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MEDIATION IN STRATEGIC MANAGEMENT RESEARCH: CONCEPTUAL BEGINNINGS, CURRENT APPLICATION, AND FUTURE RECOMMENDATIONS

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ABSTRACT

Mediating effects allow strategic management researchers to understand "black box" processes underlying complex relationships whereby the effect of an independent variable is transmitted to a dependent variable through a third variable. Since the seminal work of Baron and Kenny (1986), advancements have been made in mediation analysis. Thus, literature on the latest techniques for analyzing mediating and intervening varibales is presented. In addition, strategy literature published in the Academy of Management Journal and the Strategic Management Journal between 1986 and 2005 employing tests of mediation is reviewed to better understand how mediation techniques are used by strategy scholars. Finally, implications and limitations of current mediation analysis in strategy research are discussed, and recommendations are provided to strategy scholars examining mediation.

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Mediation exists when the relationship between a predictor and an outcome variable occurs *through* a third variable; this third variable is referred to as a mediating variable. Tests of intricate relationships, including mediating variables, have become more prevalent over the last 10 years in strategic management as researchers have been prompted to explore the processes underlying the relationships they examine (Hitt, Gimeno, & Hoskisson, 1998). While only 20 strategic management articles analyzing mediating effects were published in the *Academy of Management Journal* (*AMJ*) and the *Strategic Management Journal* (*SMJ*) between 1986 and 1995, for example, more than twice as many (45 articles) analyzing mediating effects were published in these journals between 1996 and 2005.

Strategy scholars have incorporated mediating effects in a number of diverse research settings. Yli-Renko, Autio, and Sapienza (2001), for example, found that social capital influenced knowledge exploitation *through* knowledge acquisition. In another example, Baum and Wally (2003) found that organizational structure influenced firm performance *through* strategic decision speed. Finally, Cho and Pucik (2005) found that innovativeness influenced firm profitability *through* growth. Taken together, these examples suggest the importance of mediating effects in strategic management research.

Nearly 20 years have passed since the seminal work of Baron and Kenny (1986), henceforth referred to as BK. As such, we attempt to understand how BK has influenced strategic management research through a review of strategy mediation articles. We provide three primary contributions with this article. First, we distinguish between mediating and indirect effect relationships, describe different methods available to test mediating relationships, and discuss the potential implications of this dichotomy with respect to strategy research. Second, we review the strategy research published in the *AMJ* and the *SMJ* between 1986 and 2005 to examine the norms as they pertain to mediation testing in strategy research. Finally, we provide recommendations to strategy researchers for testing mediating effects. Our efforts are not intended to criticize the work of others. Instead, we hope that this review helps scholars to better understand how mediation is used in strategy research.

MEDIATING VARIABLES

BK defined mediators as variables that allow an independent variable to influence a dependent variable. Mediation processes occur over time, such

that the independent variable occurs temporally before the mediating variable and the mediating variable occurs before the dependent variable (Baron & Kenny, 1986; Shrout & Bolger, 2002). The effect of the independent variable on the dependent variable through the mediating variable is referred to as a *mediating effect*.

Mediation may be either full (also known as "complete") or partial. In a fully mediated model, the predictor variable, x, influences the outcome variable, y, only through the mediating variable, m. In other words, the entire effect of x on y is transmitted through m (James & Brett, 1984). In a partially mediated model, however, only a portion of the total effect of x on y is due to the mediation by m (Duncan, 1970, 1975; Heise, 1975; Kenny, 1979). In other words, partial mediation suggests that an independent variable influences the dependent variable both directly and indirectly.

We should note that scholars in disciplines such as psychology, sociology, and management have relied on mediation to test hypotheses and often use different terminology. Some scholars, for example, examine *intervening variables*, which are defined as processes that intervene between a predictor variable and an outcome variable (MacCorquodale & Meehl, 1948; Tolman, 1938; Woodworth, 1928). The effect of the predictor variable on the outcome variable through the intervening variable is referred to as an *indirect effect*. These terms differ from the concept of mediation, because there is no requirement that the predictor variable have a direct effect on the outcome variable (for a detailed discussion of these terms, see Mathieu & Taylor, 2006).

While it is important to note the differences between these terms, many scholars have used these terms interchangeably (e.g., MacKinnon, Lockwood, Hoffman, West, & Sheets, 2002). Although we rely on the concept of mediation in the following sections, we examine mediation as well as other types of intervening effects in our literature review. In other words, we are primarily interested in indirect effects, and requiring a relationship between the independent and dependent variables is not our central concern.

STATISTICAL TESTS FOR MEDIATING VARIABLES

MacKinnon et al. (2002) uncovered 14 different analytical approaches that have been used to test for mediating or intervening variables. They reduced these 14 methods into three broad approaches, which we review in the following sections. The first is the causal steps approach, advanced by Judd and Kenny (1981) and BK. The other two approaches, difference in coefficients and product of coefficients, are tests for intervening variables. We refer readers to MacKinnon et al. (2002) for a complete list and a more comprehensive review of the 14 specific tests.

Causal Steps

The causal steps approach, which was developed by Judd and Kenny (1981) and BK, is a commonly used approach. This approach includes a series of tests, illustrated in Fig. 1. Path *a* represents the impact of the predictor variable on the mediating variable. Path *b* represents the impact of the mediating variable on the outcome variable. (The product of $a \times b$ in Fig. 1 constitutes the indirect effect.) Path *c* represents the impact of the predictor variable on the outcome variable in the unmediated model (the total effect in Fig. 1). Path c' represents the impact of the predictor variable on the outcome variable when the mediating variable is added to the model (the direct effect in Fig. 1) (Baron & Kenny, 1986).

According to BK, testing for mediation consists of four critical steps. First, the predictor variable must influence the outcome variable (path *c* in Fig. 1). Second, the predictor variable must influence the presumed mediator (Path *a* in Fig. 1). Third, the mediator must influence the outcome variable while controlling for the predictor variable (Path *b* in Fig. 1). Finally,

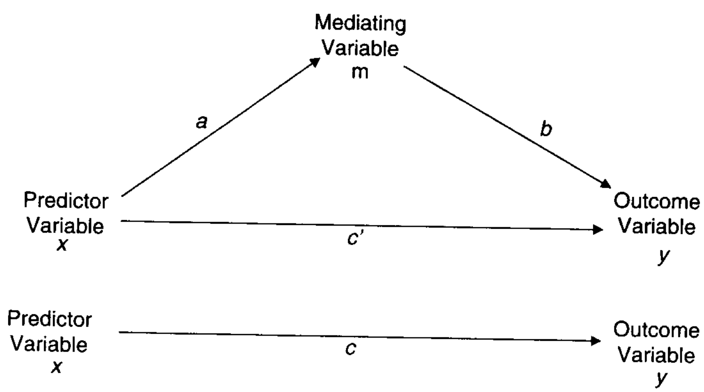

Fig. 1. Illustration of a Model with the Mediating Variable (c' Represents the Relationship between Predictor and Outcome Variables with the Mediating Variable in the Model) and without the Mediating Variable (*c* Represents the Relationship between Predictor and Outcome Variables).

a previously significant relationship between the predictor and outcome variables must be reduced in the presence of the mediator (path c' in Fig. 1).

Difference in Coefficients

The second approach, difference in coefficients, is based on comparing the relationship between the predictor and outcome variables before and after adjusting for the mediating variable. Different pairs of coefficients can be compared, including regression coefficients and correlation coefficients (MacKinnon et al., 2002). When using regression coefficients, the difference in coefficients ($c - c'$) from Fig. 1 is used. The difference in coefficients using correlation coefficients is $\rho_{xy} - \rho_{xy.m}$, where ρ_{xy} represents the correlation between the predictor variable and the outcome variable and $\rho_{xy.m}$ represents the partial correlation between the predictor variable and the outcome variable partialled for the mediating variable, *m* (MacKinnon et al., 2002). For more details on this approach, see Freedman and Schatzkin (1992), McGuigan and Langholtz (1988), and Olkin and Finn (1995).

Product of Coefficients

The third approach, product of coefficients, is based on multiplying the coefficients of the paths in a path model (Alwin & Hauser, 1975; Bollen, 1987; Fox, 1980; Sobel, 1982). The coefficients that are multiplied in this approach are represented by *a* and *b* in Fig. 1. The indirect effect of *x* on *y* through the mediating variable, *m*, is measured as the product of the *a* and *b* paths depicted in Fig. 1 (Preacher & Hayes, 2004). MacKinnon, Warsi, and Dwyer (1995) demonstrated that this measure of the indirect effect is algebraically equal to the difference in coefficients ($c - c'$) for ordinary least-squares regression. This approach tests the significance of the mediating effect by dividing the estimate of the mediating effect, $a \times b$, by its standard error and comparing this value to a standard normal distribution (MacKinnon et al., 2002). The most commonly used product of coefficients formula is that of Sobel (1982), but there are other similar tests (MacKinnon et al., 2002).

To summarize, we have distinguished between the terms "mediate" and "indirect effect" and have discussed various statistical tests to examine potential mediating variables. In the following sections, we assess how strategy researchers have examined potential mediating relationships. After describing our methodology, we discuss the findings of our literature review and assess those findings in light of more recent methodological advancements published since BK (1986).

METHODOLOGY

Our survey of the tests for mediation in strategy research included all strategy articles published in *SMJ* and *AMJ* between 1986 and 2005. Articles from *SMJ* and *AMJ* were examined because they are generally representative of the high-quality strategy research that the field endeavors to conduct. The beginning of the sample window coincides with the publication of BK's seminal work on mediation. In order to select the sample of articles, we first searched for the terms "mediation," "mediating," "mediate," "intervening," "indirect effect," and "intervene" in the text of all articles published in *SMJ* and *AMJ* using *Proquest's ABI/Inform Global Business* database. In addition, we searched for articles published in these two journals using "structural equation(s) modeling (SEM)" or "path analysis" during the years of 2003–2005, to include the time period after the Shook, Ketchen Jr., Hult, and Kacmar (2004) study. All articles in Shook et al. (2004) review on SEM were examined individually to determine whether mediation was analyzed. Only articles presenting and discussing some analysis of indirect or mediating effects were included; those making no mention of mediating effects in their analysis or theory were excluded. The resulting set of articles was then further screened to ensure that all *SMJ* articles in our sample were empirical and that all *AMJ* articles fell under the umbrella of strategy.

To distinguish between strategy and non-strategy articles in *AMJ*, we relied upon multiple criteria. First, we turned to the criteria provided by Rumelt, Schendel, and Teece (1994) who suggested that the domain of strategy research is largely concerned with answering four key questions: (1) How do firms behave? (2) Why are firms different? (3) What is the function of, or value added by, the headquarters unit in a multibusiness firm? and (4) What determines the success or failure of the firm in international competition? Articles that addressed any of these questions were included in the sample. Articles examining issues related to corporate governance and strategic leadership were also included (Finkelstein & Hambrick, 1996). Second, articles were evaluated under the Summer et al. (1990) criteria, whereby research investing strategy, environment,

leadership/organization, and performance are included in the strategy domain. To increase the objectivity of the analysis, all of the articles were independently coded by two of the authors. Interrater reliabilities, Intraclass correlation coefficient (ICC) (Shrout & Fleiss, 1979) ranged from .70 to 1, with an average of .86. Disagreements were resolved through discussion between the two coders. This process resulted in 64 articles assessing mediation in strategy research.

FINDINGS

From 1986 to 2005, 64 strategy articles published in *AMJ* or *SMJ* hypothesized and tested for mediation. Table 1 summarizes the methods that were used to test mediation. The majority of the strategy papers that we reviewed, 55%, employed structural equations modeling to test for potential mediating effects. In recent years, however, researchers have increasingly relied on SEM to test for mediation. Our content analysis revealed that 26 of the 64 articles in our sample used regression approaches. There were also

Table 1. Summary of Strategic Management Articles with Mediating Variables.

	1986–2005
	Number of Studies (%)
Total number of studies	64
Data type	
Primary	28 (44)
Secondary	15 (23)
Both	21 (33)
Primary methodological approaches	
Regression	26 (41)
SEM/path analysis	35 (55)
ANOVA, MANOVA	2 (3)
Partial correlations	1 (2)
Mediating effect found	54 (83)
Supplementary tests of indirect effects	
Sobel	5 (8)
Goodman	1 (2)*
Bootstrapping	1 (2)

*One study used both Sobel and Goodman. Therefore, the total number of studies testing the significance of the indirect effect is 6.

two articles that used analysis of covariance (ANCOVA) to test for mediation in the articles analyzed. Because ANCOVA was used by only two studies, we will not discuss this further. For a critique of ANCOVA for testing mediators, see Fiske, Kenny, and Taylor (1982). In the following sections, we highlight several observations uncovered through the review.

Dominant Use of BK's (1986) Four-Step Method

The review of strategy articles revealed that nearly all of the studies in our sample incorporated various aspects of BK's logic in their methodology whether using regression or SEM in their analysis. BK's process for testing for mediators includes four steps, as mentioned earlier. In our sample, authors inconsistently completed all four steps. In a small number of cases, authors omitted the first step, which requires a relationship between the predictor variable and the outcome variable.

Although it was rare for authors to exclude the first of BK's four steps, there are two important reasons why strategy researchers might want to exclude the first step. First, the relationships analyzed in strategy research are frequently distal as opposed to proximal, which makes it more difficult to identify a significant direct effect of the predictor variable on the outcome variable (Shrout & Bolger, 2002). Shrout and Bolger (2002, p. 429) specifically suggested that omitting the first step is logical when the mediator is distal, as opposed to proximal because the distal effect is more apt to be "(a) transmitted through additional links in a causal chain, (b) affected by competing causes, and (c) affected by random factors."

This distinction between proximal and distal mediators is particularly important in strategy research where distal relationships, longitudinal data, and repeated-measures designs are frequent. Strategy research is concerned with understanding the effects of strategic actions on firm performance where actions and performance outcomes often take place months or even years apart. Relationships between strategic actions and firm performance are complex and distant in time. For example, Krishnan, Miller, and Judge (1997) suggested that top management team (TMT) turnover mediates the relationship between complementarity of the functional backgrounds of the acquired and acquiring firm's TMTs and postacquisition performance. They measured the dependent variable three years after acquisition to allow time for the complementarity of the executive teams to influence turnover and subsequently firm performance. While distal effects are common in strategy literature, they carry implications for mediation analyses. When the

predictor and outcome variables are temporally separated and the effect is fairly small, it becomes more likely that the effect of x on y is transmitted through other intervening variables. This makes it unlikely that a significant direct relationship between x and y would exist, as is required in the first step of BK. Forbes and Milliken (1999), for example, acknowledge the difficulty in finding a relationship between board characteristics and firm performance:

> The influence of board demography on firm performance may not be simple and direct, as past studies presume, but rather, complex and indirect. To account for this possibility, researchers must begin to explore more precise ways of studying board demography that account for the role of intervening processes. (p. 490)

Because it is difficult to find a relationship between the predictor and outcome variables when relationships are distal, some scholars assert that mediation analyses may remain useful even when the relationship between the predictor and the outcome variables is not significant (Collins et al., 1998; MacKinnon, 2000; MacKinnon, Krull, & Lockwood, 2000). For example, James and Brett (1984) did not require a direct effect of the predictor on the outcome variable in order to establish mediation.

Second, researchers may also want to skip BK's first step when a negative mediator is posited because the mediator may cancel out the previous positive relationship between x and y (Collins et al., 1998; Frazier, Tix, & Barron, 2004). The mediator may be the root of the failure to find the direct relationship because it may cancel out the direct effect (Collins et al., 1998). MacKinnon et al. (2001) demonstrated the impact of a negative mediator on a positive relationship, showing that the x–y relationship may be undetected.

For these reasons, requiring a direct relationship between the predictor and outcome variables may impede research in strategic management. The difficulty in finding distal relationships may discourage researchers from continuing mediation analysis if the relationship between the predictor and the outcome is not found to be statistically significant per BK's first step. One study in our analysis did not find mediation because they did not find significance in the first step (Green, Welsh, & Dehler, 2003). Green et al. (2003, p. 429) commented that "this finding [that x was not significantly related to y] obviously precludes the possibility of advocacy's mediating the relationships between project characteristics and project terminations." Because strategy researchers may have difficulty finding significance in the first step when testing distal relationships, there may be several mediation relationships in strategy that we have no knowledge of due to the file drawer problem (Rosenthal, 1979). Rosenthal (1979) believed that there is a publication bias that occurs when the probability that a study gets published is based on the statistical significance of the results. One reason why we may find so few published strategy articles with mediation is, perhaps, that many fail to establish the conditions necessary to proceed to BK's second step.

Issues Regarding Statistical Power

Our review of the strategy literature also highlighted the need to incorporate statistical power in tests of mediation. Statistical power is defined as the ability of a technique to detect relationships present in the data (Vogt, 1993). Cohen (1988, 1992) suggested that researchers should aim to achieve a power level of .80. In this section, we discuss several issues that may affect power when testing for mediation, including the statistical test, collinearity between the predictor and mediator variables, reliability of the mediator, and sample size.

Recent research has questioned the statistical power associated with the BK approach, which represents the most dominantly used approach to test for mediation in the sample (MacKinnon et al., 2002). In a simulation study comparing methods for testing intervening effects, MacKinnon et al. (2002) found that the BK and Judd and Kenny (1981) methods had very low power for detecting small and medium effect sizes. MacKinnon et al. (2002, p. 96) suggested that "studies that use the causal steps methods described by Kenny and colleagues are the most likely to miss real effects." In their simulation, MacKinnon et al. (2002) found that BK only had power ranging from 0.0040 to 0.1060 for small effect sizes ranging in sample size from 50 to 1,000 respectively. Other methods, such as Freedman and Schatzkin's (1992) difference in coefficient method, have power as high as .99 for small effect sizes with a sample size of 1,000 (MacKinnon et al., 2002). Therefore, reliance on the BK method is concerning because strategy research tends to have small effect sizes (Hitt, Boyd, & Li, 2004), which puts such studies at risk of missing effects.

Aside from the fact that the BK approach has low power to detect small effect sizes like those common in strategic management research, there are additional factors that may further reduce power. For instance, the relationship between the mediator, predictor, and outcome variables can influence the power of the test of mediation (Frazier et al., 2004). The power of the test of the mediator–outcome relationship (path b in Fig. 1) and the predictor–outcome relationship when controlling for the mediator variable (path c' in Fig. 1) decreases as the relationship between the predictor variable and the mediator variable (path a in Fig. 1) increases (Frazier et al., 2004; Kenny, Kashy, & Bolger, 1998). In other words, as more variance in the mediator is explained by the predictor variable, there is less variance in the mediator to predict the outcome variable. Therefore, as the relationship between the predictor variable and the mediator variable increases (path a in Fig. 1 gets larger), researchers must rely on larger samples in order to have enough power to test the effects of the other two paths in the model (Frazier et al., 2004; Kenny et al., 1998).

Kenny et al. (1998) provide a formula to demonstrate how power diminishes as the correlation between the predictor variable and mediator grows. They found that power is reduced in mediation analyses, making the effective sample size equal to $N(1-r_{xi}^2)$, where N is the sample size and r_{xi} is the predictor (x) to mediator (m) correlation. According to their framework, a sample size of 100 and a correlation of .80 between the predictor and the mediator ($r_{xi} = .80$) implies an effective sample size of 36 (e.g., $N(1 - r_{xi}^2) = 100(.36) = 36$). Because power is often an issue in the BK causal steps regression approach, determining the necessary sample size represents a step toward addressing the limitations of that approach.

The reliability of the mediator may also influence the power of mediation tests (Frazier et al., 2004). Reliability is important in strategy research, as demonstrated by the fact that 49 of the 64 articles reviewed used some method of primary data that often used surveys where reliability was computed and reported. Reliability is frequently measured with Cronbach's alpha (Cronbach, 1951), using the rule of .70 or greater reliability as acceptable (Nunnally, 1978).

When reliability is low, the effect of the mediator variable on the outcome variable (path b in Fig. 1) is underestimated and the effect of the predictor variable on the outcome variable (path c' in Fig. 1) is overestimated (Baron & Kenny, 1986; Judd & Kenny, 1981; Kenny et al., 1998). Therefore, statistical analyses such as multiple regression, which ignore measurement error, may underestimate the mediation effects (Frazier et al., 2004). Hoyle and Kenny (1999) and Hoyle and Robinson (2003) provided a formula for estimating the effect of low reliability on tests of mediation.

Because of the power problems that can arise due to low reliability and collinearity, several researchers have offered heuristics to help ensure tests of mediation have adequate power. Hoyle and Kenny (1999) suggested that when the mediator is highly reliable ($\alpha = .90$), a sample size of 100 will yield the necessary power. However, they suggested a sample size of at least 200 when mediators have moderate reliability ($\alpha = .70$). Additionally, Kenny et al. (1998) stated that researchers testing for mediation often need a sample size greater than the average study in their field because of low reliability and high collinearity between the predictor and mediator variables, which lowers power.

Although Hoyle and Kenny (1999) and Kenny et al. (1998) offered these heuristics, none of the studies that we reviewed mentioned whether they considered these or other guidelines pertaining to statistical power. Reliabilities of the measures used were most often between .70 and .80. While the average sample size did not appear to be a problem in the majority of studies, effect sizes in strategy research appear to be fairly small, warranting other methods than BK to be used.

Testing for the Significance of the Indirect Effect

Traditionally, scholars have held that full mediation is established and significant only when the predictor–outcome effect goes from "significant" to "not significant" once the mediator is added to the model (Holmbeck, 2002). However, Holmbeck (2002, p. 88) pointed out that this measurement might not be precise enough because "a drop in significance to non-significance may occur … when a regression coefficient drops from .28 to .27 but not when it drops from .75 to .35." In other words, it is possible to have the predictor–outcome relationship drop from significant to not significant when accounting for the mediator even though there is no significant mediation, or for a mediating effect to be present when the predictor–outcome relationship continues to be statistically significant even after adding the mediator into the model. Therefore, Holmbeck (2002) concluded that researchers must test for the significance of the mediating effect because the results of studies that do not test the significance of the mediating effect may be spurious.

Frazier et al. (2004, p. 128) corroborated Holmbeck's argument and stated that "it is not enough to show that the relation between the predictor and outcome is smaller or no longer significant when the mediator is added to the model." Instead, a method for testing the significance of the mediating effect should be used. Preacher and Hayes (2004) also argued for formally testing the indirect effect. They agreed with Holmbeck (2002) that without testing the indirect effect, researchers are more likely to make Type I errors if the addition of the mediator to the model causes a very small change such that a statistically significant relationship between x and y becomes non-significant. This is true especially when the sample size is large and even small regression weights

are statistically significant (Preacher & Hayes, 2004). Researchers are also more likely to make Type II errors when there is a large change in the relationship between x and y, but there is no observed drop in significance. Therefore, failing to test for the significance of the indirect effect may result in spurious findings.

There are many approaches for testing the significance of mediation effects, such as the Sobel's first-order solution, the Goodman unbiased solution, and the Freedman and Schatzkin method (MacKinnon et al., 2002). In order to calculate the indirect effect, the weights for paths a and b as well as their respective standard errors are required. Sobel (1982) is a commonly used method to test for the indirect effect. In order to perform this test, the indirect effect, ab, is divided by the standard error of ab, s_{ab} which is defined as: $s_{ab} = \sqrt{b^2 s_a^2 + a^2 s_b^2 + s_a^2 s_b^2}$. The formula yields a ratio that is compared with the critical value from the standard normal distribution to determine whether the indirect effect is statistically significant (Preacher & Hayes, 2004). Preacher and Leonardelli (2003) have even posted a web page with a Sobel calculation tool for mediation tests, which can be found at: http://www.unc.edu/~preacher/sobel/sobel.htm

Because of the simplicity of testing the indirect effect, the benefits of testing for the indirect effect far outweigh the costs. However, only 10% of strategy studies in our review used any of these tests. Testing for statistically significant indirect effects in the articles analyzed varied based on whether the authors used regression or SEM for mediation analysis. Only five articles that we analyzed tested the significance of the indirect effect. Of those five articles, we identified four that used Sobel's (1982) test in addition to the BK approach. For example, after analyzing MANCOVA results, Sapienza and Korsgaard (1996) evaluated whether perceptions of procedural justice mediate the effect of timely feedback on entrepreneur–investor relations and then estimated the significance of the indirect effect using Sobel. Although the use of the Sobel test was discussed in BK's work, 90% of the studies in our sample did not mention the significance of the indirect effect.

To summarize, our literature review of strategy articles revealed that the BK approach is overwhelmingly the most common method used to test for mediation. While strategy scholars have displayed a mastery of the BK method, several issues should be considered, including whether BK's first step should always be followed, issues regarding statistical power, and the importance of testing for the statistical significance of the indirect effect. Therefore, in the next section, recommendations are provided for strategy scholars examining mediation.

RECOMMENDATIONS

Mediation analysis is critical to strategy research because it detects the mechanism by which a predictor variable influences an outcome variable. As such, the use of mediation has the potential to explain complex relationships in the strategic management literature. Therefore, we provide a number of recommendations for mediation analysis.

Tips from the Trenches for Beginners Using BK

First, we offer some fundamental tips for beginners learning how to run mediated regression using BK's four-step method. When beginning mediation analysis, it is a good idea to look at the correlation matrix in order to understand the magnitude of the correlations between the variables in question. This will help you understand the nature of the bivariate relationship between the x, m, and y variables. For example, if the $x \rightarrow y$ relationship is weaker than the $m \rightarrow y$ relationship, this provides initial support for mediation. This is because the mediator is more proximal to the dependent variable and thus should have a stronger relationship with it.

It is also advisable to look at the signs of the correlations between the x, m, and y variables. If the $x \rightarrow m$ and the $m \rightarrow y$ relationships have opposite signs (i.e., one is negative and one is positive), this may explain a situation where there is no significant relationship between the x and y variables. Because the two relationships are in opposite directions, they cancel out and produce no obvious relationship between x and y. This could then be a good reason to skip Step 1 of BK since a non-significant relationship between x and y should not preclude you from completing the other BK steps (Shrout & Bolger, 2002).

When you are ready to run mediated regression, be sure to input the variables into three regressions (assuming you will complete all four steps of BK). To illustrate, below are the steps of how variables are entered into each equation:

Step 1: In the first regression, regress the outcome variable (y) on the predictor variable (x) to establish that there is a relationship between x and y.

Step 2: In the second regression, regress the mediator (m) on the predictor variable (x) to estimate the relationship between x and m.

Step 3: In the third regression, regress the outcome variable (y) on both the predictor (x) and the mediator (m) simultaneously to assess the relationship between x and y while controlling for m.

Step 4 of the BK method is where you interpret whether the results show full or partial mediation, or any mediation for that matter. This step requires no additional computation; it relies on interpretation of the first three steps. Now, we will interpret a simple example of mediated regression.

Let us assume that we are testing the hypothesis that the relationship between TMT heterogeneity and firm performance is mediated by cognitive conflict. (Please see Table 2 for the sample data.) Here, we can see in Step 1 that TMT heterogeneity significantly predicts firm performance ($p < .01$). In Step 2, TMT heterogeneity is a significant predictor of cognitive conflict ($p < .01$). However, if TMT heterogeneity was not significantly related to cognitive conflict, there would be no support for mediation. In Step 3, TMT heterogeneity is no longer a significant predictor of firm performance when cognitive conflict is also entered, and cognitive conflict is a significant predictor of firm performance ($p < .01$). Therefore, this is an example of full mediation, because the significant effect of TMT heterogeneity as a predictor of firm performance is no longer significant when cognitive conflict is in the model. The effect of TMT heterogeneity on firm performance is transmitted through the mediator, cognitive conflict.

Table 2. Interpretation of Sample-Mediated Regression Results.

Variable	b	β	SE	t	R^2	F
Step 1						
DV = Firm performance						
1. TMT heterogeneity	.44**	.22**	.15	2.97	.05	8.81**
Step 2						
DV = Cognitive conflict						
1. TMT heterogeneity	.37**	.32**	.08	4.40	.10	19.36**
Step 3						
DV = Performance						
1. TMT heterogeneity	.20	.10	.15	1.39		
2. Cognitive conflict	.63**	.37**	.13	5.00	.17	17.54*

*$p < .05$.
**$p < .01$.

If the TMT heterogeneity variable had been reduced in significance (down to the .05 level, for example) in Step 3, there would be evidence of partial mediation. Here, we would say this is a partially mediated relationship, because the significance of TMT heterogeneity as a predictor of firm performance is reduced when cognitive conflict is in the model. This means that some of the effect of TMT heterogeneity on firm performance is transmitted through cognitive conflict, but not all. Finally, if the statistical significance of TMT heterogeneity had remained unchanged (at the $p<.01$ level) in Step 3 or cognitive conflict was not significantly related to firm performance controlling for TMT heterogeneity in Step 3, then there would be no evidence of mediation at all.

If a mediating effect is identified as a result of BK Step 4, the final step in the test of mediation should be testing the statistical significance of the indirect effect. Please see Table 3 for an example showing a manual calculation of the Sobel formula to test the significance of the indirect effect using the data from the paths a and b standard errors and coefficients in the TMT heterogeneity mediation example from Table 2. The result of the Sobel formula is also interpreted in Table 3, showing that the indirect effect is statistically significant.

Table 3. Example Test of the Sobel Equation to Test the Statistical Significance of the Indirect Effect.

$$Z = ab\Big/\sqrt{S_a^2 S_b^2 + b^2 S_a^2 + a^2 S_b^2}$$

a = Path a from Fig. 1
b = Path b from Fig. 1
S_a = standard error of path a
S_b = standard error of path b

Sobel (1980) test for indirect effect	
a	0.37
b	0.63
S_a	0.08
S_b	0.13
Numerator $a \times b$ (indirect effect)	0.23
Denominator	0.07
Z-score for indirect effect	3.28

The Z-score of 3.28 is greater than the Z critical value of 1.96, which means the Z score for the indirect effect is statistically significant ($p<.01$).

Tips for Those Who are More Familiar with BK

While the BK approach for detecting and testing mediation remains one of the most influential approaches, strategic management researchers should consider more recent advancements in mediation testing that have been published since BK's seminal work. Therefore, we offer some more advanced recommendations, highlighted in Table 4, for researchers who already understand the mechanics of the BK method. First, when the predictor–outcome relationship is distal, we recommend considering whether BK's first step is relevant (Collins et al., 1998; Shrout & Bolger, 2002). Our recommendations follow the advice of Shrout and Bolger (2002, p. 430) who write, "Relaxing the requirement that $x \rightarrow y$ be statistically significant before going on to study mediation is likely to be especially important for ... researchers who track long-term processes." With the prevalence of distal relationships in strategy research, scholars should think about the conceptual importance of the direct effect. If the direct effect is not conceptually important, the indirect effect through the intervening variable is just as theoretically valuable, and the researcher may omit the first step of BK. Relaxing this assumption may reduce rejection of studies that may have indirect effects, as well as the file drawer problem whereby researchers stop the research when they do not find a significant relationship in BK's first step.

Second, researchers should consider those elements that may reduce power to detect a mediating effect. The relationship between the mediator variable and the predictor variable can affect the power of the test of

Table 4. Recommendations for Strategy Scholars.

Recommendation	Suggested Reading
Consider the need to skip Baron and Kenny's Step 1	Shrout and Bolger (2002), Collins, Graham, and Flaherty (1998), Frazier et al. (2004)
Evaluate the reliabilities of the variables and the implications on power	Hoyle and Kenny (1999), Frazier et al. (2004), Kenny et al. (1998), MacKinnon et al. (2002)
Evaluate the possibility of error term correlation	Shaver (2005)
Test the significance of the indirect effect	Holmbeck (2002), MacKinnon et al. (2002), Preacher and Hayes (2004), Holmbeck (2002)
Consider using structural equation modeling for mediation analyses	James et al. (2006), Hoyle and Smith (2004), Bollen (1987), Brown (1997)

mediation (Frazier et al., 2004). Therefore, scholars need to consider the collinearity between these two variables and its effect on power. We recommend Kenny et al.'s (1998) formula as way to evaluate this effect.

In addition, an unreliable mediator underestimates the mediator's effect on the outcome variable (Baron & Kenny, 1986; Judd & Kenny, 1981). Due to the problems that can arise with low reliability, Hoyle and Robinson (2003) suggested using a measurement instrument with a reliability of .90 or higher, and Hoyle and Kenny (1999) recommended sample sizes of 100 for highly reliable mediators or 200 for moderately reliable mediators. Because none of the articles reviewed discussed power, this could possibly indicate that strategy researchers, on the whole, pay little attention to power with regard to mediation. Thus, we urge scholars to consider power, and we suggest Cohen's (1992) work which provides a concise benchmark for assessing sample size given desired power, estimated effect size, and alpha as a starting point.

Third, we urge researchers to test the statistical significance of the indirect effect. Similar to MacKinnon et al. (2002), we found that most scholars did not test the statistical significance of the mediator. Given the power issues associated with both mediation and strategic management research in general, researchers should test the significance of the indirect effect (Hitt et al., 2004; MacKinnon et al., 2002). In extant research, Sobel's (1982) test has been the most popular approach. (For a description of how SPSS and SAS calculate the Sobel test, see Preacher & Hayes, 2004.) However, there are also other formulas to test for the statistical significance of the indirect effect. In MacKinnon's review, the difference in coefficients method by Freedman and Schatzkin (1992) had the highest power of all 14 methods tested.

Finally, we direct those testing mediation using multiple regression to some helpful tools developed recently by mediation experts. Frazier et al. (2004) includes an appendix with a helpful checklist for mediation analysis including questions such as "Was the predictor significantly related to the outcome? If not, was there a convincing rationale for examining mediation?" "What is the 'effective sample size' given the correlation between the predictor and the mediator?" "Was power mentioned either as an a priori consideration or as a limitation?" "Was unreliability in the mediators (e.g., $\alpha < .70$) addressed through tests that estimate the effects of unreliability…?", and "Was the significance of the mediation effect formally tested?" In addition to this checklist, both Kenny (http://davidakenny.net/cm/mediate.htm) and MacKinnon (http://www.public.asu.edu/~davidpm/ripl/mediate.htm) have web sites on mediation.

We also suggest SEM as an alternative to the BK causal steps approach. We observed that over half of the studies testing mediation use SEM (e.g., Robins, Tallman, & Fladmoe-Lindquist, 2002; Simonin, 1999; Tippins & Sohi, 2003). We agree that this approach may be helpful because SEM allows the researcher to look at all the data simultaneously without necessarily making causal inferences. SEM also has the capacity to compare and contrast alternative models to identify the most likely causal direction. This methodology, combined with good theoretical rationale, can provide authors with some insight into the nature of the relationships present in the data even in non-lagged data.

James, Mulaik, and Brett (2006, p. 243) strongly urged that researchers "add tests of alternative causal models to basic mediation analysis" and suggest this as one of the key advantages of SEM. Because of the difficulty in establishing temporal priority in non-experimental research, studies that have improperly specified models are at risk of testing incorrect models (Stone-Romero & Rosopa, 2004). In addition, competing models may often fit the data similarly (Stelzl, 1986). Alternative models may be tested to lessen this risk. However, our review indicated only limited use of alternative models. Clearly, SEM can never overcome a flawed research design or substitute for having the appropriate lags between variables. Nonetheless, this technique can potentially help researchers better understand the nature of the relationships between variables and inform researchers of the viability of each model (Jermier & Schriesheim, 1978). Because of this, we recommend that researchers consider using SEM to test for mediating effects.

Tests of the significance of the indirect effect are also available in most SEM programs (Frazier et al., 2004). (See Brown (1997) for a description of testing mediation models in LISREL.) Because of SEM's sophistication and flexibility, many researchers, including BK, have described SEM as the "most efficient and least problematic means of testing mediation" (Hoyle & Smith, 1994, p. 438).

Shaver (2005) suggested that an additional advantage to using SEM is that it can help address problems resulting from correlated error terms. Measurement error may have a detrimental effect on the interpretation of mediation analysis because it may induce the error terms to correlate (Shaver, 2005). When a variable affects both m and y in the same way, it causes correlation of the error terms in the second and third steps of BK. In a review of management articles, Shaver (2005) found that the error terms could correlate due to missing variables, measurement error, and truly random effects. Correlation becomes a problem because the coefficient estimates are inconsistent to the extent that they are correlated. Hence, Shaver (2005) recommended simultaneous equation problem techniques such as SEM to deal with these issues.

Like other methods, SEM is not perfect. SEM suffers from the problem of omitted variables that can affect the models being tested (Cliff, 1983; Freedman, 1987; Tomarken & Waller, 2005). SEM has also been criticized for encouraging researchers to focus on global fit of the model at the expense of lower-order model components that may affect the model (Tomarken & Waller, 2003). Finally, researchers have also noted that using SEM to conduct multilevel analysis can become unwieldy as the model becomes more complex (Chen, Bliese, & Mathieu, 2005). Despite these limitations, SEM provides a number of unique and important benefits which researchers should consider (Baron & Kenny, 1986; Hoyle & Smith, 1994; Judd & Kenny, 1981). (For a review and suggestions on how to best use SEM in strategic management research, see Shook et al., 2004).

CONCLUSION

Strategic management is a relatively young yet maturing academic discipline. As such, many propose that it is necessary to examine the state of the field's methodological sophistication and maturity. The purpose of this study has been to assess how mediation analyses are used in strategy research and to assess this methodology in light of methodological advancements published in the last 20 years since BK's seminal work. In order to achieve this end, we examine articles published in *AMJ* and *SMJ* from 1986 to 2005. We find that tests of mediation in published strategy research are relatively infrequent. The results of our review reveal that while BK remains the approach most commonly cited by strategy researchers, there is variance in how BK's approach is implemented. Specifically, we find that researchers tend to rely heavily on BK's step. In addition, they infrequently omit the first step, discuss the implications of power, or test the significance of the indirect effect.

Drawing on extant literature on mediation, we suggest that the BK approach should be used with caution due to its low power (MacKinnon et al., 2002) and the distal relationships associated with strategy research (Shrout & Bolger, 2002). As a result, we recommend that strategy researchers open a dialogue about how best to test for mediating relationships in strategy research. It is our hope that this study will spark discussion concerning how best to test for mediating effects in strategy research.

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Amy L. Pablo

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