASEM's ability to provide insight into the intermediate mechanisms in a chain of relationships. Earnest, Allen, and Landis (2011) implemented a MASEM study to conduct a "horse race" among four competing mediation mechanisms for the effect of realistic job previews on voluntary turnover. Specifically, the authors specified met expectations, role clarity, perceptions of honesty, and attraction to the organization as competing mediating mechanisms, thereby making use of MASEM's ability to provide insight into intermediate mechanisms within these models.

MASEM is also subject to several boundary conditions. First, MASEM is not as useful in situations lacking competing hypotheses or models, such as when a research domain of interest is emergent. Second, MASEM is not practically feasible when there is limited availability of prior studies providing the needed meta-analytic correlations or primary study correlations to test one's specified models. Third, MASEM does not provide immunity to construct validity threats. Much as is the case for meta-analysis, there is the concern that the input (i.e., primary-level studies) can be "a mass of reports—good, bad, and indifferent" (Eysenck, 1978: 517). Fourth, MASEM will fail to produce useful results when missing data substitution or imputation techniques are used excessively. For example, dealing with missing cells by replacing a large number of existing variables with conceptually similar (i.e., surrogate) variables will not be very trustworthy to a practitioner who is interested in conclusions that are based on the actual variables of interest. Fifth, MASEM may have difficulties with testing moderation, due to the bivariate nature of the meta-analysis effect size data, as well as limitations in conducting moderation tests within most SEM packages.

A sixth limitation of MASEM is the inability to make conclusive causal inferences based on data from nonexperimental studies. Unless all of the studies that are used as input to a MASEM rely on experimental designs, MASEM cannot provide unequivocal evidence regarding causality, even if the data come from studies using lagged/longitudinal research designs. Indeed, while the majority of strategy research provides evidence regarding covariation between antecedent and outcome variables, covariation alone does not address all three conditions needed to establish causality: (1) the cause preceded the effect, (2) the cause was related to the effect, and (3) there is no plausible alternative explanation for the effect other than the cause. In fact, one perspective is that it is simply impossible to make any claims about causality unless using the "gold standard" of internal validity and causal evidence experimental design (Antonakis *et al.*, 2010; Campbell and Stanley, 1963). Because the overwhelming majority of strategic management studies use nonexperimental designs, and the field is very likely to continue using such designs in the future, strategy researchers should refrain from making causal statements when they use MASEM and instead use the technique to evaluate the comparative fit of alternative models and provide guidance for future investigations, perhaps adopting an experimental design approach, in showing which models fit empirical reality best.

Finally, related to issues of causality, the data used in meta-analysis computations (means, standard deviations, sample sizes) could have been derived from research designs that are vulnerable to endogeneity.[1] The possible presence of endogeneity may further narrow the studies that could be included in a MASEM, or strategists may be required to conduct additional logical argumentation and statistical procedures (discussed below) to help address it.[2]

Despite these boundary conditions, MASEM provides researchers with a stronger and more powerful technique than traditional meta-analysis. MASEM allows researchers to take the findings from an entire stream of research and use them as the basis for testing complex models. By using a field's accumulated data, MASEM enables researchers to examine fundamentally important questions about the viability of theoretical and

[1] Endogeneity is a statistical bias that results from correlations between an independent variable and the error term in an ordinary least squares regression model. It can arise from one or more several reasons such as measurement error, autoregression, omitted variables, selection bias in collecting the sample, and simultaneous causality among the variables (Antonakis *et al.*, 2010; Semadeni, Withers and Certo, 2014).

[2] We thank an anonymous reviewer for identifying this point.

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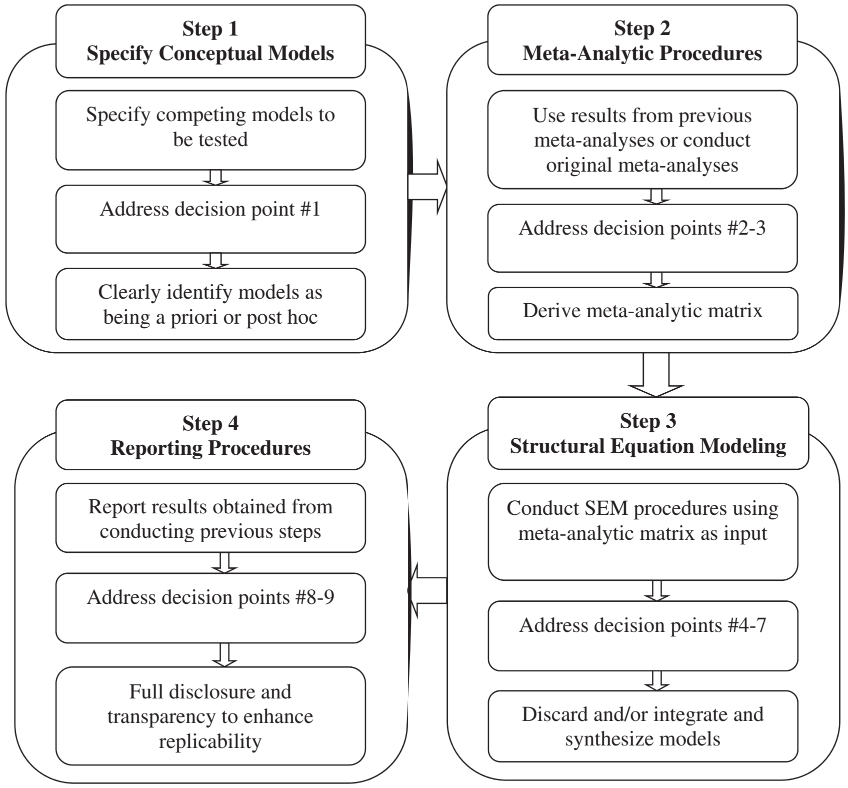

Figure 1. Steps and decision points in conducting meta-analytic structural equation modeling

conceptual frameworks. Although MASEM does not allow conclusions about causal structures, it does provide a vehicle for comparing alternative models and enable researchers to retain the structure that is empirically superior. This approach is consistent with the philosophy of science literature, which suggests that science aspires to retain models that are most plausible given the available data (Popper, 1963) and discards those that are inferior or falsified.

MASEM: IMPLEMENTATION

Implementing MASEM requires four general steps. Figure 1 displays the process and shows where nine critical decision points arise. Not all MASEM processes will include all of the decision points depending on the theoretical models to be tested and the type of data available. However, we err in the direction of comprehensiveness with the goal of providing a useful resource for those interested in conducting a MASEM study or evaluating a MASEM as a reader, journal reviewer, or editor.

Step 1: Specify variables and conceptual models

First, researchers need to specify the variables and models that will be evaluated. The nature of these models is driven by the research questions under investigation.

Decision point #1

The first step in a MASEM involves specifying the study variables, models, and focal relationships. These models should be based on an exhaustive literature review of the pertinent theories and extant empirical studies to identify relevant variables and reduce the threat of omitted variables as a source of possible endogeneity. This step involves specifying an outcome predicted by two or more antecedent variables, where all the predictors fully or partially covary with one another. In addition, if a research question requires pitting mediation hypotheses or models against one another in terms of the existence, ordering, directions, or magnitudes of mediation mechanism(s), then the specified model can also take advantage of MASEM's ability to provide insight into a chain's

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intermediate mechanisms. For example, in a simple case involving four variables, this approach is realized by specifying A and B → C → D vs. A and C → B → D. Moreover, these models could be compared against a simpler one involving just one predictor such as A → C → D. At the end of this process, the researcher can then present one or two superior models. In some cases, none of the prespecified models may fit the data well, and researchers may offer *post hoc* models that are created inductively based on the obtained results. Further, specifying competing models can present an opportunity for ruling out endogeneity as a threat to interpreting the findings. Thus, the *a priori* or *post hoc* nature of models should be made explicit.

Step 2: Meta-analytic procedures

The second step is to collect meta-analytic data. This involves identifying meta-analytically derived effect sizes reported in prior meta-analyses or by estimating these effects by performing a meta-analysis of the bivariate correlations from primary studies. As is the case within all meta-analyses, effect size estimates must be converted to a common standardized metric across primary-level studies before being synthesized. This is why correlation coefficients are the most typical effect size metric rather than regression coefficients—the size and sometimes even the signs of regression coefficients are affected by the metrics of the particular measures used as well as the number of variables in a regression model (cf. Hunter and Schmidt, 2004).

Decision point #2

When conducting meta-analyses, strategy researchers are likely to encounter situations whereby some meta-analytic effects cannot be computed due to missing studies. The possible solutions to this problem include (1) search again for relevant studies based on the same and/or different search criteria, (2) contact other researchers to request correlation values (Shadish, 1996), (3) conduct original primary-level studies, (4) replace some existing variables with conceptually similar "surrogate" variables (e.g., Eby *et al.*, 1999), (5) group specific constructs into broader construct(s) by deriving composite correlations (Viswesvaran and Ones, 1995), (6) use a two-stage structural equation modeling (TSSEM), which manages missing values automatically (Cheung and Chan, 2005; Fan *et al.*, 2010), (7) implement advanced data imputation techniques such as full information maximum likelihood (FIML) (Cheung, 2008), (8) use the average effect size across all nonmissing effect sizes (Viswesvaran and Ones, 1995), or (9) rely on subject matter experts or expertise to estimate the value for the missing effect sizes (e.g., Robbins *et al.*, 2009). The first three options are the most desirable because all of them involve using actual data without any conceptual or empirical manipulation. If none of the above possible solutions are available, the remaining option is to limit the scope of inquiry (Viswesvaran and Ones, 1995).

Decision point #3

Strategy researchers performing meta-analyses across several different pairs of variables are likely to face a situation wherein a different sample size value is used to compute each meta-analytically derived correlation. The options to address this situation include using (1) the harmonic mean (Burke and Landis, 2003), (2) the smallest total sample size (e.g., Roesch and Weiner, 2001), (3) the median (Tokunaga and Rains, 2010), or (4) the arithmetic mean (Graham, 2011; Judge *et al.*, 2002). The harmonic mean is calculated by $k/(1/N_1 + 1/N_2 + \ldots + 1/N_k)$, where k equals the number of meta-analytic correlations, and $N_1 \ldots N_k$ refer to each of the total sample sizes used to compute each of the meta-analytically derived correlations (Brown *et al.*, 2008). The harmonic mean is the preferred option because it limits the influence of very large values and also increases the influence of smaller values, in addition to being in most if not all cases smaller than the arithmetic mean (Johnson *et al.*, 2001; Landis, 2013).

Step 3: Structural equation modeling

Before we discuss specific decision points, we note a general issue of implementation, which is choosing a particular software package. Several alternatives are available including IBM-SPSS Amos, EQS, Mplus, and R. Each of these packages offers similar capabilities, and the main difference is how the meta-analytic matrix used as input should be prepared for the analysis. This information is included in each of the packages' manuals. Given their similar capabilities, our recommendation is for

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users to choose the package with which they are already familiar.

Decision point #4

Strategy researchers also need to recognize that the likelihood of obtaining a nonpositive definite meta-analytic matrix (i.e., ill-defined matrix including zero or negative eigenvalues) increases in a MASEM study. This problem arises from several sources, including some meta-analytically derived matrixes may have a small total number for some cells, two variables may be very highly correlated, and the presence of empty cells may lead to an overuse of missing data imputation techniques. Eby *et al.* (1999) suggested several possible solutions available in LISREL, such as choosing alternative global starting values or selecting more precise starting values for parameter estimates. In addition, researchers can anticipate this problem by expanding the article pool and reducing the set of variables.

Decision point #5

Within-study or within-sample dependency refers to overrepresentation of the same study or sample, or very similar types of studies or samples, in the estimation of an effect size. Such dependencies (e.g., an effect size derived from a set of studies that relies on a single database) are problematic in part because they limit the generalizability of meta-analytic findings (Combs *et al.*, 2011). As noted by Glass, McGaw, and Smith (1981: 200), "the data set to be [meta-analyzed] will invariably contain complicated patterns of statistical dependence … [Because] each study is likely to yield more than one finding … the simple (but risky) solution … is to regard each finding as independent of the others." When sample dependencies are present, Geyskens, Steenkamp, and Kumar (2006) offered the following recommendations: (1) include all substantively relevant correlations from each sample for further consideration; (2) derive a composite correlation from conceptually similar individual component correlations from each sample; and then (3) if multiple studies were based on completely or partially overlapping data sets, choose correlation(s) based on the larger sample size(s). Researchers can also use a generalized least squares (GLS) procedure that accounts for the dependencies in effect sizes and, therefore, may yield more accurate parameter estimates than does the traditional ordinary least squares procedure (Furlow and Beretvas, 2005; Shadish, 1996). Finally, another alternative is to apply random effects meta-analyses, or multilevel meta-analytic approaches in combination with MASEM (Erez, Bloom, and Wells, 1996; Van Den Noortgate and Onghena, 2003).

Decision point #6

Apply multiple fit measures. While chi-square is a commonly used index of fit in SEM, it is highly dependent on sample size. Consequently, given the large number of observations usually seen in MASEM, the chi-square statistic might indicate poor fit, even if the discrepancy between the correlation matrix underlying the hypothesized model and the empirically obtained correlation matrix is very small (Aguinis and Harden, 2009). One recommended approach to addressing the matter is to use multiple fit indices (e.g., Shook *et al.*, 2004), such as the comparative fit index (CFI), goodness-of-fit index (GFI), and the root mean square residual (RMR). Although there are general guidelines regarding cutoffs for satisfactory fit (e.g., Hu and Bentler, 1999), some recent analytical and simulation work demonstrated that many of the assumptions underlying these cut-off recommendations may be untenable (Lance, Butts, and Michels, 2006) and cutoffs are often context-specific (Nye and Drasgow, 2011). So, although we refer to specific indexes, care should be taken when specifying cut-off values. An important issue to consider, however, is the relative fit of the models being compared.

Decision point #7

Strategy researchers need to distinguish between suitable and unsuitable meta-analytic correlations for a MASEM study. A researcher can apply the following criteria: (1) choose meta-analytic correlations corresponding to variables whose operationalizations are consistent with *a priori* definitions of interest (e.g., Combs *et al.*, 2011; Eby *et al.*, 1999), (2) select meta-analytic correlations reported by meta-analyses that used prespecified meta-analytic techniques (e.g., how unreliability was corrected) (e.g., Ng and Feldman, 2010), and (3) use meta-analytic correlations reported by meta-analyses based on the largest sample sizes.

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Because MASEM is based on syntheses of others' reported findings, it is important to recognize that those results may be based on designs vulnerable to endogeneity. At present, meta-analysis does not have any techniques to retroactively correct for such issues. We therefore recommend that strategy researchers recognize the possible threat of endogeneity to their population of correlations that could be used in the MASEM. Some researchers may elect to discard a study if its regression analyses indicate that endogeneity was a significant factor afflicting the relationships among the variables that would be used in the meta-analysis. However, Bettis and colleagues (2014: 951) suggest that strategy researchers can make logical arguments based on facts, rule out alternative explanations, provide evidence of theoretical mechanisms, and offer arguments that an instrument has a logical relationship with the endogenous variable, is correlated with the dependent variable only through the endogenous variable, and is not itself endogenous.

In addition, as Semadeni, Withers, and Certo (2014) note, strategic management researchers seeking to conduct meta-analyses do have options to help relieve the sources of endogeneity, including (1) using lagged data models to help account for autocorrelation, (2) recognizing measurement error among the variables in the model, (3) expanding the variables in the model to help mitigate the omitted variables problem, and (4) testing competing models that may reflect alternative—and endogenous—views. There may be multiple and often unknown reasons for why endogeneity may exist (e.g., omitted variables), but based on current knowledge, all researchers can do is rule out as many of these sources as possible. Such a process of addressing threats to internal validity is similar to those reported by Campbell and Stanley (1963) and Cook and Campbell (1979). As a result of implementing SEM, the researcher will be able to discard and/or integrate and synthesize models. The last step in the process involves reporting of results, which we address next.

Step 4: Reporting procedures

Decision point #8

We recommend following the meta-analysis reporting standards (MARS) in order to maximize standardization, transparency, and replicability (Aytug *et al.*, 2012; Kepes *et al.*, 2013). The standards include, for instance, the need to describe how studies were obtained and content analyzed (e.g., Decision point #2 regarding missing cells), and the nature of constructs or variables specified in the models. Consistent with standard practice in the microliterature, we recommend using ovals in figures to represent latent variables (i.e., underlying constructs) and using rectangles for observable variables (i.e., indicators). Note that models including observed variables only would be drawn using rectangles for all variables, and the procedures involved would then be labeled meta-analytic path analysis rather than MASEM.

Decision point #9

The MARS guidelines leave a few important issues unaddressed. In addition to following the MARS guidelines, strategy researchers using MASEM should (1) create a table that includes all estimated bivariate meta-analytic correlations (including the 95% confidence interval for each correlation), number of studies for each correlation (k), and total sample size (*N*); (2) report the results of each tested model by creating a figure including ovals representing latent factors (i.e., underlying constructs) and rectangles representing observable variables; (3) report coefficients (which are always standardized in MASEM), their statistical significance level, standard errors, and 95 percent confidence intervals; (4) report the results of each tested MASEM model by discussing the procedures used to address Decision points #4–7; (5) if applicable, report formal tests of comparisons between coefficients in the model; and (6) clearly state that the reported results do not provide direct and unequivocal evidence regarding causality if the primary-level studies were not experimental in nature.

AN ILLUSTRATION OF MASEM: STRATEGIC LEADERSHIP AND PERFORMANCE

We implemented the above process to reexamine a popular strategic management research question: "Is strategic leadership related to firm performance?" We performed an original meta-analysis to demonstrate the points of similarity and differences between traditional meta-analysis and MASEM, and to offer a contribution to the strategic leadership literature. Further, the study approaches used to test the strategic leadership-performance

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association tend to use nonexperimental research designs and are representative of the strategic management field at large.

Overview

A central question in strategic management centers on the value added of the strategic leadership of the firm: Are strategic leaders, which generally include the board of directors, the chief executive officer (CEO), and their top management team, related to differences in firm performance? The association between strategic leaders and firm performance has become one of the most studied relationships in strategic management, as "there are few more important subjects … than the link between the people at the strategic apex of the organization and the organization's performance" (Carpenter, Geletkanycz, and Sanders, 2004; Pitcher and Smith, 2001: 1).

Assessments of findings on the strategic leader and performance relationship have focused on one-to-one associations between measures of strategic leadership (such as attributes of the CEO, top management team, and board of directors) with firm performance (Certo *et al.*, 2006; Dalton *et al.*, 1998; Rhoades, Rechner, and Sundaramurthy, 2001). Overall, these assessments indicate that the relationships between strategic leaders and firm performance are generally low and that the body of findings contains inconsistent results.

MASEM provides opportunities to increase understanding of the relationship between strategic leadership and firm performance. First, MASEM can yield insights into the importance of each leadership attribute while accounting for interdependencies with other leadership attributes. Whereas prior syntheses of the literature have tended to focus on a single element of leadership, few if any have fully considered the potential for interdependencies between the board or top management team that could jointly affect their association with firm performance. Second, MASEM can advance strategic leadership research by evaluating alternative models of the interrelationships among leadership variables using the field's cumulative corpus of findings.

MASEM and the decision points

In accordance with Decision point #1 above (specifying variables and models), we identified the most commonly studied and accepted variables based on studies that provide comprehensive reviews of the strategic leadership literature (Carpenter *et al.*, 2004; Finkelstein and Hambrick, 1996; Finkelstein, Hambrick, and Cannella, 2009). Eight constructs were selected for analysis (three related to boards of directors, four to top management teams, and firm performance). Next, three alternative models of the strategic leadership-performance relationship appearing in the strategic leadership literature were identified[3]: (1) the conventional "direct effects" model that links boards and top managers directly to performance (Carpenter *et al.*, 2004; Certo *et al.*, 2006; Dalton *et al.*, 1998, 1999); (2) a mediated model that bivariate meta-analyses could not consider: the dominant agency theory proposition that boards of directors monitor and shape the strategic decisions of CEOs and top management teams, which take actions thought to influence firm outcomes (Fama and Jensen, 1983; Pfeffer and Salancik, 1978; Zald, 1969); and (3) a mediated model that reverses the order of the board and top management team. This latter model suggests that top management team members and CEOs participate in identifying board members sympathetic to their views, educate, and then persuade board members to approve their strategies (also, the top managers may sit on the boards of their own board members' corporations' boards, and each would have incentives to approve the decisions of the other). In this conceptualization, board members may be conceived as "rubber stamps" that appear as intermediaries that go along with the managers' interests (Golden and Zajac, 2001; Pearce and Zahra, 1991; Westphal, 1999).[4]

Conducting the meta-analysis

Sample and data collection

In accordance with Decision point #8, we report the original sample and all methods used for collecting

[3] We report when each decision point arose during the process of our study, rather than arrange the study's sequences in terms of the decision points. All decision points were used except numbers 5 (sample dependency was not a problem because of the large and diverse article pool) and 7 (unsuitable meta-analyses did not create bias since our study involved original data).

[4] These models imply a temporal design to account for time differences with respect to antecedent, mediator, and performance. We recognize that some studies may not have used such a structure. Therefore, we tested whether the findings vary based on the use of temporal factors. We found that only one leadership variable—board size—was larger with the use of concurrent data. We therefore interpret the findings regarding board size using that caveat.

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data. The sampling frame consisted of all available published empirical articles on the strategic leadership and firm performance relationship that appeared in double-blind scholarly journals from 1980 to 2009. To identify studies, we first conducted electronic keyword searches using the ABI Inform, Business Premier, JSTOR, and the Web of Science electronic abstracting services. For studies on CEOs and top management teams, the search terms included "upper-echelons," "CEO/chief executive," "senior team," "senior manager," "top manager," "executive team," "strategic leadership," "executive," and "TMT/top management" in order to identify strategic leadership studies. The search terms for board of director studies included "agency theory," "corporate governance," "governance," "board of directors," "board composition," "board incentives," "board structure," "board involvement," and "board vigilance." The keyword searches included all the management journals used most frequently in content analyses of research results (Podsakoff *et al.*, 2005) as well as several other journals not on that list. We also searched the leading accounting (Chan *et al.*, 2009), finance (Chen and Huang, 2007), and economics journals according to reviews and impact rankings provided in those areas. We focused on these journals to ensure study quality, consistency, article visibility, and to capture the work likely to have the largest influence on subsequent research.

This diverse range of journals represents the most extensive synthesis of the strategic leadership and performance relationship to date, and, through its size, provides an alternative for guarding against the likelihood of obtaining a nonpositive definite meta-analysis matrix (Decision point #4). Like past meta-analyses (e.g., Crook *et al.*, 2008; Dalton and Dalton, 2005), we excluded unpublished studies, as (1) we cannot determine whether any responses that we might receive to an open call would resemble a representative sample of the population of nonpublished studies; (2) absent peer review, we have no control for study quality; and (3) excluding such studies has been found to have no influence on meta-analytic findings (Dalton *et al.*, 2012). Overall, we identified all strategic leadership articles appearing in the 56 leading academic journals listed in Table 1.

Second, we manually examined the references sections of all identified articles to locate other studies that were not uncovered using the database searches. Third, we conducted an ancestry search of review articles (e.g., Carpenter *et al.*, 2004) and research volumes (Finkelstein and Hambrick, 1996; Finkelstein *et al.*, 2009). All told, we identified more than 700 articles across 56 journals. We then examined the title, abstract, and results section of each article to identity correlations relevant to our meta-analysis. Each identified article was retained if it involved an empirical analysis, provided the statistical information needed for a meta-analysis (e.g., correlation coefficient and sample size), and leadership and performance measures were consistent with conventional definitions. The final sample consists of 208 articles that collectively report 871 unique effect sizes based on a sample of 495,638 observations. The articles were identified by three members of our author team; all discrepancies regarding whether an article should be included were resolved via discussion, in a manner similar to other meta-analyses (e.g., Crook *et al.*, 2008).

Because some research streams rely on large, accessible databases, there is a concern about the dependence (or nonindependence) of samples that could be used in a meta-analysis. Although nonindependence of samples is a potential limitation of our demonstration (Decision point #5), we believe it was not a major problem in our illustration because the variables are drawn from different sources (e.g., proxy statements, various annual and quarterly reports, investor registers, and guides). Further, our meta-analysis consisted of studies published over a period of thirty years and uses articles from different disciplines, so the variations in data sources would seem to be maximized.

Coding process

The coding process followed Duriau, Reger, and Pfarrer's (2007) recommendations for conducting content analysis. One of the authors, who holds a Ph.D. and has expertise in strategic leadership, oversaw a team of four management graduate students who collected the data. Each was trained in the strategic leadership literature through taking doctoral seminars and coursework, additional readings, as well as having frequent meetings with the team leader. Each was provided with a coding protocol and a list of definitions for the variables of interest.

Board independence is typically measured as the percentage/proportion/ratio of outside directors, where outsiders are expected to represent owners and act independently from managerial influence. *Board size* is defined and measured as the number

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Table 1. List of journals included in meta-analytic structural equation modeling study of the strategic leadership-performance relationship

Management journals (31)	Accounting journals (6)
1. Academy of Management Journal	1. The Accounting Review
2. Administrative Science Quarterly	2. Journal of Accounting Research
3. Asia-Pacific Journal of Management	3. Accounting Organizations and Society
4. British Journal of Management	4. Journal of Accounting and Economics
5. Business Strategy and the Environment	5. Contemporary Accounting Research
6. Corporate Governance: An International Review	6. Accounting Horizons
7. Decision Sciences	**Finance journals (10)**
8. Group and Organization Management	1. Journal of Finance
9. Human Relations	2. Review of Financial Studies
10. Human Resource Management	3. Journal of Financial Economics
11. Industrial & Labor Relations Review	4. Journal of Finance and Quantitative Analysis
12. Journal of Economics & Management Strategy	5. Journal of Business
13. Journal of International Business Studies	6. Journal of Corporate Finance
14. Journal of Applied Psychology	7. Journal of Financial Markets
15. Journal of Business Research	8. Financial Analysts Journal
16. Journal of Business Venturing	9. Financial Management
17. Journal of International Management	10. Journal of Financial Intermediation
18. Journal of Management	**Economics journals (9)**
19. Journal of Management Studies	1. Journal of Economic Literature
20. Journal of Operations Management	2. Quarterly Journal of Economics
21. Journal of Organizational Behavior	3. Journal of Political Economy
22. Leadership Quarterly	4. Journal of Economic Perspectives
23. Long Range Planning	5. Econometrica
24. Management Science	6. Journal of Accounting and Economics
25. Organizational Behavior and Human Decision Processes	7. Journal of Economic Geography
26. Organization Science	8. Review of Economic Studies
27. Organization Studies	9. American Economic Review
28. Personnel Psychology	
29. Strategic Entrepreneurship Journal	
30. Strategic Management Journal	
31. Strategic Organization	

The list of individual articles is available upon request.

of directors. *Board leadership structure* refers to whether the same person jointly holds the titles of chief executive and chairperson of the board (i.e., CEO duality). *CEO tenure* is the number of years since appointment as CEO. *Top management team (TMT) size* is the number of executives that constitute a firm's top management team, while *TMT tenure* is the average tenure of all TMT members. *TMT diversity* is the degree of variability among team members in terms of their tenure, education, or functional background, and is typically measured using a standard deviation, a coefficient of variation or a Herfindahl score. Finally, firm *performance* was measured using accounting-based financial measures (e.g., return on assets [ROA], return on sales [ROS], return on equity [ROE]) and market-based measures (e.g., market-to-book, stock returns). While capturing different facets of performance, accounting- and market-based measures are both underlying manifestations of how well a firm is performing (Combs, Crook, and Shook, 2005). The vast majority of studies in our sample (73%) used a single measure of performance.[5] In addition, for cases where accounting and financial measures were used within the same study, the correlation between these two measures was 0.21, ($p < 0.001$, $k = 82$; $N = 54{,}077$; 95% *CI* 0.17–0.24). Given theoretical justification and empirical justification including the fact that the majority of studies included a single dimension and the positive relationship between the two types

[5] Of the 190 studies with a performance variable included in the study, 138 (73%) studies relied on a single measure of firm performance and 52 (27%) studies used multiple measures. Of the studies using a single measure of performance, more than half rely on accounting-based metrics (75 studies, 54% of single measure studies), with return on assets (ROA) being the most frequently used measure of accounting performance.

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of measures, we aggregated performance measures across studies (i.e., by computing a sample-size weighted average).

Interrater reliability was determined using correlation analyses of the coders' retesting of study variables (Carmines and Zeller, 1979; LeBreton and Senter, 2008). The coders exchanged articles twice during the coding process, recoded variables, and then compared their findings using correlation analysis. The average correlation across the recoding points was 0.95. Differences were discussed until 100 percent agreement was reached. Finally, for each article, the coders recorded the relevant effect size (i.e., correlation coefficient) and the associated sample size.

Meta-analysis

In conducting a meta-analysis, researchers have the choice to focus on articles or effect sizes as the unit of analysis. Focusing on articles as the unit of analysis has the advantage that each sample in each article is included only once in the meta-analysis, giving the impression that there are no duplicate studies (cf. Wood, 2008). However, focusing on articles as the unit of analysis requires that all relationships among different operationalizations of the same constructs are precisely identical. In other words, the use of the article as the unit of analysis requires aggregation of all effect sizes reported within each article, thereby losing information about the precise nature of the various combinations of variable operationalizations.

Further, due to the heterogeneity of effect size estimates and because they provide unique information about a relationship, aggregation of effect sizes computed using different operationalizations within studies is rarely justified (van Mierlo, Vermunt, and Rutte, 2009). Accordingly, we followed guidelines offered by recently published reviews of other types of effect sizes and focused on the effect size instead of the article as the unit of analysis (e.g., Aguinis *et al.*, 2005, 2011b). Although in some cases there is overlap in terms of the variables used to compute effect sizes within an article (which we corrected by creating a weighted composite effect size), the majority of effects do not share the measures and constructs underlying effect sizes.

Our analytical procedure followed the guidelines and formulae of Hunter and Schmidt (2004) and Dalton and Dalton (2005). Specifically, we first extracted bivariate correlations (r) between board of directors, TMT, and CEO measures with performance from the primary-level studies. Second, we computed mean correlations that were weighted by their respective sample sizes.[6] Third, we used a conservative 0.80 reliability estimate for the TMT variables and a 1.0 reliability for board and performance measures (Dalton *et al.*, 1998). The use of the 0.80 level is the recommended conservative value for meta-analyses based on a review of almost 6,000 effect sizes reported in management journals (Aguinis *et al.*, 2011b).[7] We used 1.0 for the board and performance variables because the vast majority of the firms included in our study will have these measures verified by independent external auditors who apply legal regulations to attest to their accuracy.[8]

Finally, we also computed confidence intervals for each meta-analytically derived mean correlation using equations from Hunter and Schmidt (2004: 205–207). To avoid any potential computational errors, we performed all calculations using Schmidt and Le's (2005) software, which implements the Hunter and Schmidt (2004) equations.

Structural equation modeling

We arranged the meta-analytic findings into a correlation matrix (Table 2), which served as the basis for subsequent SEM analyses. Based on recommendations by Aguinis, Gottfredson, and Wright (2011a), the tables include information on confidence intervals and credibility intervals. Confidence intervals assume a single population

[6] We predominantly relied upon the number of firms as the sample size. In a small number of cases, mostly involving panel designs, we used firm-years as the sample size. We did so only when it was clearly apparent that firm year was the statistical unit of analysis.

[7] Dalton *et al.* (1998: 277) tested whether different levels of reliability impacted the findings of their meta-analyses, finding that the "choice of reliability level … had little consequence to our results." Following their precedent, and subsequent examinations, we applied the 0.80 level in our study.

[8] As a check, we also used the 0.80 level of reliability for all constructs and recomputed the models and analyses. The findings were not substantively different from the use of 1.0 levels. Outside stakeholders can have confidence in reported measures of performance and board composition, as those variables go through a legally required audit for all public firms. In both cases, there is little if any room for researcher choice and subjectivity, which represent the sources of measurement error. While an argument can be made that all measures are subject to error, those having to pass such legal scrutiny certainly have less error than those where researchers decide the parameters. Researcher subjectivity does exist when it comes to defining the TMT—the parameters of what constitutes the team and reflects the use of self-report data. In these latter conditions, we adopted the conventional 0.8 standard.

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Table 2. Meta-analytic correlations among antecedent, mediator, and outcome variables

	1	2	3	4	5	6	7	8
1. CEO tenure	*0.80*							
2. TMT tenure		*0.80*						
ρ (r)	0.27 (0.22)							
*CI*95	0.10: 0.44							
*CR*80	−0.10: 0.65							
k(N)	12 (5,958)							
3. TMT diversity			*0.80*					
ρ (r)	0.020 (0.016)	−0.057 (−0.046)						
*CI*95	−0.07: 0.12	−0.10: −0.02						
*CR*80	−0.21: 025	−0.30: 0.19						
k(N)	14 (8,060)	86 (24,456)						
4. TMT size				*0.80*				
ρ (r)	−0.034 (−0.027)	−0.032 (−0.025)	0.14 (0.12)					
*CI*95	−0.07: 0.01	−0.10: 0.04	0.08: 0.20					
*CR*80	−0.12: 0.05	−0.32:0.26	−0.20: 0.48					
k(N)	12 (2,398)	42 (9,037)	76 (17,963)					
5. Board size					*1.0*			
ρ (r)	−0.086 (−0.077)	0.17 (0.15)	0.30 (0.27)	0.35 (0.31)				
*CI*95	−0.12: −0.05	0.04: 0.31	0.17: 0.42	0.22: 0.47				
*CR*80	−0.16:−0.01	−0.02: 0.37	0.16: 0.43	0.17: 0.53				
k(N)	12 (11,494)	5 (573)	3 (3,736)	5 (911)				
6. Board leadership structure						*1.0*		
ρ (r)	0.19 (0.17)	0.13 (0.12)	0.018 (0.016)	−0.09 (−0.08)	0.024 (0.024)			
*CI*95	0.14: 0.25	0: 0.26	−0.03: 0.06	−0.15: −0.05	−0.01: 0.06			
*CR*80	−0.03: 0.41	−0.08: 0.34	−0.09: 0.12	−0.089: −0.09	−0.07: 0.12			
k(N)	36 (25,711)	6 (768)	15 (13,369)	2 (516)	22 (15,636)			
7. Board independence							*1.0*	
ρ (r)	−0.10 (−0.09)	−0.05 (−0.05)	0.08 (0.07)	0.02 (0.015)	0.16 (0.16)	−0.014 (−0.014)		
*CI*95	−0.14, −0.05	−0.18: 0.07	0.01: 0.17	−0.02: 0.06	0.08: 0.23	−0.06: 0.03		
*CR*80	−0.25: 0.05	−0.37:0.26	0.078:0:08	0.017: 0.018	−0.09: 0.41	−0.18: 0.15		
k(N)	24 (9,050)	16 (9,452)	3 (312)	4 (937)	27 (13,316)	29 (13,031)		
8. Firm performance								*1.0*
ρ (r)	0.019 (0.017)	0.036 (0.032)	−0.015 (−0.014)	0.049 (0.043)	0.07 (0.07)	0.01 (0.01)	0.023 (0.023)	
*CI*95	0: 0.03	0.01: 0.07	−0.04: 0.01	0.03: 0.07	0.04: 0.09	−0.02: 0.03	0.01: 0.04	
*CR*80	−0.07: 0.11	−0.07: 0.14	−0.14: 0.11	−0.04: 0.14	−0.06: 0.19	−0.12: 0.13	−0.08: 0.12	
k(N)	79 (105,030)	33 (9,033)	43 (6,901)	39 (7,007)	59 (86,121)	74 (54,839)	93 (40,021)	

Italicized numbers on the main diagonal are reliability coefficients. ρ: mean true score (corrected) correlation; r: observed correlation; *CI*95: 95 percent confidence interval for ρ; *CR*80: 80 percent credibility interval for ρ; k: number of studies used in computing ρ; N; sample size used in computing ρ. In some cases, the total number of studies and observations shown in this table exceed the totals listed in the manuscript's text because, similar to Crook *et al.* (2008) and Aguinis *et al.* (2011a), some studies report multiple effect sizes for pairs of variables.

estimate and provide information on the cross-study variability around the single estimate. On the other hand, credibility interval assumes the presence of more than one population estimate such that the lower bound of an 80 percent credibility interval is the value above which 80 percent of the population effect sizes are expected to lie. In spite of the different information they provide, Table 3 shows that confidence and credibility intervals offer consistent information regarding the variability of effects.

In accordance with Decision point #2, no cells contained missing values. For Decision point #3 (addressing different sample sizes across the cells), consistent with similar studies (e.g., Colquitt, LePine, and Noe, 2000; Earnest *et al.*, 2011), we used the harmonic mean (2,216) for computing significance levels for the coefficients (Viswesvaran and Ones, 1995). We selected the maximum likelihood estimation approach and used Amos 18 for the analyses. The analyses tested the fit of each

Table 3. Coefficients for direct-effect model (see Figure 2)

	Coefficient	SE	95% CI	*t* value	*p* value
CEO tenure → firm performance	0.02	0.022	−0.02: 0.06	1.030	0.303
TMT tenure → firm performance	0.02	0.022	−0.02: 0.06	0.792	0.43
TMT diversity → firm performance	−0.04	0.021	−0.08: 0.001	−1.896	0.058
TMT size → firm performance	0.03	0.021	−0.01: 0.07	1.536	0.125
Board size → firm performance	0.07	0.021	0.03: 0.11	3.107	0.002
Board leadership structure → firm performance	0.01	0.021	−0.03: 0.05	0.272	0.785
Board independence → firm performance	0.02	0.021	−0.02: 0.06	0.847	0.397
Model fit: $\chi^2(12) = 769.33$, $p < 0.001$. CFI = 0.28; GFI = 0.93; NFI = 0.28; RMR = 0.096					

SE = standard error; 95 percent CI = confidence interval for coefficient; CFI = comparative fit index; GFI = goodness-of-fit statistic; NFI = normed fit index; RMR = root mean square residual; TMT = top management team

model and provided individual coefficients. Consistent with Decision point #6, we used multiple fit indices which, as mentioned earlier, include CFI, GFI, and RMR to assess the models.

We also recognize that endogeneity is a possible alternative explanation, particularly with respect to performance. Specifically, an alternative hypothesis is that prior performance could influence the values of the leadership variables. We therefore tested whether the bivariate effect sizes varied with respect to whether prior performance was considered. The results show no consistent impact on the predictors or mediators in both models (e.g., top management team size, board size), and both models received lower fit levels. In addition, we tested each of the available sources of endogeneity, including a lagged term to account for autocorrelation, testing different levels of measurement error, using a diverse and broader set of top leadership variables than previously appeared in a meta-analysis of such factors, and we compared alternative competing models against one another. The results of our tests are reported below.

Results

Results of testing the traditional bivariate meta-analyses are reported in Table 2, and indicate that four antecedents are significantly associated with performance (i.e., 95% confidence intervals exclude zero): top management team tenure (0.04), top management team size (0.05), board size (0.07), and board independence (0.02). However, these findings offer a less-than-complete understanding and are not consistent with those of MASEM. In Figure 2, we report the results of a baseline, one-to-one direct model, whereby each strategic leadership variable is related directly to performance (the levels of each variable covary with the other variables at the corresponding level, such that board variables only covaried with other board variables) within a MASEM structure. Note that the board variables and performance variable are represented with rectangles in Figure 2 and the other figures as they are designated as observed variables, while the leadership constructs are represented with ovals to indicate latent factors. The coefficients for this model are reported in Table 3. The findings indicate that top management team diversity is negatively associated with performance at a marginally significant level (-0.04, $p < 0.058$) and that board size is again related positively (0.07). Only the results related to board size are consistent across the bivariate and MASEM techniques, suggesting that traditional bivariate meta-analysis and MASEM provide different findings. In addition, the direct effects model does not fit the data well ($\chi^2(12) = 769.33$; $p < 0.001$, GFI = 0.93, CFI = 0.28, normed fit index [NFI] = 0.28, RMR = 0.10). These results provide an additional reason to consider expanding the structure of the leadership model to include the more complex mediating relationships specified in the conceptual frameworks.

We next tested two competing mediated models, as these provide insights into both the conceptual alternatives of the relationships while offering one test of possible endogenous relationships. The first model is based on the agency theory proposition that the association of board leadership attributes with performance is mediated by top management team attributes. This view posits that boards do not directly participate in the strategic actions of the firm, but instead shape firm performance through their influence on monitoring and disciplining as well as shaping the composition and structure of the top management team. This model (Figure 3)

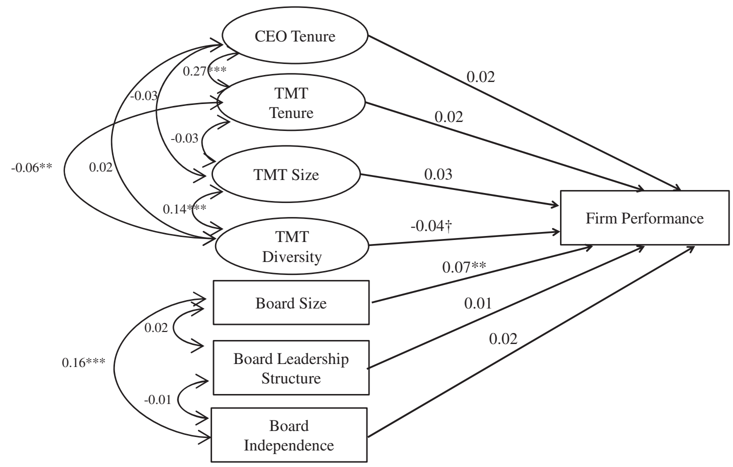

Figure 2. Direct effects model. For clarity of presentation, this figure does not include endogenous error terms (***$p<0.001$, **$p<0.01$, *$p<0.05$, †$p<0.10$)

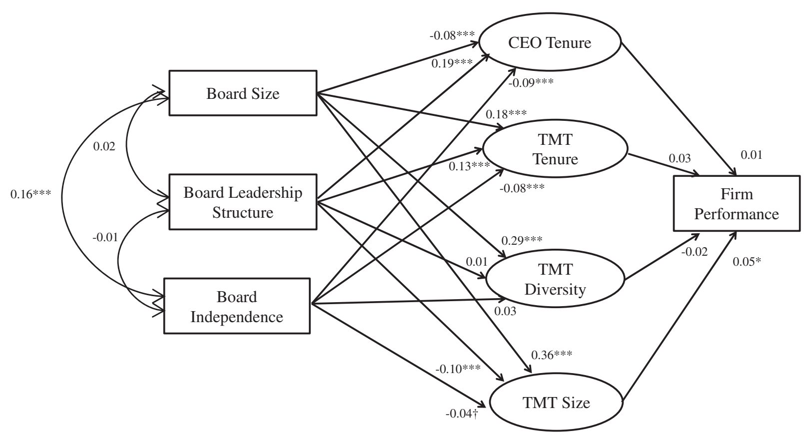

Figure 3. Mediated (board → TMT → firm performance) model. For clarity of presentation, this figure does not include endogenous error terms (***$p<0.001$, **$p<0.01$, *$p<0.05$, †$p<0.10$)

achieves better fit ($\chi^2(9)=242.479$; $p<0.001$, GFI = 0.98, CFI = 0.77, NFI = 0.77, RMR = 0.05) than the direct effects model ($\Delta\chi^2(3)=526.85$; $p<0.001$).

The coefficients reported in Table 4 reveal that several board attributes are associated with CEO and TMT attributes. Board size is positively associated with TMT tenure (0.18), TMT diversity (0.29), and TMT size (0.36), but negatively associated with CEO tenure (-0.08). Board leadership structure is positively associated with CEO tenure (0.19) and TMT tenure (0.13), but negatively associated with TMT size (-0.10), while board independence is negatively associated with CEO tenure (-0.09) and TMT tenure (-0.08). Finally, only top management team size is related to performance (0.05). Collectively, these results suggest two paths to performance: (1) board size is related positively to TMT size, which is associated with higher performance; and (2) board leadership is related to smaller TMT size, which is linked with performance. It should be recognized that the board size effects tend to be higher in studies using designs that do not account for temporal designs, so these effects may be slightly smaller for the lagged designs. Importantly, these relationships are impossible to identify using meta-analysis alone (i.e., bivariate assessments).

To help rule out one source of endogeneity, we compared the foregoing multivariate model with an alternative depiction of strategic leadership that involves the top management team variables as antecedents to the board variables, which in turn are antecedents to performance. This model

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Table 4. Coefficients for mediated (board →TMT → performance) model (see Figure 3)

	Coefficient	SE	95% CI	*t* value	*p* value
Board size → CEO tenure	−0.08	0.021	−0.12: −0.04	−3.670	0.0001
Board leadership structure → CEO tenure	0.19	0.021	0.15: 0.23	9.209	0.0001
Board independence → CEO tenure	−0.09	0.021	−0.13: −0.05	−4.054	0.0001
Board size → TMT tenure	0.18	0.021	0.14: 0.22	8.547	0.0001
Board leadership structure → TMT tenure	0.13	0.021	0.09: 0.17	6.016	0.0001
Board independence → TMT tenure	−0.08	0.021	−0.12: −0.04	−3.668	0.0001
Board size → TMT diversity	0.29	0.021	0.25: 0.33	14.344	0.0001
Board leadership structure → TMT diversity	0.01	0.020	−0.03: 0.05	0.562	0.574
Board independence → TMT diversity	0.03	0.021	−0.01: 0.07	1.610	0.107
Board size → TMT size	0.36	0.020	0.32: 0.40	17.891	0.0001
Board leadership structure → TMT size	−0.10	0.020	−0.14: −0.06	−5.011	0.0001
Board independence → TMT size	−0.04	0.020	−0.08: −0.001	−1.934	0.053
CEO tenure → firm performance	0.01	0.021	−0.03: 0.05	0.578	0.563
TMT tenure → firm performance	0.03	0.021	−0.01: 0.07	1.563	0.118
TMT diversity → firm performance	−0.02	0.021	−0.06: 0.02	−0.976	0.329
TMT size → firm performance	0.05	0.021	0.01: 0.09	2.500	0.012
Model fit: $\chi^2(9) = 242.479$, $p < 0.001$. CFI = 0.77; GFI = 0.98; NFI = 0.77; RMR = 0.050					

SE = standard error; 95 percent CI = confidence interval for coefficient; CFI = comparative fit index; GFI = goodness-of-fit statistic; NFI = normed fit index; RMR = root mean square residual; TMT = top management team

reverses agency theory logic to suggest that top management teams may work through the boards of directors to approve their decisions and even help shape their composition and structure (Figure 4). Tests of this latter model revealed even better fit indexes ($\chi^2(7) = 63.795$; $p < 0.001$, GFI = 0.99, CFI = 0.95, NFI = 0.94, and RMR = 0.03), and it fits the data significantly better than the agency multivariate model ($\Delta\chi^2(2) = 178.68$; $p < 0.001$). As a further test of endogeneity, we tested two alternative models: (1) where performance preceded the board variables, which preceded the top management team variables; and (2) where performance preceded the top management team variables, which then preceded the board variables. Both of these models were statistically inferior to the others.

First, CEO tenure is related negatively to board size (-0.14) and board independence (-0.10) and is related positively to board leadership (0.16). Second, top management team tenure is related positively to board size (0.23) and to board leadership (0.09). Third, top management team diversity also is positively associated with board size (0.27) and board independence (0.08). Fourth, while top management team size is positively related to board size (0.31), it is negatively related to board leadership (-0.09). Finally, board size is related positively to performance (0.07). See Table 5.

These results suggest several pathways to improved performance. Shorter CEO tenure, longer TMT tenure, greater TMT diversity, and larger TMTs are all associated with larger boards, which in turn are linked to higher levels of performance. While CEOs with short tenure would likely have less influence over boards, top management teams that are more diverse, those having more tenure, and those that are larger would likely have more information and power to work with their boards as they tried to manage strategic decisions. Again, these relationships may be slightly smaller, due to the possible upward bias associated with nonlagged designs.

Overall, consistent with Decision point #9, we find substantive differences in the coefficients across the models, as comparing the bivariate, direct, and mediated models provides for a more nuanced depiction of strategic leadership effects. Because MASEM incorporates the field's accumulated data and accounts for the interplay between the board and the firm's top executives, the multivariate model would seem to open new insights for the field. MASEM creates opportunities for additional theorizing that would not be generated via traditional meta-analysis.

DISCUSSION

This paper describes how strategic management researchers can leverage MASEM and provides an

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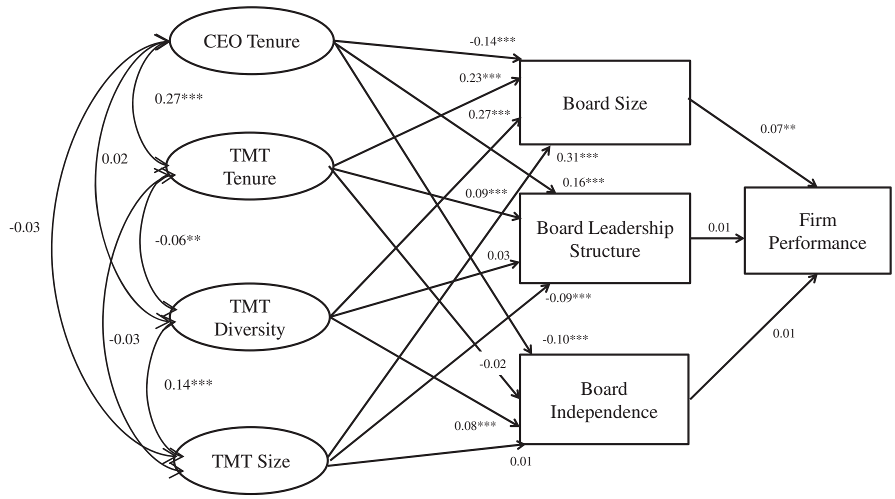

Figure 4. Mediated (board → TMT → firm performance) model. For clarity of presentation, this figure does not include endogenous error terms (***$p < 0.001$, **$p < 0.01$, *$p < 0.05$, †$p < 0.10$)

Table 5. Coefficients for mediated (TMT → board → performance) model (see Figure 4)

	Coefficient	**SE**	**95% CI**	***t* value**	***p* value**
CEO tenure → board size	−0.14	0.019	−0.17: −0.10	−7.499	0.0001
TMT tenure → board size	0.23	0.019	0.19: 0.27	12.193	0.0001
TMT diversity → board size	0.27	0.019	0.23: 0.31	14.557	0.0001
TMT size → board size	0.31	0.019	0.27: 0.35	16.842	0.0001
CEO tenure → board leadership structure	0.16	0.022	0.12: 0.20	7.595	0.0001
TMT tenure → board leadership structure	0.09	0.022	0.05: 0.13	3.939	0.0001
TMT diversity → board leadership structure	0.03	0.021	−0.01: 0.07	1.509	0.131
TMT size → board leadership structure	−0.09	0.021	−0.13: −0.05	−4.117	0.0001
CEO tenure → board independence	−0.10	0.022	−0.14: −0.06	−4.393	0.0001
TMT tenure → board independence	−0.02	0.022	−0.06: 0.02	−0.880	0.379
TMT diversity → board independence	0.08	0.021	0.04: 0.12	3.758	0.0001
TMT size → board independence	0.01	0.021	−0.03: 0.05	0.230	0.818
Board size → firm performance	0.07	0.021	0.03: 0.11	3.199	0.001
Board leadership structure → firm performance	0.01	0.021	−0.03: 0.05	0.403	0.687
Board independence → firm performance	0.01	0.021	−0.03: 0.05	0.578	0.563
Model fit: $\chi^2(7) = 63.795$, $p < 0.001$. CFI = 0.95; GFI = 0.99; NFI = 0.94; RMR = 0.025					

SE = standard error; 95 percent CI = confidence interval for coefficient; CFI = comparative fit index; GFI = goodness-of-fit statistic; NFI = normed fit index; RMR = root mean square residual; TMT = top management team

empirical illustration. Based on an original study of the strategic leadership-performance relationship, we consider how findings and conclusions for theory development can vary based on whether conventional meta-analysis or MASEM is used. The MASEM approach also highlights the ability to test previously unconsidered relationships in previous meta-analytical syntheses.

In addition, there are empirical bases for distinguishing the value of MASEM. For example, scholars could quantify how much more explanatory power MASEM offers relative to meta-analysis via the use of simulations.[9] This approach would involve specifying underlying relationships and then comparing the accuracy of the estimates provided by MASEM and meta-analysis. Although methodological research has established that MASEM offers greater utility than traditional meta-analysis, identifying the magnitude of this difference would help strategy researchers decide how much effort to devote to using MASEM.

[9] We are grateful to an anonymous reviewer for pointing out this potential benefit of simulations.

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The greater the difference, for example, the more valuable it would be to revisit the findings of past meta-analyses using MASEM.

In general, MASEM provides opportunities to build upon evidence already reported in the strategic management literature to gain new insights into important relationships. One possible contribution of MASEM relative to the traditional application of meta-analyses is to redirect thinking from resolving inconsistencies in reported findings to expanding knowledge of the boundaries of phenomena and theories. For instance, Lee and Madhavan's (2010) synthesis of the divestiture and performance literature examined whether strategic, implementation, and methodological choices might serve as moderators that in turn account for differences in observed findings. MASEM would allow divestiture researchers to explore another direction by depicting divestitures in accordance with their theoretical heritage as a corrective mechanism to problematic strategies (Bergh, Johnson, and DeWitt, 2008; Hoskisson, Johnson, and Moesel, 1994). Viewed from this perspective, the antecedents of divestiture, such as excessive diversification, corporate governance pressures, and environmental uncertainty could be related to divestiture, which would then be related to firm performance. These relationships represent new opportunities for knowledge development that cannot be effectively exploited using traditional meta-analyses.

MASEM also provides strategy researchers with an opportunity to reach a higher level of understanding by pitting the explanatory power of alternative theoretical models against one another. Some have argued that organizational research may now have too many theories, and it is now time to test their validity and utility through competitive comparisons (Davis, 2010; Edwards, 2010). MASEM facilitates such analyses by allowing various models to be constructed to represent alternative theories, followed by the aggregation of data pertaining to those theories, and then provides a direct testing of the model parameters to determine which theory receives the strongest support. For example, MASEM could be used to ascertain the extent to which ecological models, resource dependence theory, and institutional theory explain organizational failure. Such a competitive evaluation process could lead to one or more theories being discarded or to a synthesis that incorporates insights from different theories in order to assemble a more comprehensive model.

The ability to test competing models, while synthesizing data from multiple studies, is a major benefit of the MASEM approach. For virtually every strategic management topic, there are multiple theoretical perspectives, often with competing views on the ordering of variables. For instance, using similar data, studies by Amihud and Lev (1981) and Lane, Cannella, and Lubatkin (1998) drew on dramatically different conclusions on the applicability of agency theory to diversification. Similarly, Rindova *et al.* (2005) and Boyd, Bergh, and Ketchen (2010) used competing theoretical perspectives to drill down into the "black box" of the reputation–performance connection. In the latter case, the author teams each provided structural equation models reporting support for their respective arguments. In both cases, the debate about theory provides the real payoff, as scholars strive to build more accurate models. By applying MASEM, the ability to test competing frameworks grows dramatically. In addition, such an approach is consistent with the attempt to rule out possible determinants of endogeneity. MASEM can also advance strategic management theory and research by unpacking and permitting fine-grained insights into the individual elements of theoretical frameworks and perspectives. For example, using MASEM procedures, while Drees and Heugens (2013) found overall support for resource dependence theory, they also found that not all types of interorganizational arrangements are equally effective in managing resource dependencies.

MASEM also could be applied to extend the findings of prior traditional meta-analyses. For example, Deutsch (2005) examined the implications of board composition for a number of issues, including CEO pay, antitakeover provisions, diversification, R&D spending, and the use of debt. The results were largely counter to predictions, and the magnitude of the effect sizes was small. In this scenario, a mediation model similar to the one presented in our strategic leadership illustration could provide a more nuanced view. A model could be developed wherein the outsider ratio might have a direct effect on alignment variables (i.e., pay and poison pills), which in turn may shape an executive's decision to focus on short- versus long-term outcomes (i.e., cash flow versus investment for the future). In a second example, Capon, Farley, and Hoenig (1990) integrated 320 studies that examined various determinants of firm performance. Based on their analysis,

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they constructed a conceptual model with three categories of predictors: environment, strategy, and organization. In turn, each category has numerous indicators. Data from this study could be used to (1) develop and validate confirmatory factor models for each of these dimensions, (2) concurrently test the effects of each dimension, and (3) test different multistep structural models using MASEM.

CONCLUSION

There has long been a mismatch between the multifaceted nature of strategic management theories and the methodological tools available to assess how well bodies of findings support these theories. Strategic management theories tend to involve complex webs of relationships, and MASEM offers strategy researchers the potential to use a literature's data to examine the multivariate structure of important research questions. Further, rather than relying on the traditional scientific process of replication and an ever increasing refinement to create and establish more specific insights about two constructs, MASEM offers an expanding perspective whereby researchers can turn their attention to models that reflect entire frameworks and theoretical perspectives. Considered in conjunction with MASEM's boundary conditions described earlier in our manuscript, such an approach will allow strategy researchers to identify which relationships are more or less important for their colleagues and executives to consider. Overall, MASEM holds the potential to reshape a literature's development.

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