

# A Marginal Effects Approach to Interpreting Main Effects and Moderation

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## Abstract

This Short Methodological Report builds on research about moderation practices by focusing on a marginal effects approach to interpreting how a main effect is informed by the presence of a moderating variable. Following a content analysis of published studies and a survey of management researchers, our findings suggest there is a great deal of confusion about the ways in which to interpret how a main effect may fluctuate owing to a moderating variable. We therefore provide explicit instructions on how to implement and interpret a marginal effects approach that depicts the nature of a main effect in the presence of a moderator. We use different scenarios and examples to illustrate how researchers can employ the marginal effects technique, which provides an indication of the relationship between the independent and dependent variables over different values of the moderator. We argue and demonstrate that the marginal effects approach helps resolve conflicting findings that may arise from using other prevailing techniques to interpret both main effects and moderation.

## Keywords

interactions, marginal effects, moderation, nonlinear modeling, main effects, linear modeling including categorical dependent variables

## Introduction

Empirical management research often focuses on how the relationship between two variables may change because of a third, moderating variable. There is thus a great deal of scholarship on the best practices and appropriate interpretations of moderators (e.g., Aguinis et al., 2017; Boyd et al., 2012;

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Dawson, 2014; Edwards et al., 2009; Venkatraman, 1989; Wiersema & Bowen, 2009). Although the literature on how to implement and interpret interactions is vast, there remains confusion and disconsensus among researchers about how to interpret a main effect in the presence of moderation. In fact, in their recent review of moderation practices, Aguinis et al. (2017) highlighted that nearly half of the articles they examined incorrectly interpreted such a direct effect.<sup>1</sup> Although Aguinis et al. urged researchers to draw “conclusions based on simple slopes computed and tested at meaningful levels of the moderator variables” (p. 672), they did not explain how researchers can implement this approach, likely because it was outside the scope of their study. Moreover, seminal statistical texts explicate a simple slopes technique that sheds light on the nature of such a main effect (Aguinis, 2004; Aiken & West, 1991; Cohen et al., 2003), but this work provides a relatively broad overview of the technique and does not discuss nuanced direct effects.

Given the dearth of research on the nature of main effects in the presence of moderation, we seek to accomplish several objectives in this Short Methodological Report. First, to confirm that confusion and disconsensus remain even after recommendations by Aguinis et al. (2017) and earlier research, we investigate published studies and results from a survey of researchers. Each endeavor illustrates substantial confusion about the appropriate ways to interpret main effects in the presence of moderation. Second, we review the most common approaches to interpreting such a main effect by consulting research on moderation, including the work that describes a simple slopes technique similar to the marginal effects approach that we advocate (Aguinis, 2004; Aguinis et al., 2017; Cohen et al., 2003). Our aim in this regard is to describe what techniques researchers tend to employ, how they are beneficial and detrimental, and how they relate to the marginal effects approach.

Third, we introduce the marginal effects approach and discuss how it works to overcome the detriments associated with more common practices. Specifically, we explicate the intuition behind the marginal effects approach, including how it both incorporates and enhances other more common techniques. Finally, we describe how scholars can implement and interpret the marginal effects approach in four different scenarios by providing information on how to calculate marginal effects manually or via code in Stata and R. In the process, we offer several reasons why researchers may have been hesitant to adopt the marginal effects approach or why there remains confusion and disconsensus in the literature, and we provide recommendations to help assuage these concerns.

## **Main Effects and Moderation in Practice**

### *Examination of Practices in Management Research*

Despite recent recommendations by Aguinis et al. (2017) and seminal statistical texts that intimate a marginal effects approach to interpreting a main effect in the presence of moderation (Aguinis, 2004; Aiken & West, 1991; Cohen et al., 2003), we suspect that confusion and disconsensus remains. To confirm this suspicion and the idea that a Short Methodological Report on the topic would prove beneficial, we conducted a content analysis and surveyed researchers on how to interpret main effects in the presence of moderation. Whereas the content analysis determines what practices are conducted in published research, the survey assesses if researchers are familiar with appropriate approaches but have not been able to publish work that breaks from convention.

For our content analysis, we reviewed three management journals—*Academy of Management Journal (AMJ)*, *Strategic Management Journal (SMJ)*, and *Journal of Applied Psychology (JAP)*—for the years 2015–2018, 2011–2018, and 2015–2018, respectively.<sup>2</sup> We searched for studies that included main and moderating effects, ultimately finding 151 articles. We coded how these studies interpreted a main effect in the presence of a moderator, and the results (displayed in Table 1) are indicative of continued disconsensus given that multiple approaches were evident. Although over 93% of the studies examined the isolated main effect coefficient an approach—we contend is

**Table 1.** Content Analysis Results.

Interpretation Method	Total Articles	Total Percentages	% of <i>SMJ</i>	% of <i>AMJ</i>	% of <i>JAP</i>
Isolated coefficient (no interaction term)	99	65.56%	60.00%	72.34%	78.57%
Isolated coefficient (interaction term)	17	11.26%	12.22%	12.77%	0.00%
Combination of both isolated coefficients	25	16.56%	17.78%	12.77%	21.43%
Simple slopes analyses	10	6.62%	10.00%	2.13%	0.00%
Total	151	100%	100%	100%	100%

Note: *AMJ* = *Academy of Management Journal*; *SMJ* = *Strategic Management Journal*; *JAP* = *Journal of Applied Psychology*.

**Table 2.** Overall Survey Results.

Coefficient(s)	Frequency	Percentage
Isolated coefficient (no interaction term)	79	49.38%
Isolated coefficient (interaction term)	14	8.75%
Combination of both isolated coefficients	28	17.50%
Simple slopes analyses	39	24.38%
Total	160	100.00%

notably deficient in the following sections—Table 1 illustrates that there was remarkable inconsistency in terms of whether researchers isolated this main effect in a model with or without the interaction term included. Even more, less than 7% of researchers use a simple slopes analysis as suggested by Aguinis et al. (2017), which we propose is the most appropriate technique.

For our survey, we solicited responses from Academy of Management members as well as from 103 researchers from around the globe who we contacted directly (e.g., Nag et al., 2007) for their views on interpreting a main effect in the presence of a moderator. The 160 responses we received again suggest discord about appropriate interpretation techniques. As shown in Table 2, over 75% of respondents believe interpreting the coefficient of the main effect in isolation alone is the most appropriate means to examine main effects in the presence of moderation, but there is again confusion about whether this involves a model with or without the interaction term. Almost 25% of the respondents believe either a simple slopes or marginal effects approach is most appropriate, more than 3 times the rate in published work.

Furthermore, the open-ended comments reinforced the lack of consensus and need for clarification. One respondent indicated, “The key is to differentiate the equation with respect to [the independent variable] and [the moderator], which will decide what coefficients we are going to include in our explanation.” With a similar level of conviction, another researcher suggested, “[The coefficient in isolation from a model with the interaction term] is only useful [if the moderator] is not dichotomous and is mean centered.” Finally, another respondent posited, “If you want to be strict about it . . . you should only look at the moderated model”. Some comments corroborated the lack of consensus in the field. One researcher stated, “I’ve run into this issue recently, and received mildly conflicting advice. Some say ‘[The coefficient in isolation from the model without the moderator] is fine’; others ‘[The coefficient from the model with the moderator] only!’; and still others ‘It is good to know both, though only looking at [both] makes more sense for OB folks.’ This is an issue that needs further discussion!”

Another echoed this sentiment by suggesting, “I just discussed this with a colleague and we come up with different answers, both with pretty well-reasoned justifications.”

### *Prevailing Techniques to Interpret a Main Effect in the Presence of a Moderator*

We now turn our attention toward describing some of the intuition and seminal research on the topic of moderation, paying particularly close attention to the interpretation techniques that researchers tend to employ based on the content analysis and survey. Research on how to implement and interpret moderation is vast and prolific (for a further discussion, see Aguinis, 2004; Aguinis et al., 2017; Aiken & West, 1991; Cohen et al., 2003), so we provide a high-level overview since readers can consult this exhaustive and competent stream of literature for more specific guidance about moderation more broadly.

**Mathematical Underpinnings.** Before delving into the details of each approach, we review what multiplicative interaction entails and the calculus underlying it (e.g., Aguinis et al., 2017; Cohen et al., 2003; Gardner et al., 2017). This is an important step because the mathematical underpinnings are relevant to understanding each of the approaches and specifically serve as the basis for the marginal effects technique.

$$y = \beta_1 x + \beta_2 z + \beta_3 xz + e \quad (1)$$

$$\delta y / \delta x = \beta_1 + \beta_3 z \quad (2)$$

Equation 1 represents the appropriate functional form for a multiplicative interaction model (Aguinis, 2004; Aguinis et al., 2017; Cohen et al., 2003). In this equation, Y represents a dependent variable, X represents an independent variable with a hypothesized main effect, Z reflects a moderating variable, and the term XZ indicates the interaction between the two variables to achieve multiplicative interaction. Mathematically, the main effect of X on Y (i.e.,  $\delta y / \delta x$ , or the change in Y owing to a unit change in X) is most comprehensively captured with Equation 2 (Brambor et al., 2006; Wooldridge, 2010), which represents the first derivative of Equation 1. Equation 2 suggests that the main effect of X on Y depends on  $\beta_1$ ,  $\beta_3$ , and Z. Specifically, Equation 2 implies that the main effect of X on Y (or  $\delta y / \delta x$ ) changes owing to different values of Z because  $\beta_1$  and  $\beta_3$  remain constant as a prediction from the regression.

**The Coefficient of the Independent Variable in Isolation.** The most common approach to interpreting a main effect ( $\beta_1$ ) in the presence of a moderator variable (Z) involves examining the coefficient of the independent variable (X) in isolation. Our content analysis and survey indicate that there are two primary ways management researchers explore this main effect. In the first approach, researchers employ a model similar to what we specified in Equation 1 but without the interaction term ( $\beta_3$ ). The thought behind interpreting a main effect in a model without the interaction term is that the coefficient for the direct effect represents the *average relationship* between X and Y across all values of Z (Cohen et al., 2003; Cortina, 1993; Gardner et al., 2017). This is problematic because a model without the interaction term violates assumptions of the model in the sense that it is not fully specified (Aguinis et al., 2017) and ignores the fact that the relationship between X and Y changes due to a third variable (Edwards et al., 2009). This approach is also limited because it holds assumptions about the moderator given that the coefficient may be distorted by skewness or extreme values (Brambor et al., 2006; Cohen et al., 2003).

The second method management scholars apply involves examining the coefficient of the independent variable (X) in isolation ( $\beta_1$ ) but from a model with the interaction term included (i.e., a model identical to Equation 1). This coefficient represents the relationship between an independent variable (X) and a dependent variable (Y) in a fully specified model when the value for the moderator (Z) *takes the value of 0* (Cohen et al., 2003; Edwards et al., 2009; Gardner et al., 2017), which is also the average effect when the moderator is mean-centered. Kennedy (2008)

**Table 3.** Statistical Significance and Direction of the Main Effect Based on a Model With or Without the Interaction Term.

	Change in Direction of Coefficient	No Change in Direction of Coefficient
Change in statistical significance	10.60%	23.84%
No change in statistical significance	8.61%	56.95%

argued this is more appropriate and cautioned against the mistake of “forgetting interaction . . . terms when assessing variable influence” because the derivative of the relationship between independent and dependent variables is not accurately reflected by “just the coefficient on that variable” (p. 372). This approach, however, has been described as “arbitrary nonsense” (Cohen, 1978, p. 861) and “useless” (Allison, 1977, p. 148) because it only represents the relationship between the independent and dependent variables when the moderator takes the value of 0, which is something that rarely occurs in more macro-oriented research. It also does not consider how variations, skewness, or extreme values of  $Z$  may inform  $\delta y/\delta x$ .

Although the differences in isolating the main effect from a model with and without the interaction term may seem semantic, in practice, the distinctions are potentially drastic. Based on the content analysis of *AMJ*, *SMJ*, and *JAP*, in Table 3, we depict how often isolating the main effect in each of these two models leads to different interpretations of statistical significance and the direction of the coefficient. Over a third of the published relationships have differences in statistical significance based solely on which of the two models researchers use to isolate a main effect, and nearly 20% have main effects with different coefficient directions. Furthermore, over 10% of the relationships have changes in statistical significance *and* different coefficient directions based on the model a researcher uses to examine the main effect.

Researchers have also adopted the practice of examining both of these models in sequence to determine how much additional variance the interaction term explains in the dependent variable (i.e., the change in  $R^2$ ; e.g., Carte & Russell, 2003; Murphy & Russell, 2017). This is intuitively appealing because it affords researchers a single number that represents the ostensible value added by considering the moderated relationship in addition to the main effects. Despite its appeal, however, researchers caution against examining the change in  $R^2$  (particularly exploring if there is a statistically significant change) between models because it is misleading and almost futile with the large sample sizes that management scholars tend to employ in recent years (Carte & Russell, 2003; Murphy & Russell, 2017).

*The Marginal Effects Technique (or Extended Simple Slopes Analyses).* Another approach—one numerous researchers implicitly recommend (e.g., Aguinis, 2004; Aguinis et al., 2017; Aiken & West, 1991; Cohen et al., 2003; Gardner et al., 2017) and that we advocate in this study—involves looking simultaneously at the parameter estimates for the independent variable ( $\beta_1$ ) and interaction term ( $\beta_3$ ) from the model including both. Although much less common in management research than isolating a main effect coefficient (our content analysis suggests this was employed in fewer than 7% of studies compared to isolating the independent variable in over 93% of studies), this approach has gained traction in recent years largely due to an expanded literature on limited dependent variables (e.g., Hoetker, 2007; Wiersema & Bowen, 2009). As Brambor et al. (2006) noted,

Just as we have come to recognize that coefficients in logit and probit models cannot be interpreted as unconditional marginal effects, we should recognize that the coefficients on

constitutive [(lower order)] terms in interaction models cannot be interpreted in this way either. (p. 72)

In this procedure, researchers implement Equation 2 for  $\delta y/\delta x$  by considering how the relationship changes as a function of varying values for  $Z$ . Specifically, scholars calculate the changing effect of  $X$  on  $Y$  (i.e., the marginal effects) at different values of the moderator (hence why we call this the *marginal effects* approach).<sup>3</sup> This technique is likely the most precise way to interpret a main effect in the presence of a moderator because it addresses the disadvantages of looking at only the main effect in isolation as well as of using just conventional simple slopes analyses. Whereas the main effect in isolation (i.e., just  $\beta_1$ ) is imprecise if the moderator has values that distort the relationship, the marginal effects approach incorporates multiple values of the moderator, allowing researchers to determine if the relationship is meaningful at specific values and distorted at others. The marginal effects approach also depicts whether the change in  $Y$  owing to a unit change in  $X$  is statistically different from 0 (and different from one another, which we describe as well) at different values of the moderator rather than a single relationship.

As it relates to the marginal effects as a conceptual relative of the simple slopes technique, Gardner et al. (2017) argued that the “simple slopes approach . . . does provide some insights as to the patterns of effects, [but] it connotes the false impression that such points are substantively meaningful” (p. 262). They also argued that most researchers arbitrarily select values of the moderator one standard deviation higher and lower than the mean value. Whereas the simple slopes technique typically graphs the association between the independent variable (on the x-axis) and the dependent variable (on the y-axis), the marginal effects technique graphs the relationship between  $X$  and  $Y$  (y-axis) over different values of the moderator (x-axis). We provide several examples in this regard in the next section. Furthermore, the simple slopes technique is unable to account for situations in which there is more than one multiplicative interaction term involving the independent variable in the model, in which case, the main effect varies across multiple moderators. The marginal effects approach, however, can accommodate this by establishing a fixed value of any other moderator while examining the marginal effects owing to a change in the levels of a focal moderator (Brambor et al., 2006; Hoetker, 2007).<sup>4</sup>

At the same time, this approach does have a disadvantage—carrying out the marginal effects involves graphing and/or providing a table with  $\delta y/\delta x$  at several different values of  $Z$  (e.g., Oliver et al., 2018; Wiersema & Bowen, 2009), which may consume valuable space in a manuscript. We provide suggestions on how researchers can do this parsimoniously, especially considering that the marginal effects approach offers notably more information about the nature of relationships in a single graphic compared to a conventional simple slopes technique.

## Implementing and Interpreting the Marginal Effects Approach

We next turn our attention to detailing how researchers can implement and interpret the marginal effects approach. We seek to accomplish this by detailing potential impediments that researchers may have faced in adopting the marginal effects approach, which may have created the confusion and disconsensus among management scholars, and we offer a roadmap for how to overcome these issues. To help ease understanding, we infuse the example of R&D expenditures and firm performance throughout these sections. Innovation research suggests a positive relationship between R&D expenditures ( $X$ ) and firm performance ( $Y$ ), but it also theorizes that the relationship may be moderated (or have boundary conditions) explained by firm size ( $Z$ ) because of the relative impact of expenditures by firms with different asset bases (Bromiley et al., 2017; Ettlie, 1998; Greve, 2003; Mudambi & Swift, 2014).

### *Appropriateness of the Marginal Effects Approach*

One potential impediment to embracing the marginal effects approach involves concerns about the appropriateness of this technique. Specifically, some researchers believe it is tenuous to examine a main effect when moderation is also hypothesized (Birnbaum, 1974).<sup>5</sup> After all, if the relationship between an independent and dependent variable is contingent, perhaps there is no rationale to examine that single relationship. This is especially true in literature domains that are already well established and are rife with contingent factors.

Although we agree this is sometimes the case (Birnbaum, 1974), an abundance of research—including the aforementioned line of inquiry on R&D, firm performance, and firm size (Bromiley et al., 2017; Ettlie, 1998; Greve, 2003; Mudambi & Swift, 2014)—notes that moderators are sometimes used to reinforce the theoretical mechanisms of the main effect or to establish boundary conditions (e.g., Baron & Kenny, 1986; Bromiley et al., 2017; Campbell et al., 2019; Shi et al., 2017). Each of these rationales requires examining a main effect without the moderator to establish whether a general or overall relationship exists between independent and dependent variables because there may exist myriad other potential contingent influences that are not within the scope of a given study.

To help alleviate these concerns about appropriateness, we continue to integrate the example about R&D expenditures (X or the independent variable), firm performance (Y or the dependent variable), and the moderating role of firm size (Z or the moderating variable) because this is an instance when researchers suggest it is tenable to examine a main effect even if moderation is also hypothesized. Throughout this section, we focus on testing the following hypotheses:

*Hypothesis 1:* There is a positive relationship between R&D expenditures and firm performance.

*Hypothesis 2:* Firm size moderates the positive relationship between R&D expenditures and firm performance such that the relationship is weakened when the firm is larger and strengthened when the firm is smaller.

### *Accessibility of the Marginal Effects Technique*

Another potential impediment to adopting the marginal effects approach involves concerns about the accessibility of this technique. Researchers may have reservations about how to use this approach given that prior discussions of this technique largely employ a mathematical lens to explicate the nature of moderation and main effects (Aguinis, 2004; Aiken & West, 1991; Cohen et al., 2003; Edwards et al., 2009). Such a treatment of the topic may seem too esoteric for scholars who are increasingly primed to explore data with software packages rather than with mathematical proofs. Researchers may also be hesitant to adopt this technique because they are comfortable with procedures—albeit ones that, as we discussed, are fallible—focused on isolating a main effect coefficient. To remedy these accessibility concerns, we detail how to carry out the marginal effects approach manually and via two popular software packages.

*Computing the Mathematical Derivative.* One technique scholars could apply to understand the relationship between X (e.g., R&D expenditures) and Y (e.g., firm performance) involves manually computing the marginal effects (i.e.,  $\delta y / \delta x$ ) at different values of Z (e.g., firm size). As we illustrate in Equation 2 (reproduced for convenience), the direct effect of X on Y in the presence of a moderator is contingent on different values of Z (i.e., the marginal effect changes). It is thus



inappropriate to interpret only one value (i.e., the main effect coefficient in isolation) to capture statistical inference for a direct effect of X on Y.

$$\delta y / \delta x = \beta_1 + \beta_3 z \quad (2)$$

Instead, researchers can explore the nature of the relationship between X and Y (and thus the marginal effect) by calculating  $\delta y / \delta x$  at different values of Z and either graphing those values or depicting them in a table. We provide examples later in Figures 2 through 5 of how to graph this relationship, but we recognize scholars can communicate this same information in tabular format (e.g., Oliver et al., 2018). It is helpful to calculate  $\delta y / \delta x$  over several meaningful and reasonable values of Z—such as the minimum, low percentiles (e.g., 20th), medium percentiles (e.g., 50th), high percentiles (e.g., 80th), and the maximum—thus spanning the entire gambit of potential values the moderator can take. To calculate the marginal effects, researchers can use the coefficients  $\beta_1$  and  $\beta_3$  from their estimator and determine how  $\delta y / \delta x$  changes as the value of Z varies. Stated differently, scholars can apply different values of Z in Equation 2 to determine outcomes corresponding  $\delta y / \delta x$ , or the marginal effect of Y owing to a unit change in X.

**Marginal Effects in Stata.** A second way to compute and interpret the marginal effect of X (e.g., R&D expenditures) on Y (e.g., firm performance) over different values of Z (e.g., firm size) involves the command *margins* in the software package Stata. The *margins* command is an invaluable tool for making predictions and calculating  $\delta y / \delta x$  over different values of an informative variable such as Z. In Figure 1a, we provide an overview of the Stata code to compute  $\delta y / \delta x$  at values of Z and automatically incorporate the marginal effects approach. It is important to note that the variables researchers specify in Stata are unlikely to have the names of “x,” “y,” and “z,” but the option in the Stata *margins* command to calculate  $\delta y / \delta x$  is always “dydx” regardless of the actual name of the independent and dependent variables. We illustrate this with code for our R&D expenditures example that substitutes real variable names from Compustat for their mathematical indicator counterparts.

**Marginal Effects in R.** A third way to examine the marginal effect of X (e.g., R&D expenditures) on Y (e.g., firm performance) at different values of Z (e.g., firm size) is in the free software package R. Although nearly all programs in R are user-generated, R users created an analog to the *margins* command from Stata that allows researchers to implement the marginal effects approach in a similar way. We provide the R code in Figure 1b but recognize that the code may change at any time depending on if the developers update or remove their code. Much like with Stata, we note that it is unlikely researchers will name their variables “x,” “y,” and “z,” but the actual code requires specific verbiage regardless of the variable names. We again provide a line of code substituting variable names from Compustat for the R&D example in lieu of the mathematical analogs.

### Application of the Marginal Effects Approach

Another salient impediment to the marginal effects approach is that researchers may have reservations about precisely how to apply it. This may be the case given that researchers could encounter multiple scenarios as it relates to whether parameter estimates suggest a significant main effect or moderating effect. Indeed, researchers could encounter four general scenarios: (a) a statistically significant main effect and moderating effect, (b) a statistically significant main effect but no significant moderating effect, (c) a statistically significant moderating effect but no significant main effect, and (d) no statistically significant main effect or moderating effect. To help address this concern, we walk through each of these four scenarios to illustrate how scholars can apply the marginal effects approach to each scenario. We also highlight how the marginal effects technique



**Step 1:** Start by first specifying a regression that includes X, Z, and XZ.

*Code:* regress y c.x###c.z controls<sub>1-n</sub>

*Code for R&D Example:* regress ni c.xrd###c.at controls<sub>1-n</sub>

**Step 2:** Compute the marginal effect of X on Y over different values of Z, noting that researchers can include any number of different values for Z in the code. In our example, we would insert actual numbers that represent the values for each of these conditions, as we did with the values for total assets. The option “dydx” instructs Stata to provide the first derivative from Equation 2 as the output variable.

*Code:* margins, dydx(x) at(z=(verylow low medium high veryhigh))

*Code for R&D Example:* margins, dydx(xrd) at(at=(0 3 20 150 1000 5300))

**Step 3:** Create a marginal effects graph. The options in this command are cosmetic to make the graph easier to interpret.

*Code:* marginsplot, xlabel(, angle(45))

**Figure 1a.** Stata code to produce the marginal effect of X on Y over values of Z.

**Step 1:** Start by first specifying a regression that includes X, Z, and XZ. In our example regression, we have denoted an example data set name and code specification of “marginal effects,” but researchers are welcome to call it something more consistent with their actual data.

*Code:* margineffects <- lm(y ~ x\*z, data=margineffects)

*Code for example:* margineffects <- lm(ni ~ zrd\*at, data=margineffects)

**Step 2:** Compute the marginal effect of X on Y over different values of Z, noting that researchers can include any number of different values for Z in the code. In our example, we would insert actual numbers that represent the values for each of these conditions. Unlike Stata, the default option in R is “dydx,” meaning it is not necessary to instruct R to calculate the marginal effect because doing so is what this command produces.

*Code:* margins(margineffects, at = list(z = verylow low medium high veryhigh))

*Code:* margins(margineffects, at = list(at = 0 3 20 150 1000 5300))

**Step 3:** Create a marginal effects graph. The options in this command are cosmetic to make the graph easier to interpret.

*Code:* cplot(margineffects, “Percentile value of the moderator”, what = “Marginal effect of x”, main = “Marginal effect of X at Different Values of the Moderator”)

**Figure 1b.** R code to produce the marginal effect of X on Y over values of Z.

**Notes:** The code pertaining to the R&D example involve variables downloaded from Compustat. xrd = R&D expenditures, ni = net income (firm performance), and at = total assets (firm size). Of course, these could be substituted with literally any variables. We incorporate these following our example, but the software packages are by no means limited to these variables.

**Table 4.** Regression Results for Scenario 1.

Variable	Model 1 Main Effect		Model 2 Main and Moderated Effect	
	Coefficient	p Value	Coefficient	p Value
Constant	Included		Included	
Controls				
R&D expenditures	Coefficient 1 (+)	***	Coefficient 2 (+)	***
Firm size	Included		Included	
R&D × Firm Size			Coefficient 3 (–)	***

\*\*\*A coefficient that is statistically significant at any desired threshold.

resolves conflicting findings from examining a single coefficient in isolation across different model specifications by affording researchers more nuanced results.

We present tables and figures corresponding to hypothetical empirical outcomes for each of the potential interpretations of the empirical estimates. The tables contain Coefficients 1 through 3, which correspond to the parameter estimates for R&D expenditures in a model without the interaction (Coefficient 1) and in a model with the interaction (Coefficient 2) and the interaction term between R&D expenditures and firm size (Coefficient 3). We also provide an indicator of statistical significance. For the sake of parsimony, \*\*\* represents a coefficient that is statistically significant (at any desired threshold), and *n.s.* represents a coefficient that is not.

The figures we provide correspond to the tables and represent a key component in the marginal effects approach. The y-axis in the figures shows the hypothetical relationship between R&D expenditures (i.e., X or the independent variable) and firm performance (i.e., Y or the dependent variable). The y-axis thus reflects  $\delta y/\delta x$  or the marginal effect. The x-axis reflects different values of firm size (i.e., Z or the moderator variable). This is important to reiterate because it differs from conventional simple slopes graphs; in marginal effects graphs, the y-axis represents the slope (or the relationship between X and Y), whereas this is depicted by an actual slope in simple slopes graphs. The gray vertical line at each point reflects a confidence interval associated with the parameter estimate (this is modally 95% in management research). The dotted horizontal line denotes a value of 0. If the confidence interval includes 0, the relationship is not significant, although it still may have practical relevance.

**Scenario 1: Statistically Significant Main Effect and Moderation.** The first scenario occurs when the hypothetical parameter estimate for R&D expenditures and the interaction of R&D expenditures and firm size are both statistically significant, thus supporting Hypotheses 1 and 2. We display one potential hypothetical outcome corresponding to this causal inference in Table 4. In Table 4, Coefficients 1 through 3 are all statistically significant, meaning the main effect of R&D expenditures and its interaction parameter with firm size are statistically significantly related to firm performance. The fact that Coefficient 1 is statistically significant implies that the average relationship between R&D expenditures and firm performance across all values of firm size is different than 0 (Cohen et al., 2003). Because Coefficient 2 is significant, researchers can infer that the relationship between R&D expenditures and firm performance is significant when firm size takes a value of 0 (Aiken & West, 1991).

In Figure 2a, we provide hypothetical results corresponding to the marginal effects approach that apply to the same scenario we describe in Table 4. This graphical interpretation of the marginal effects approach is produced using any of the three methods we described previously in Figure 1. As shown in Figure 2a, the relationship between R&D expenditures and firm performance is

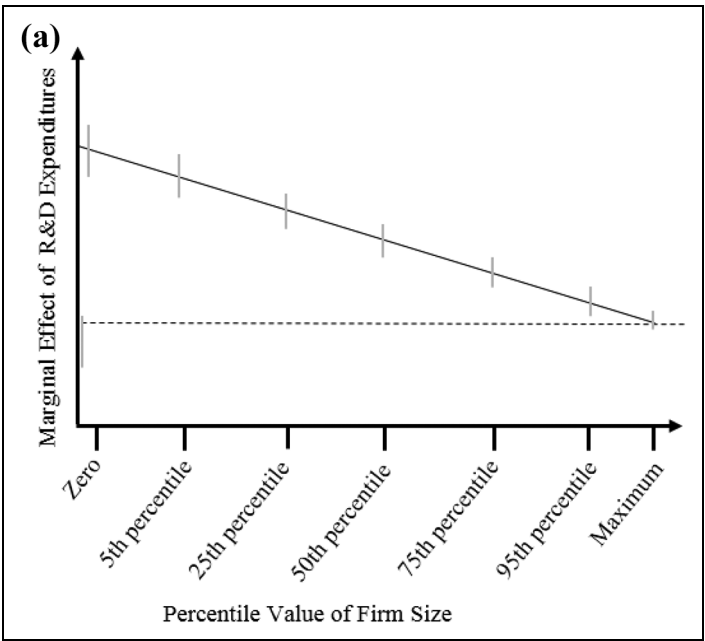


Figure 2a. Marginal effects for Scenario 1.

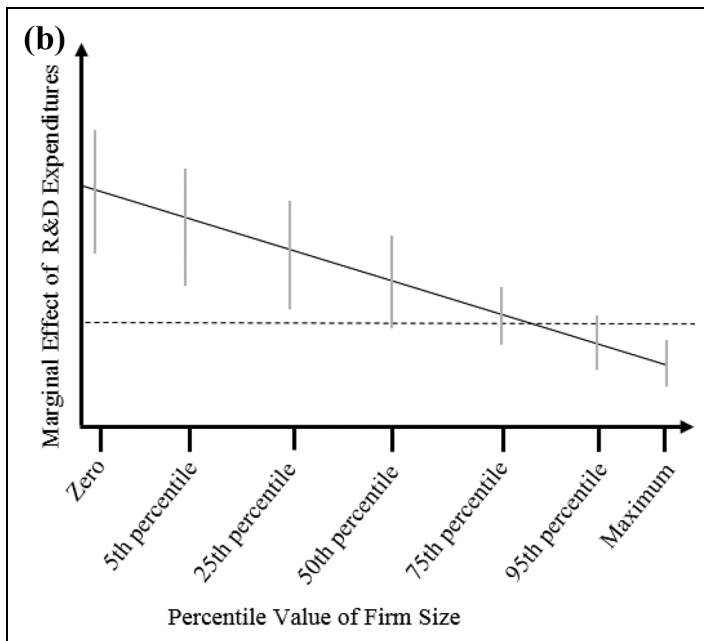
Table 5. Alternative Regression Results for Scenario 1.

Variable	Model 1			Model 2		
	Main Effect			Main and Moderated Effect		
Constant	Coefficient	Included	<i>p</i> Value	Coefficient	Included	<i>p</i> Value
Controls						
R&D expenditures	Coefficient 1 (+)	Included	N/S	Coefficient 2 (+)	Included	***
Firm size						
R&D × Firm Size				Coefficient 3 (−)		

\*\*\*A coefficient that is statistically significant at any desired threshold.

statistically significant when firm size takes the value of 0 (thus consistent with Coefficient 2) and across the majority of the values of firm size (thus consistent with Coefficient 1). Even more, Figure 2a illustrates that there are meaningful differences between the marginal effects at different levels of firm size, which reinforces the fact that there is a moderating effect (and thus consistent with Coefficient 3). Indeed, the marginal effect when firm size takes a value of 0 is statistically different (based on the confidence intervals) than the marginal effect when firm size takes the median value, and the marginal effect at the maximum value is different than at the median value of firm size.

In Table 5, we present a different hypothetical scenario in which Coefficient 2 and Coefficient 3 are statistically significant but Coefficient 1 is not. This may present a puzzle for researchers because it is unclear if Hypothesis 1 is supported. Given our content analysis and survey, we estimate at least 50% of management researchers would suggest Hypothesis 1 is not supported in this scenario.



**Figure 2b.** Alternative marginal effects for Scenario 1. The horizontal dotted line represents the value 0. The vertical gray lines represent the 95% confidence interval for any given marginal effect.

Nevertheless, examining these coefficients in isolation does not provide a comprehensive empirical test of Hypothesis 1.

In Figure 2b, however, we depict the hypothetical marginal effects outcomes that may underlay the results from Table 5. Specifically, we illustrate in Figure 2b that the relationship between R&D expenditures and firm performance is positive and statistically significant when firm size is 0 (hence the significant Coefficient 2 in Table 5) and that this relationship remains statistically significant until firm size takes approximately its median value. After that value of firm size, the relationship is nonsignificant and even turns negative at the maximum value. In this way, the marginal effects approach provides much more insight into the main effect as a researcher may indicate Hypothesis 1 is partially supported or might perhaps even suggest larger or smaller firms are more representative of the population. Again, the marginal effects in Figure 2b are consistent with Coefficient 3 insofar as the relationship between R&D expenditures and firm performance clearly decreases as firm size increases.

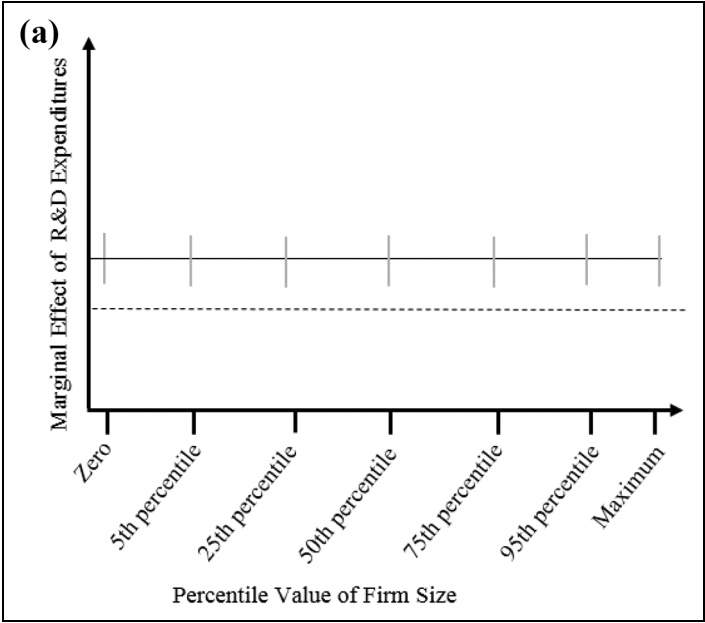
*Scenario 2: Statistically Significant Main Effect but No Significant Moderation.* The second scenario researchers may encounter is when the main effect is statistically significant but there does not appear to be a moderated influence of that relationship. We depict one hypothetical outcome of results corresponding to this scenario in Table 6, in which Coefficients 1 and 2 are statistically significant but Coefficient 3 is not. Interpreting these results is relatively noncontroversial, an idea that the marginal effects in Figure 3a reinforce. As we show in Figure 3a, the relationship between R&D expenditures and firm performance is positive and statistically significant across all values of firm size. At the same time, the relationship does not appear to change as firm size increases, meaning there is no moderating effect.

In Table 7 and Figure 3b, we provide hypothetical results that correspond to this same scenario but with an interpretation that is less obvious and requires a bit more of a nuanced approach. In

**Table 6.** Regression Results for Scenario 2.

Variable	Model 1 Main Effect		Model 2 Main and Moderated Effect	
	Coefficient	p Value	Coefficient	p Value
Constant	Included		Included	
Controls				
R&D expenditures	Coefficient 1 (+)	***	Coefficient 2 (+)	***
Firm size	Included		Included	
R&D × Firm Size			Coefficient 3 (–)	n.s.

\*\*\*A coefficient that is statistically significant at any desired threshold.

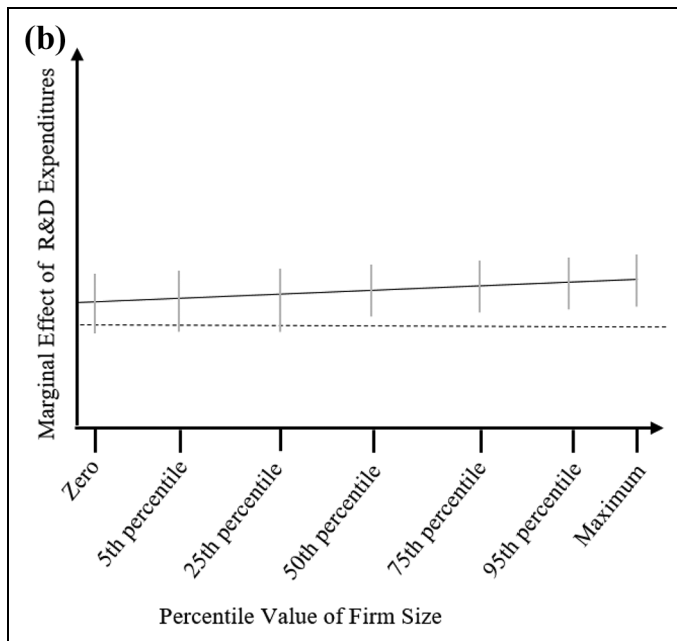


**Figure 3a.** Marginal effects for Scenario 2.

**Table 7.** Alternative Regression Results for Scenario 2.

Variable	Model 1 Main Effect		Model 2 Main and Moderated Effect	
	Coefficient	p Value	Coefficient	p Value
Constant	Included		Included	
Controls				
R&D expenditures	Coefficient 1 (+)	***	Coefficient 2 (+)	n.s.
Firm size	Included		Included	
R&D × Firm Size			Coefficient 3 (–)	n.s.

\*\*\*A coefficient that is statistically significant at any desired threshold.



**Figure 3b.** Alternative marginal effects for Scenario 2. The horizontal dotted line represents the value 0. The vertical gray lines represent the 95% confidence interval for any given marginal effect.

Table 7, we describe an estimation procedure in which Coefficient 1 is significant but not Coefficients 2 and 3. In this case, researchers may suggest support for Hypothesis 1 because the average relationship between R&D expenditures and firm performance across all values of firm size is significant but that relationship is not significant when firm size takes a value of 0. In Figure 3b, we therefore unpack the marginal effects of R&D expenditures on firm performance across all values of firm size to get a better sense for the nature of the relationship. As we show in Figure 3b, the relationship is not differentiated from 0 when firm size is 0 through the 25th percentile, but it does appear to be statistically significant across virtually all of the other values of firm size. Researchers may therefore offer support for their hypothesis if they believe firms in the larger portions of assets are more meaningful, or they may reject (or offer partial support) if smaller firms are meaningful.

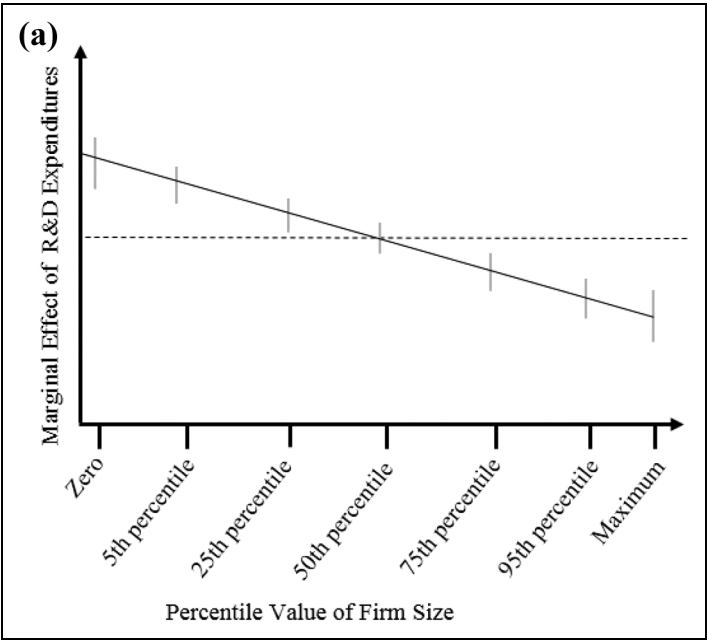
Although the hypothetical relationship strengthens as firm size increases, it does not appear as if there is a moderating effect because the increased marginal effects are trivial and not statistically significantly different from one another. Although it is apparent by examining Figure 3b that the marginal effects do not meaningfully increase, researchers can also compare the marginal effects and corresponding standard errors at different values of firm size to determine if the relationship is significantly different. In this case, the strongest marginal effect occurs when firm size takes its maximum value, and this does not appear to fall outside the confidence interval of the weakest marginal effect.

**Scenario 3: Statistically Significant Moderation but No Significant Main Effect.** The third scenario involves a situation when there is no main effect but there is a moderated relationship. Table 8 depicts hypothetical parameter estimation results associated with this scenario. In Table 8, we document that Coefficient 1 is not statistically significant but Coefficient 2 and the interaction term represented by Coefficient 3 are significant. This means that the average relationship between R&D

**Table 8.** Regression Results for Scenario 3.

Variable	Model 1 Main Effect		Model 2 Main and Moderated Effect	
	Coefficient	p Value	Coefficient	p Value
Constant	Included		Included	
Controls				
R&D expenditures	Coefficient 1 (+)	n.s.	Coefficient 2 (+)	***
Firm size	Included		Included	
R&D × Firm Size			Coefficient 3 (-)	***

\*\*\*A coefficient that is statistically significant at any desired threshold.

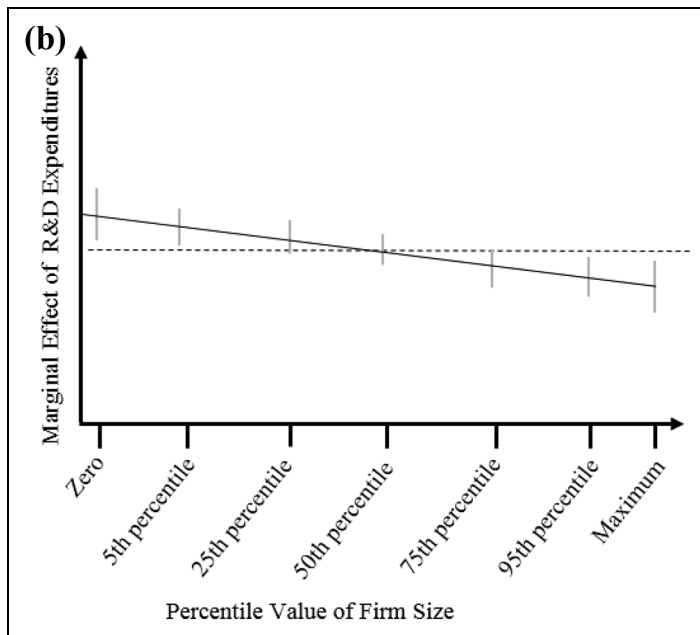


**Figure 4a.** Marginal effects for Scenario 3.

expenditures and firm performance across all values of firm size is not differentiated from 0, but the relationship when firm size takes the value of 0 is statistically significant, and the relationship meaningfully decreases as firm size increases. Given these results, our content analysis and survey suggest at least 10% of management researchers would suggest support for Hypotheses 1 and 2, whereas approximately 50% of management scholars would suggest only Hypothesis 2 is supported.

Given the potential for conflicting causal inference stemming from these results, we provide the hypothetical marginal effects outcomes in Figure 4a as a means to dive deeper into the estimated relationships. There are several elements of interest in Figure 4a that can help researchers make more comprehensive and accurate inferences based on the parameter estimates depicted in Table 6. First, it does appear as though firm size moderates the relationship between R&D expenditures and firm performance. Indeed, the marginal effects significantly decrease as firm size increases. Again, researchers can determine whether this is the case by observing the extent





**Figure 4b.** Alternative marginal effects for Scenario 3. The horizontal dotted line represents the value 0. The vertical gray lines represent the 95% confidence interval for any given marginal effect.

to which the marginal effects at different values of firm size are significantly different from one another.

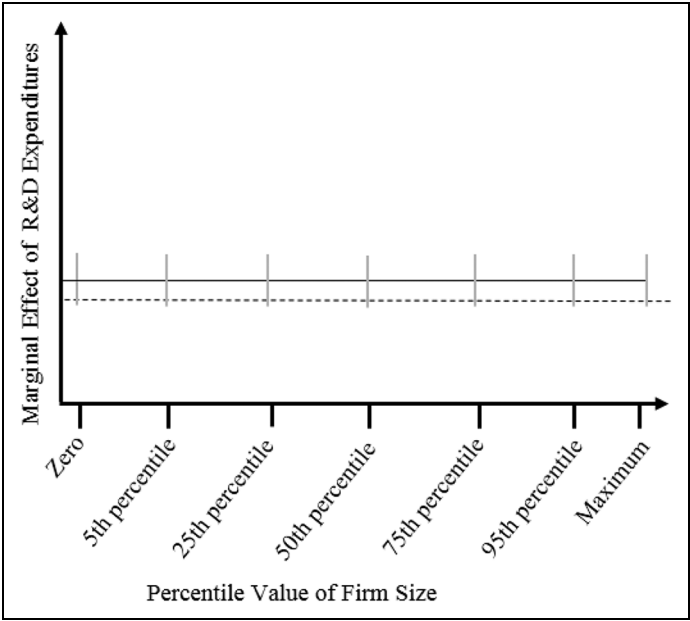
Second, Figure 4a demonstrates that there is a positive relationship between R&D expenditures and firm performance when the value of firm size is 0. In fact, there is a positive relationship until firm size takes approximately its median value. Although researchers may be tempted to infer that this provides support for Hypothesis 1, it is important to also consider the marginal effects when firm size takes values above the median. This brings us to the third important implication of Figure 4a, that there is a statistically significant negative relationship between R&D expenditures and firm performance when firm size assumes larger values. Indeed, this explains why Coefficient 1 is not statistically significant. Because the relationship is symmetrically positive and negative, the average marginal effect of R&D expenditures on firm performance is inconsequential. Researchers may thus suggest Hypothesis 1 is not supported.

Finally, the marginal effects approach demonstrated in Figure 4a allows researchers to make more comprehensive inferences about hypothesized relationships because of the fact it demonstrates both positive and negative marginal effects. Although researchers may suggest Hypothesis 1 is not supported based on these marginal effects, they may also seek to theorize about why the relationship turns negative for larger firms. We recognize a conventional simple slopes technique may provide this same insight, but the marginal effects approach is much more nuanced. Whereas a simple slopes graphic may provide information about two or three different slopes (i.e., relationships between R&D expenditures and firm performance), the marginal effects approach covers the entire spectrum of relationships. This is particularly helpful when the marginal effects are significant at different values of the moderator.

To this point, we also provide Figure 4b. In Figure 4b, we illustrate a situation in which the marginal effects are only positive until firm size reaches approximately its 15th percentile value and only turn significantly negative at approximately the 85th percentile of firm size. Although the

**Table 9.** Regression Results for Scenario 4.

Variable	Model 1 Main Effect		Model 2 Main and Moderated Effect	
	Coefficient	p Value	Coefficient	p Value
Constant	Included		Included	
Controls				
R&D expenditures	Coefficient 1 (+)	n.s.	Coefficient 2 (+)	n.s.
Firm size	Included		Included	
R&D × Firm Size			Coefficient 3 (–)	n.s.



**Figure 5.** Marginal effects for Scenario 4. The horizontal dotted line represents the value 0. The vertical gray lines represent the 95% confidence interval for any given marginal effect.

statistical inferences corresponding to Figure 4b are identical to those presented in Table 6, Figure 4b affords researchers even more insight into the relationships. In this case, scholars may pay closer attention to firms that are especially small or notably large, which offers the opportunity for even more involved theorization about the relationship between R&D expenditures and firm performance. It would prove difficult to determine at which values the relationship changes from positive to 0 to negative in a simple slopes approach without considerable guesswork. By contrast, it is easily apparent using the marginal effects technique.

*Scenario 4: No Statistically Significant Main Effect or Moderation.* The final potential scenario is when there is no statistically significant relationship between R&D expenditures and firm performance and firm size does not appear to moderate the relationship. We present hypothetical parameter estimates consistent with this scenario in Table 9. As expected, Table 9 demonstrates that Coefficients 1 through 3 are all not statistically significant, meaning researchers should not suggest

Hypotheses 1 and 2 are supported. Figure 5 depicts how these relationships manifest in the marginal effects approach. As Figure 5 shows, the marginal effects line is horizontal, which signifies that the relationship between R&D expenditures and firm performance does not change over different firm sizes. The confidence intervals that correspond to each of the marginal effects suggest the relationship is not differentiated from 0.

### *Accommodation of the Marginal Effects Approach*

A final potential impediment to applying the marginal effects technique involves whether it can accommodate the types of empirical estimators and variable operationalizations that are becoming increasingly prevalent in management research. To this point, in the scenarios and examples in the preceding subsection, we focused on conventional multiplicative interactions, continuous variables, and ordinary least squares estimators. We recognize, however, that researchers may face a host of other situations in which they might want to use the marginal effects approach but are not sure about whether it can accommodate their data.

**Variable Operationalizations.** Empirical models increasingly feature noncontinuous variables for predictors, outcomes, and moderators alike (e.g., Bowen, 2012; Ketchen et al., 2008; Wiersema & Bowen, 2009). As such, research often discusses how variable operationalization may influence the appropriateness and nature of multiplicative interaction models (e.g., Arnold & Evans, 1979; Cohen et al., 2003; Schmidt, 1973). One pervasive notion from the research on multiplicative interaction is that it is not possible to derive an accurate main effect when the variables incorporated are interval measures (i.e., scales that do not include 0), whereas ratio measures (i.e., scales that do include the value of 0) produce accurate estimates (Arnold & Evans, 1979; Schmidt, 1973).

Although it is well beyond the scope of our Short Report to address this general debate, we do not find this is the case as it relates to the marginal effects approach. In an unreported simulation procedure that follows the protocols of research on the topic (e.g., Certo et al., 2016; Kalnins, 2018; Semadeni et al., 2014), we found that the marginal effects approach provides estimates consistent with the values we established in the simulation regardless of whether the variables are interval or ratio scales. Stated differently, we specified relationships between variables in conditions that include interval and ratio scales, and our results were nearly identical regardless of the type of scale used.

We recognize that these ratio scales are wholly distinct from ratio variables (i.e., a numerator divided by a denominator), but it is nevertheless relevant to also examine the accuracy of the marginal effects approach in the presence of ratio variables (i.e., not ratio scales, as discussed in the previous paragraph). This is particularly relevant for more macro-oriented research that tends to specify a host of different ratio variables (e.g., ROA, R&D intensity, percentages of outcomes, etc.; Certo et al., 2020; Wiseman, 2009). Interestingly, and consistent with research on mathematical ratios (Certo et al., 2020; Wiseman, 2009), our unreported simulation revealed that the parameter estimates and the marginal effects outcomes corresponding to numerators divided by a denominator were wildly inaccurate. It is important to note, however, that these inaccuracies in the marginal effects of ratio variables are unrelated to the effectiveness of the marginal effects technique and instead reflect the fact that parameter estimation of ratio variables is spurious at best.

**Variable Distributions.** Over the past couple of decades, researchers have become interested in how the general distributions of variables may influence outcomes (Bowen, 2012; Long & Freese, 2014; Wiersema & Bowen, 2009). For instance, research often integrates moderators that take categorical, truncated, or binary values (Baum, 2006; Cohen et al., 2003; Kennedy, 2008). As it relates to the marginal effects approach, such variables simply inform the values of the moderator over which to

examine the marginal effects of the relationship between the independent and dependent variables. For instance, if the moderator is binary, researchers should only examine the marginal effects when the moderator takes a value of 0 and 1. Relatedly, if the moderator is truncated (e.g., at 0, like our firm size example was), 0 should reflect the lowest value of the moderator over which to examine marginal effects. In this vein, if the moderator is categorical, researchers should take care to only consider the marginal effects at meaningful categories of the moderator.

**Limited Dependent Variables.** Researchers are also often interested in how to interpret interactions when the dependent variable takes a limited—for example, logistic, Poisson, truncated—distribution (Bowen, 2012; Hoetker, 2007; Long & Freese, 2014). Fortunately, the marginal effects approach is particularly well suited to address these types of variables. In fact, authors of studies on the marginal effects approach have explicitly credited the research on limited dependent variables for introducing and explicating the value of the technique (Brambor et al., 2006). If researchers apply one of the two popular software packages for which we provided code (i.e., Stata and/or R), the *margins* command will automatically make the requisite adjustments to interpret the marginal relationships. Of course, this is assuming the base estimator is appropriate (e.g., using a probit model for a binary dependent variable rather than ordinary least squares).

If scholars are interested in manually calculating the marginal effects, it will prove helpful to examine what the parameter estimates from these types of models (often using maximum likelihood estimation) represent (Baum, 2006; Kennedy, 2008; Wooldridge, 2010). For instance, the actual marginal effect of the relationship between an independent variable and a binary dependent variable depends on several other factors, including the value of the independent variable and the value of controls, in addition to the value of the moderator (Hoetker, 2007). Nevertheless, manually calculating the marginal effects is not an impossible task—the calculus underlying the marginal effects approach holds for any type of estimation procedure, including maximum likelihood estimation (Kennedy, 2008).

The ability to examine nuanced relationships in nonlinear models represents a chief advantage of the marginal effects approach over the simple slopes technique. This is especially the case as it relates to models that require maximum likelihood estimation, a procedure that is becoming far more pervasive in management research and has even become more popular than least squares techniques in some management journals (Ketchen et al., 2008). Whereas simple slopes examine a linear relationship between the X and Y at different values of the moderator, the marginal effects approach easily unveils nonlinear relationships between focal constructs.

**Mean-Centering and Unstandardized Variables.** Another central discussion involves the differences in mean-centered versus unstandardized variables (Aiken & West, 1991; Cohen et al., 2003; Edwards et al., 2009). When the moderating variable is mean-centered, the parameter estimate for the independent variable in a model with the interaction term (i.e., Coefficient 2 from our examples) represents the marginal effect when the moderator takes its mean value (Cohen et al., 2003; Edwards et al., 2009). This interpretation is identical to our earlier discussion about the coefficient reflecting the relationship when the moderator takes a value of 0, except in this circumstance, 0 represents the average value. It is important to note that this main effect at the average value is not identical to the coefficient from the model without the interaction term (i.e., Coefficient 1 from our example), which reflects the average overall marginal effect. In practice, these will likely be closely related, but in situations with distorted or skewed moderators, they may differ noticeably from one another.

Whether the moderator is mean-centered or standardized helps inform the values over which researchers can examine the marginal effect. In the previous sections, we advocated calculating and depicting  $\delta y / \delta x$  over a swath of values for the moderator variable (Z). As an example, if Z is mean-centered or standardized, we suggest that researchers should use the value 0 as the medium value and

then examine  $\delta y/\delta x$  at meaningful negative and positive values for  $Z$ . It is imperative to indicate, however, that there is little advantage to mean-centering if the value of 0 is practically meaningful for the variable.

**Model Specification and Causal Inference.** Like all other interpretation techniques, the veracity of the marginal effects approach is dependent on the empirical estimation procedure. Indeed, empirical estimators that are improperly specified (e.g., nonspherical disturbances, contamination, deficiency, etc.) produce biased estimates that will create incorrect marginal effects (such as is the case with ratio variables). Scholars have offered an overwhelming amount of guidance as to how practitioners can minimize bias and enhance accuracy. As these techniques relate to moderation, investigators have proposed quasiexperimental designs (e.g., Dahlke & Sackett, 2018), two-stage instrumental variable models (e.g., Bun & Harrison, 2019), and difference-in-difference modeling (e.g., Kennedy, 2008), among myriad others.

A related consideration involves causal inference/statistical significance. For decades, researchers have debated the merits of null hypothesis significance testing against offering a practical interpretation of the results (e.g., Goldfarb & King, 2016; Schwab, 2005), a discussion that has even been explicitly addressed by the editors of top management journals (Bettis et al., 2014). One benefit of the marginal effects approach is that it does not necessarily require researchers to make decisions about statistical significance. The marginal effects analysis provides specific effect sizes for the independent variable at different levels of the moderator. Researchers can therefore make nuanced and meaningful decisions about whether those effect sizes seem to make a substantive difference in the dependent variable as well as vary meaningfully across different levels of the moderator. We thus perceive the marginal effects approach as a valuable technique to move away from null hypothesis significance testing and toward a more holistic view of empirical relationships.

**Multiple Moderators for the Same Independent Variable.** In addition to the single-moderator example we describe here, it is also possible for scholars to examine a focal independent variable across multiple contingent factors. Extending our example, researchers are sometimes interested in the association between R&D spending and firm performance as a contingent function of financial slack (Greve, 2003; Kim et al., 2008). The marginal effects approach is able to accommodate such scenarios quite adeptly using one of two different techniques. In one technique, researchers can affix the values of the nonfocal moderators for any particular marginal effects analysis to their mean level (Bowen, 2012; Hoetker, 2007). This is easily implementable in Stata, for instance, by typing the option *atmeans* at the end of the marginal effects code. The second specification involves setting the nonfocal moderators to other values aside from their mean and perhaps even examining different permutations of marginal effects at several values of multiple moderators. Scholars can accomplish this in Stata, for instance, by inserting more moderators and their relevant values in the *at* portion of the options. The options are similar in the R software, or scholars could calculate the marginal effects from Equation 2 by including more parameters for additional moderators.

## Conclusion

A marginal effects approach to interpreting main effects and moderation involves examining the relationship between the independent and dependent variables (i.e.,  $\delta y/\delta x$ ) at different values of the moderating variable. As we describe, the majority of management researchers have adopted deficient, incomplete, and often conflicting practices to examine such a main effect. We propose the marginal effect approach because it resolves a great deal of the tension in the other popular techniques and affords the most empirical precision. Utilizing a marginal effects approach can thus help

to deter conflicting findings that could result from using other approaches that may hinder theory development.

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## Notes

1. We use the terms *main effect* and *direct effect* interchangeably. The terms *main effect* and *direct effect* refer to the relationship between a focal independent variable and dependent variable. As we describe throughout this research, the term *marginal effect* refers to the *main* or *direct* effect changing owing to a moderating variable. The marginal effects approach thus quantifies the varying values of the main effect at different levels of the moderator. The term *overall effect* involves the combination of all main effects at different values of the moderator.
2. We analyzed the years 2011–2018 for *Strategic Management Journal* to directly follow the time period Boyd et al. (2012) examined, and we selected 2015–2018 for *Academy of Management Journal* and *Journal of Applied Psychology* to extend the period Aguinis et al. (2017) investigated.
3. Statistical treatments of moderation commonly refer to a similar technique as a simple slopes approach toward moderation (Aiken & West, 1991; Cohen et al., 2003). A simple slopes approach involves calculating and graphing the slope of the relationship between the independent and dependent variable, typically at high and low values of the moderator (Cohen et al., 2003; Gardner et al., 2017). As we will describe and illustrate throughout this article, the marginal effects approach enhances and expounds on the logic from the simple slopes technique.
4. Scholars often advocate for setting the nonfocal contingent variables to their mean value, although researchers could select any level they deem appropriate. Although beyond the scope of this Short Report, the marginal effects approach also affords researchers the ability to examine  $dy/dx$  at any permutation of different values of the moderators.
5. We thank the anonymous members of the review team for pointing out this potential issue.

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