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Right Metric for the Right Decision: A Behavioral Model to Infer Metric Effectiveness in Managerial Marketing-Mix Decision-Making

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Short Abstract

This study proposes and models a behavioral framework for the use and effectiveness of individual metrics for different marketing-mix decisions in the context of managerial, firm, and industry characteristics. While there has been progress on the development of metrics to improve managerial decision quality, little or no research uses performance data on specific marketing-mix decisions by managers to assess the use and infer the effectiveness of individual metrics. Our empirical model adjusts for potential endogeneity bias in metric effectiveness due to selection effects and differs from past literature in that we expect managers employ metrics based on their ex-ante expected effectiveness, as opposed to their ex-post effectiveness, which would be unknown to the manager when the decision is made. The main findings are that awareness and willingness to recommend are the metrics most often beneficial for managers to employ while target volume and net present value are the least; and managers are more uncertain about the ex-ante effectiveness of marketing as compared to financial metrics, which attenuates marketing metric use.

Keywords: Managerial Decision-Making; Metrics; Endogenous Regression; Hierarchical Bayes; Rational Expectations

In this research, we propose three central research questions: (i) What is the effectiveness of a specific metric employed for a particular marketing-mix decision? (ii) What drives this effect? and (iii) How do we empirically model this relationship? Managers make a variety of marketing-mix decisions such as running a promotion, altering a price, starting a social media campaign, etc. While the marketing-mix decision is being made, managers *use* or employ individual metrics such as awareness, customer lifetime value (CLV), market share, net profit, return on investment (ROI), satisfaction, etc. as decision aids (e.g., for benchmarking or monitoring) to assist their decisions. From a behavioral point of view, whether the ultimate outcome of that marketing-mix decision exceeds, meets, or is less than the firm's expectations is the *performance* of the marketing-mix decision. The *effectiveness* of the metric is the relationship between using the individual metric and the ultimate performance of the marketing-mix decision.

Evaluating the effectiveness of each metric employed by managers for different decisions is important for firms to understand so they can improve managerial decision quality and, ultimately, marketing-mix performance. That is, to improve marketing decision-making and performance, managers across the firm who are involved in making a marketing-mix decision need to understand whether individual metrics employed in that decision are associated with better or worse decision performance outcomes. Hence, for more than a decade, the Marketing Science Institute (MSI) and the Institute for the Study of Business Markets (ISBM) have continuously encouraged research on metrics to improve managerial decision quality (e.g., see MSI Research Priorities 2002-2020; ISBM B-to-B Marketing Trends 2008-2014).

In response, current research related to metric use in marketing has primarily focused on (i) *proposing* a variety of metrics (e.g., Farris et al. 2010), (ii) identifying conditions under which managers employ a *larger total number* of metrics *across* marketing-mix decisions (e.g., Mintz and Currim 2013), and (iii) linking *aggregate* use of metrics to firm performance (e.g., Frösén et al. 2016). For example, Ambler (2003), Farris et al. (2010), and Lehmann and Reibstein (2006) provide normative recommendations for which metrics managers should employ for a number of different marketing-mix activities, such as advertising, pricing, new product development (NPD), and distribution. Deshpandé and Zaltman (1982, 1984), Glazer et al. (1992), Glazer and Weiss (1993), Hult et al. (2017), Lee et al. (1987), Mintz and Currim (2013), and Morgan et al. (2005) propose conceptual models for what drives the use of certain types of information or types of metrics by managers. Bauer et al. (2013), Chng et al. (2015), Menon and Varadarajan (1992), Moorman (1995), Sinkula (1994), Sinkula et al. (1997), and Venkatesan (2017) propose that certain organizational and managerial characteristics should influence the availability and use of certain types of information in firms. Homburg et al. (2012), Frösén et al. (2016), Menon et al. (1999), Mintz and Currim (2015), and O'Sullivan and Abela (2007) examine the relationship between the total number of metrics used in marketing performance measurement systems and firm performance.

Yet, as summarized in Table 1 (shown following the references), there remains an important gap in the metrics literature between, on the one hand, *proposing* metrics and providing insights on managerial (total) use of metrics *across* decisions, and on the other hand, providing insight on which *specific* metrics are effective for *particular* decisions. This gap is important to address because managers rarely have a shortage of metrics to employ when making a marketing-mix decision, but instead have difficulty understanding which metrics are best for a particular decision (Lehmann and Reibstein 2006). Some managers could be employing certain metrics that turn out to be less effective for their marketing-mix decision, or not employing metrics that would be more effective, reducing the efficacy of that marketing-mix decision (Morgan and Piercy 1998). Further, managers cannot employ every metric in every decision, some metrics can contain more valuable (or detrimental) information than others, and some information used can be irrelevant to the goal of the decision, which could negatively affect the decision's outcome (Glazer et al. 1992). Consequently, this gap has left managers and researchers unsure of which metrics perform best in different decisions (Moorman and Day 2016; Stewart 2009). Hence, there have been numerous calls by marketing scholars advocating for research to identify which metrics will help or hurt marketing performance when employed in managerial decisions (e.g., Lehmann 2004; Mittal 2017; Pauwels et al. 2009; Rust et al. 2004; Stock et al. 2010; Wind 2009).

This paper attempts to address this gap and answer such research calls in three steps. First, we develop a generalized theoretical framework and propose a series of hypotheses that focus on whether and why metrics vary in their effectiveness. Based on value chain theory (e.g., Lehmann and Reibstein 2006), we propose that the alignment between the information provided by an individual metric and the goals of a type of marketing-mix decision is fundamental in determining which metrics will be effective. The use of a metric should help align ex-ante goals of marketing decisions with ex-post outcomes. Hence, those metrics in alignment (misalignment) with the decision's goals should associate with better (worse) outcomes when managers employ them for their marketing-mix decisions.

Second, we augment this conceptual framework with a statistical model that estimates the specific relationships among the effectiveness of individual metrics, their use, and the outcome of marketing-mix decisions. This model highlights the logical necessity of distinguishing between ex-ante expectations in the choice of metrics for different marketing-mix decisions and ex-post realizations of metric effectiveness after observing the results of the decisions. The model corrects for selection effects when managers pick metrics they believe ex-ante to be more effective. The statistical model also estimates the heterogeneity in metric effectiveness across contexts, which includes individual metric (i.e., CLV, market share, ROI, etc.), decision, managerial, firm, and industry covariates that are drawn from the literature.

Third, we empirically test our expectations by calibrating our models with data at the marketing-mix decision level collected by Mintz and Currim (2013). The data includes 1,287 specific marketing-mix decisions made by 439 U.S. managers and includes which of 24 metrics they used for a given decision as well as the outcome of that decisions. Importantly, the unit of analysis is measured at the individual manager and decision level since our focus is on which metrics were employed and what was the outcome of that specific decision. This is in contrast to aggregate measures of firm performance, such as stock market returns or sales, which result from a multiplicity of decisions and metrics adopted by the firm, and would make it difficult if not nearly impossible to measure the impact of using a specific metric for a particular decision.[1] Consequently, without data at the marketing-mix decision level, managers will be unsure which metrics work best for their specific situations, potentially limiting the applicability of knowledge on metric effectiveness and use for specific everyday decisions.

The main substantive findings are fivefold. First, after controlling for covariates and correcting for endogeneity bias due to selection effects, we find metrics vary in their effectiveness; i.e., employing different individual metrics is *associated with differences* in perceived decision performance outcomes. Hence, research examining why such metrics vary in their effectiveness is important. Second, the type of marketing-mix decision is found as a major driver of why metrics vary in their effectiveness, which allows us to infer which metrics are most effective and ineffective across different marketing-mix decision settings. For example, for price promotion decisions, we find the use of awareness, customer loyalty, and consideration set are significantly associated with improved performance, while the use of net present value (NPV) and share of voice are significantly associated with worse performance. Third, among the metrics in our study, awareness and willingness to recommend stand out as "silver bullets" that tend to be associated with better performance across the majority of marketing-mix decision. The other metrics are better suited for some decisions and disadvantageous for others. Fourth, accounting for managerial, firm, and industry characteristics of the decision setting is important and not including such variables leads to unobserved heterogeneity biases. Fifth, managers tend to use metrics that they view to be more effective. This result is hardly surprising, but supports our argument for the use of econometric methods that adjust for selection effect biases when evaluating metric effectiveness. Overall, these empirical findings provide much needed operational, decision-level managerial recommendations on metric effectiveness.

The remainder of this paper proceeds as follows. In the next section, we propose a general conceptual framework and a series of hypotheses examining whether and why metrics vary in their effectiveness (summarized in Figure 1). Because of the considerable amount of individual metrics available for managers to employ across a large range of marketing-mix decisions, this framework focuses on broader drivers of metric effectiveness and use. Our model and analysis also consider the context of metric use, which depends on the manager, decision, firm, and industry because ignoring these sources of variation can bias conclusions. Subsequently, we present our statistical model (Figure 2) for testing these hypotheses. Then, we describe our data (summarized in Figure 3 and Tables 2 and 3) and discuss our results (summarized in Tables 4–7), which includes analysis on the effectiveness of each of the 24 individual metrics in our empirical setting across 10 types of marketing-mix decisions and a variety of managerial, firm, and industry characteristics. Finally, we provide managerial recommendations and discuss limitations which enable potential avenues of future research.

Theory

Conceptual Framework

In Figure 1 (shown following the references), we provide a graphical representation of six unique testable hypotheses based on proposed main and interaction effects of drivers of metric effectiveness. In this conceptual model, our central proposition is that metrics vary in effectiveness (H_1); i.e., individual metrics employed for a specific marketing-mix decision will be associated with a different performance outcome. We propose that a central driver for why there is such variation is the type of marketing-mix decision (H_2) and the interaction between metric and decision types (H_3). Further, we suggest that the characteristics of the decision setting (i.e., characteristics of the manager, firm, and industry in which the decision is being made) will also influence metric effectiveness (H_4), along with interactions between these contextual covariates and individual metric (H_5) and decision type (H_6). Value chain (Lehmann and Reibstein 2006), self-efficacy (Bandura 1982), resource-based (Wernerfelt 1984), and contingency theories (Donaldson 2001) help guide these expectations.

In the following subsections, we expand on this conceptual framework and provide detailed theory and rationale. We note upfront that our conceptual framework focuses on broad theory-based drivers of metric effectiveness, because describing the theoretical rationale for the effectiveness of each individual metric across a range of several different types of decisions, managers, firm, and industry characteristics is not practical.

Individual Metrics Vary in Effectiveness

Our research is predicated on the expectation that individual metrics do not have equal effects on the performance of a marketing-mix decision when employed by managers making such decisions across different settings. That is, the individual metric will have a main effect on metric effectiveness. Metrics comprise of information that "quantifies a trend, dynamic, or characteristic" (Farris et al. 2010, p. 1). Their use should help managers better understand their current situations (Lehmann and Reibstein 2006) and obtain more accurate forecasted outcomes of future actions (Petersen et al. 2009). Further, their use should enable firms to more easily monitor performance relative to a benchmark prior to the decision's implementation, which is facilitated by comparisons to overall decision objectives and similar decisions in the past (Mintz and Currim 2013). Hence, prior research has generally suggested that when managers employ a greater total number of metrics, their firms should achieve better marketing-mix performance outcomes (e.g., Abramson, Currim, and Sarin 2005; O'Sullivan and Abela 2007).

However, in contrast to total metric use, individual metrics vary in characteristics, limitations, and methods used to obtain such information (Srinivasan and Hanssens 2009). Consequently, no one single metric has been theorized to be more effective in order to be employed for all types of decisions (Ambler and Roberts 2008). In contrast, the composition of the metric, what information it conveys, and how such information is gathered should create differences in metric effectiveness and decision performance outcomes when different metrics are employed for a specific marketing-mix decision. Thus, because each metric comprises of different pieces of information, when managers employ different metrics for their decisions, the metrics are expected to have differences in information acquired and considered, which should lead to variations in metric effectiveness and outcomes of such decisions. Therefore, we hypothesize:

H_1: Individual metrics vary in their effectiveness.

What Makes Individual Metrics Vary in their Effectiveness

Our central expectation is that the effectiveness of a specific metric will be dependent on the alignment between the information provided by the metric and the goal or objective of the marketing-mix decision being made. This expectation is in line with value chain theory (e.g., Lehmann and Reibstein 2006), which suggests that different marketing-mix decisions have divergent goals and objectives (Ambler 2003; Farris et al. 2010), so the effectiveness of specific metrics should be contingent on the marketing-mix decision being made.

The use of metrics in decisions allows firms to benchmark, monitor, and/or consider specific pieces of information (Petersen et al. 2009), which should help align a decision's ex-ante goals with its ex-post outcomes *only to the extent* that such information is relevant to the decision's goal. Hence, our expectation is that a metric will be more effective when its information content is relevant to the decision's goals. For example, for promotional-communication decisions such as traditional advertising, social media, and public relations (PR), three fundamental goals are to inform, persuade, and remind and reinforce customers' past decisions (Kotler and Keller 2012). Awareness is often the goal of informing efforts, likeability is often the goal of persuasion efforts, and willingness to recommend is often the goal of reminder and reinforcing customers' past decisions efforts (Farris et al. 2010). Consequently, when managers use these three metrics when making such decisions, their use should associate with greater effectiveness and better decision outcomes since the information provided by each of these metrics help align the information considered by managers in their decision processes with decision-specific goals, resulting in a process that (Jaworski 1988, p. 24) describes as helping "planned marketing activities produce desired results." In contrast, for metrics that contain less relevant information to the decision's goal, we expect less effectiveness and worse decision outcomes.

This expectation can also be extended to other marketing-mix efforts such as pricing, price promotions, NPD, sales force, and distribution decisions, where each effort has its own objective (e.g., Kotler and Keller 2012) and metrics will vary in their alignment with each objective. Hence, we expect that for each type of decision, some metrics will be more (less) appropriate for managers to benchmark, monitor, and/or consider for their decisions, which will lead to variations in effectiveness and performance outcomes. Therefore, we hypothesize:

H_2: Metric effectiveness depends on the type of marketing-mix decision.

A natural follow-up question is "are the effects of individual metrics and type of decision additive, or do they interact?" If there are interaction effects, then the effect of a particular metric will vary across different types of marketing-mix decisions. Our expectation, again based on value chain theory, is that individual metrics have greater alignment (misalignment) for the goals of certain types of marketing-mix efforts. Hence, there should be an interaction effect. For example, the effectiveness of economic value added (EVA) may be greater for product development than for social media since value added is more relevant for product development, while the effectiveness of share of voice may be greater for traditional advertising than for price promotions where the goal is more financial and results oriented. Consequently, we expect:

H_3: Metric effectiveness depends on the interaction between the type of marketing-mix decision and the individual metric.

Additional Factors Which Make Individual Metrics Vary in their Effectiveness

The effectiveness of an individual metric may also be related to characteristics of the decision setting, i.e., the manager, firm, and industry. Our theoretical basis is largely derived from Mintz and Currim (2013), who suggest the manager, firm, and industry are important drivers of managerial *use* of metrics. We now extend their framework to the metric *effectiveness* setting.

First, we consider the decision-maker's perspective (Curren et al. 1992; Perkins and Rao 1990) by accounting for managerial characteristics such as the manager's quantitative orientation, whether the manager works primarily in the marketing department, and if the manager is a top-level (vs. mid-level) manager (see Table 2 shown after the references for the full list). Self-efficacy theory (Bandura 1982; Park and John 2014) suggests that managers with greater expertise, i.e., familiarity and experience (Alba and Hutchinson 1987; Spence and Brucks 1997), will possess greater belief in their capacity to properly understand and comprehend how to employ different metrics in order to achieve better performance. In our metrics context, managers with greater work experience, for example, should have a better perceived ability to comprehend, compute, and utilize a metric such as return on marketing investments (ROMI) (Farris et al. 2015), which should lead to an improvement in ROMI's efficacy in terms of marketing-mix performance outcomes when employed.

Second, we consider the impact of firm characteristics such as the firm's strategic and market orientation, recent business performance, size, or whether it is a publicly owned or privately held firm, employs a Chief Marketing Officer (CMO), and is service vs. goods and B2C vs. B2B oriented. The resource-based view of the firm (Wernerfelt 1984; Kozlenkova et al. 2014) posits that firm characteristics provide specific resources for firms to achieve competitive advantage. In our managerial decision setting, this would indicate that certain types of firms provide their managers more resources (e.g., knowledge based, financial based, etc.) toward certain metrics, which should help such metrics related to the resources provided have better efficacy. Therefore, service-based firms who interact with their consumers on a more regular basis than goods-based firms, for example, should be more cognizant of the importance of CLV (e.g., Bolton et al. 2004; Kumar and Petersen 2005). This should lead such firms to value CLV as a more important metric and devote greater resources to help managers utilize it for their decisions, which, in turn, should help its effectiveness when employed. Finally, we consider the industry environment, such as the product life cycle, level of turbulence, concentration, and growth. Contingency theory (Donaldson 2001; Homburg et al. 1999) suggests that the use and effectiveness of information is conditional on the environment, which should imply that a metric like awareness may be more relevant to a firm in a low (vs. high) industry concentration, where it is harder for firms to break through larger amounts of competitors in the market. Therefore, we summarize the impact of the decision setting into the following hypothesis:

H_4: Metric effectiveness varies by the manager, firm, and industry.

A follow-up question is whether the effect of the covariates are additive across type of metrics or do they interact? Similar to the marketing-mix decision context, we expect an interaction effect of the decision setting. Managers with differing quantitative background, positions in the organizations, and work experiences should be more (less) competent in using different individual metrics (Perkins and Rao 1990). In addition, certain metrics are more difficult to calculate and their effectiveness may depend on other firms and competitors, and, hence, industry characteristics (Hanssens et al. 2003). Consequently, this leads to the following expectation:

H_5: Metric effectiveness depends on interactions between the characteristic of the decision setting and individual metric.

We also expect a three-way interaction effect between the characteristics of the decision setting, the type of marketing-mix decision, and the individual metric. Certain metrics should be more effective because of their alignment to the objectives of specific types of decisions, and managers, firms, and industry characteristics of the decision setting.

H_6: Metric effectiveness depends on interactions between the type of marketing-mix decision and characteristics of the decision setting.

Behavioral Statistical Model

Model Overview

To infer metric effectiveness, we propose a behavioral statistical model that distinguishes between ex-ante expectations and ex-post realization, corrects for endogeneity biases, and accounts for unobserved and observed heterogeneity. Because this model is complex, we first provide a graphical summary overview in Figure 2 and describe in words how it aligns and tests the six hypotheses presented earlier in Figure 1 (see Figures 1 and 2, following the References).

In stage 1, the manager has an initial, ex-ante belief about a metric's effectiveness. As mentioned previously (see H_1–H_3), we expect a major driver of this belief is the perceived fit of the metric for the marketing-mix decision (Ambler 2003; Farris et al. 2010; Lehmann and Reibstein 2006). Further, we expect the manager, firm, and industry decision setting to impact metric effectiveness (see H_4–H_6). For simplicity, in Figure 2, we label the main effects of individual metric and type of marketing-mix decision and their interaction term as "Decision Type by Individual Metric" and the manager, firm, and industry decision setting main effects and interaction terms with the individual metric and type of marketing-mix decision as "Controls by Individual Metric."

In stage 2, the manager forms a latent utility for a metric from these ex-ante beliefs and, in stage 3, selects to employ the metric if the utility exceeds zero (Critcher and Rosenzweig 2014). The random errors for the latent utilities are correlated to account for the possibility that groups of metrics tend to be used together. Further, in each of these first three stages, we control for the decision setting and use hierarchical Bayes methods to estimate observed and unobserved heterogeneity in metric use and effectiveness. For example, some managers may be required to use certain metrics, or managers making decisions in different settings may have better or worse availability of certain metrics.

In stage 4, the manager makes the decision and observes the outcome; however, we do not directly observe this outcome. In stage 5, the manager re-evaluates metric effectiveness based on the result of the marketing decision to obtain his or her ex-post belief about metric effectiveness. We use weak-form rational expectations (Pesaran and Weale 2006) to assume that the ex-ante and ex-post evaluations of metrics can vary across individual managers, but the evaluations across the overall population of managers does not. Finally, in stage 6, the manager reports the decision performance score and the metrics used to make the decision on our survey. In this final stage, we control for recent business performance to isolate the effect of the metric on the marketing decision from general firm performance. Further, throughout the statistical model, we control for unobservables such as the quality of implementation of a marketing-mix effort.

Since metrics are not randomly assigned to managers, the model corrects for two types of endogeneity. The first type, intercept endogeneity, results from selection effects (Heckman 1979) and occurs if the random error for the latent utility for metric use is correlated with the latent errors for the decision performance model. Figure 2 represents intercept endogeneity with a dotted line between the two error terms. The second type, slope endogeneity, occurs because metric use in the performance equation is determined by metric effectiveness in the latent utility for metric use. Figure 2 represents slope endogeneity with a solid line between stages 3 and 6. Our full-information approach to intercept and slope endogeneity detailed in the next section is motivated by Li and Tobias (2011) and follows the lead of Manchanda et al. (2004) by including metric effectiveness in both equations. We believe this approach will be useful to future research dealing with both types of endogeneity, and provide further discussion on the model's potential contribution to the literature on endogeneity in Web Appendix B.

Model Specification

We base our model specification on our six-stage behavioral model in Figure 2. We present the model in reverse order, starting with the performance evaluation of marketing-mix decisions as reported in our survey of managers. There are N subjects in the study. Subject i evaluates n_i marketing-mix decisions where decision j for $j = 1, \ldots, n_i$ is of type $d = d(i,j)$ for one of the D possible marketing-mix decisions (e.g., pricing, NPD, etc.). We assume that the type of marketing-mix decisions are exogenous to metric choice and effectiveness. Managers can use any combination of K possible metrics for each decision.[2]

Marketing-Mix Performance Equation. In the survey, subject i provides an overall performance evaluation y_{ij} for decision j of type $d = d(i,j)$:[3]

$$y_{ij} = \sum_{\boldsymbol{k=1}}^{\boldsymbol{K}} m_{idk}\theta_{idk} + \boldsymbol{x}_{ij}^{'}\boldsymbol{\beta} + \varepsilon_{ij} \qquad 1$$

The observed indicator m_{idk} is one if manager i uses metric k for decision j of decision type $d = d(i,j)$ and 0 otherwise. The random effect θ_{idk} is the latent, ex-post effectiveness for metric k and decision type d. Slope endogeneity occurs because metric effectiveness are parameters in Equation 1 along with observed metric use and because metric use depends on metric effectiveness in the latent utility for metric use (Equation 2). $\boldsymbol{x}_{ij}$ are exogenous control variables, and $\boldsymbol{\beta}$ is a vector of regression coefficients. In our analysis, recent firm performance is the control variable and is used to reflect state dependence.[4] The normally distributed random shocks ε_{ij} have mean 0 and standard deviation σ_Y.

Metric Use Equations. Next, we account for the drivers of metric selection. Manager i is more likely to use metric k if his or her ex-ante beliefs are that the metric will be effective. Since managers can use any subset of the K metrics, we use a multivariate probit model (Chib and Greenberg 1998) for the use of metrics that allows for correlations among the utilities for different metrics. In stage 3 of Figure 2, manager i uses metric k in decision j of decision type $d = d(i,j)$ if the manager's latent utility u_{idk} for the metric k is positive:

$$m_{idk} = 1 \text{ if } u_{idk} > 0, \text{and } m_{idk} = 0 \text{ if } u_{idk} \leq 0. \qquad 2$$

The latent utility for using metric k is:

$$u_{idk} = \rho_k \tilde{\theta}_{idk} + \boldsymbol{z}_{ij}^{'}\boldsymbol{\delta}_k + \nu_{idk} \qquad 3$$

where $\tilde{\theta}_{idk}$ is the managers ex-ante belief about metric effectiveness, $\boldsymbol{z}_{ij}$ are exogenous covariates with regression coefficients $\boldsymbol{\delta}_k$, and ν_{idk} are the random shocks that are normally distributed with mean 0 and variance one. The multivariate probit model constrains the variance to one to identify the model. The parameters ρ_k scale the ex-ante beliefs for metric k because decision performance in Equation 1 and metric utility in Equation 3 are measured on different scales. The parameters ρ_k are restricted to be positive to amplify ($\rho > 1$) or to attenuate ($\rho < 1$) the ex-ante metric effectiveness in metric use. The scaling varies by metric to represent a selection propensity. The presence of ρ_k and $\tilde{\theta}_{idk}$ in Equation 3 distinguishes this model from purely instrumental variable methods of addressing endogeneity such as those discussed by Heckman and Vytlacil (1998) and Wooldridge (2003) in the context of multiple treatment effects. The exogenous variables $\boldsymbol{x}$ in Equation 1 and $\boldsymbol{z}$ in Equation 3 have exclusion restrictions to identify the model by exogenous variation: $\mathbf{z}$ includes variables that are absent from $\mathbf{x}$.

The error terms in latent metric utility Equation 3 are correlated across metrics with covariance and correlation matrix $\boldsymbol{\Sigma}_U$ where the variances are one. Further, they are correlated with the random errors from Equation 1, which results in intercept endogeneity. The full correlation matrix Σ and covariance matrix Ξ for Y and U are:

$$\boldsymbol{\Sigma} = \begin{bmatrix} 1 & \boldsymbol{\Sigma}_{YU} \\ \boldsymbol{\Sigma}_{UY} & \boldsymbol{\Sigma}_U \end{bmatrix} \text{ and } \boldsymbol{\Xi} = \begin{bmatrix} \sigma_Y^2 & \sigma_Y \boldsymbol{\Sigma}_{YU} \\ \sigma_Y \boldsymbol{\Sigma}_{UY} & \boldsymbol{\Sigma}_U \end{bmatrix} \qquad 4$$

where $\boldsymbol{\Sigma}_{UY}$ is a K vector of correlations between ε_{ij} and ν_{idk} where the correlations depend on the metric and not on the type of decision, and $\boldsymbol{\Sigma}_{YU} = \boldsymbol{\Sigma}'_{UY}$. If Σ_{UY} is non-zero, then metric selection is endogenous.

Ex-Post Metric Effectiveness Heterogeneity. After observing the outcome of their decision, the ex-post metric effectiveness θ_{idk} for manager i, metric k, and decision $d = d(i,j)$ varies across managers. The heterogeneity model for these random effects is:

$$\theta_{idk} = \boldsymbol{w}_{id}^{'}\boldsymbol{\phi}_k + \eta_{idk} \quad 5$$

where $\boldsymbol{w}_{id}$ is a vector of exogenous covariates and the type of marketing decision, $\boldsymbol{\phi}_k$ is a vector of regression coefficients for metric k, and the multivariate normal random shocks $\boldsymbol{\eta}_{id} = (\eta_{id1}, \ldots, \eta_{idk})'$ have mean zero and covariance matrix $\boldsymbol{\Lambda}$. We collect the vectors of regression coefficients into a matrix $\boldsymbol{\Phi}$ with $\boldsymbol{\phi}_k$ in the row k.

Relating Ex-Ante and Ex-Post Metric Effectiveness. The strong form of rational expectations in Muth (1961) posits that each agent's distribution of ex-ante beliefs equals the true distribution of outcomes based only on public information. Private information does not play a role in this strong form of rational expectations. In contrast, Pesaran and Weale (2006) propose a weak form of rational expectations where the ex-ante and ex-post expectations across the population are equal. Each manager has his or her beliefs about effectiveness, and a manager's ex-ante and ex-post beliefs can change. However, because the information about metric effectiveness is well diffused across managers, these idiosyncratic beliefs average out across the population.

Weak-form ration expectations assumes $E(\tilde{\theta}_{idk}) = E(\theta_{idk})$ for managers with the same covariates $\boldsymbol{w}_{id}$ in Equation 5. Using the population level model for ex-post metric effectiveness in Equation 5 gives the model for ex-ante metric effectiveness:

$$\tilde{\theta}_{idk} = \boldsymbol{w}_{id}^{'}\boldsymbol{\phi}_k + \zeta_{ik} \text{ where } \zeta_{ik} \sim N(0, \sigma_{\zeta k}^2) \quad 6$$

The coefficients $\boldsymbol{\phi}_k$ is column k of $\boldsymbol{\Phi}$ in Equation 5. In our model, the ex-ante metric effectiveness for manager i deviates from the population mean by a random shock ζ_{ik}.The ex-ante shocks would not be well separated from the errors terms in Equation 5 if there were unique random shocks for each manager, decision type, and metric. Therefore, we assume that the random shocks are dependent on the manager and metric, but not on the decision type.

Combining Equations 3 and 6 gives the latent utility for metric use:

$$u_{idk} = \boldsymbol{z}'_{ij}\boldsymbol{\delta}_k + \rho_k\left[\boldsymbol{w}'_{id}\boldsymbol{\phi}_k + \zeta_{ik}\right] + \nu_{idk} \qquad 7$$

where the random shocks ζ_{ik} and ν_{idk} are mutually independent. The rational expectations shock ζ_{ik} creates a correlation structure within subjects for each metric, while the unobserved utility ν_{idk} imposes a correlation among metrics. Including the random shock ζ_{ik} in both Equations 6 and 7 creates a correlation between ex-ante metric effectiveness and the latent utility for metric use. The independent variables $\boldsymbol{z}_{ij}$ and $\boldsymbol{w}_{id}$ have exclusion restrictions: most importantly, $\boldsymbol{z}_{ij}$ does not include the type of marketing-mix decision while $\boldsymbol{w}_{id}$ does. Further rationale for this exclusion restriction is described in the data section.

Priors and Conditional Distributions. Bayesian inference requires prior distributions for the unknown parameters, and we use standard specifications: multivariate normal for regression coefficients, inverse Gamma for variances, and inverse Wishart for covariance matrices, except $\boldsymbol{\Sigma}$. We use the prior distribution of Barnard et al. (2000) for the correlation matrix $\boldsymbol{\Sigma}$ for the random shocks of Equations 1 and 3. Talhouk et al. (2012) provide an efficient algorithm for sampling from the posterior distribution of the correlation matrix. Also, we follow Lenk and Orme (2009) and impose the prior on the conditional error variance of Y given the metric utilities U instead of the error variance of Y. Web Appendix C presents the details of the prior distributions and details the full conditional distributions for the MCMC algorithm. Web Appendix D provides identification details and includes a description via reduced form models. Simulation studies, available on request, confirm the model's ability to obtain identified parameter estimates by Bayesian analysis.

Data

Data Collection and Variables

We test our model on the 1,287 marketing-mix decisions reported on by 439 U.S. managers from Mintz and Currim (2013). The managerial respondents were primarily obtained via LinkedIn professional organizations (81%). The remaining managers are MBA alumni of a U.S. west coast university (19%). The questionnaire consisted of two sections. In the first section, managers indicated which of 10 marketing-mix decisions they had recently made.[5] Subjects reported between 1 and 10 multiple decisions; the mean number of decisions per subject is 2.9, and the standard deviation is 1.9. For each decision made, managers indicated which of 12 general marketing metrics and 12 general financial metrics they employed.[6] The mean number of metrics used per decision is 4.5 with a standard deviation of 3.7. Table 3 (shown following the references) lists the 10 marketing-mix decisions and the 24 metrics considered.[7]

Next, managers assessed the performance of each marketing-mix decision based on eight subjective measures taken from Jaworski and Kohli (1993), Moorman and Rust (1999), Ramaswami et al. (2009), and Verhoef and Leeflang (2009). Following these works, we define performance of the marketing-mix activity in on our context based on a firm's stated marketing, financial, and overall outcomes, relative to similar prior activities. This combination of performance outcomes provides us a comprehensive subjective measure of performance and avoids potential biases associated with just using a single measure or type of performance.[8] Further, the composite performance score is the average of eight items and has a Cronbach α of 0.94, demonstrating very good internal consistency among the eight items and indicating that managers rated their marketing-mix performance similarly across the different performance measures. In addition, respondents did not appear to hesitate to report on marketing-mix decisions with poorer performance, as the performance score ranged from 1 to 7 with a mean of 4.9 and a standard deviation of 1.1. In the second section of the questionnaire, managers answered questions on managerial, firm, and industry characteristics. Measures were taken from the extant literature noted in Web Appendix Table 1.

Our measure of decision performance is based on subjective measures instead of objective measures such as return on investment (ROI), return on assets (ROA), etc. The primary substantive goal of this research is to infer metric effectiveness for different marketing-mix decisions. Ideally, there would be an objective measure of decision outcomes such as ROI, ROA, or ROMI that could be reported for all types of decisions. However, as Dess and Robinson (1984) argue, it would be very difficult for survey respondents to calculate the ROI, ROA, or ROMI, for that calculation to be comparable between respondents, and for that methodology to be consistently applied to all types of decisions (e.g., pricing, distribution, sales force, etc.) (see also Wilden and Gudergan 2015, pp. 188–189). Thus, any claim of objectivity would likely be illusory. Secondary data or other objective data is not available at the decision unit on analysis from a large number of firms. Further, attempting to statistically identify the effect of one metric on one particular type of decision, which is the goal of the present research, is extremely problematic with aggregate firm-level data (e.g., see Katsikeas et al. 2016 review on marketing performance measures for a similar discussion). One might be concerned that managers in our survey inflated the reported performance as either a demand effect or ego self-preservation, yet, we find significant variation in the outcome measure both within managers and across decisions. Additionally, composite measures reduce biases (Kahneman 2011). In fact, 75% of the decisions were rated less than 5.8 out of 7 points with an average score of 4.9, which provides evidence against ego self-preservation or demand effects. While we recognize the subjectivity of our dependent measure, studies by Germann et al. (2014), Germann et al. (2013), and O’Sullivan and Abela (2007) were able to test a subset their samples using both subjective and objective measures, and in each case obtained similar results.

Table 2 (shown following the references) summarizes the variables that appear in performance, metric use, and metric effectiveness models, including the theoretical justification for inclusion. For model identification, exclusion restrictions are necessary on which variables appear in each equation. In Web Appendix E, we provide a detailed discussion on theoretical and statistical rationale for how our empirical model satisfies such exclusion restrictions. Most importantly, Equation 3 on managerial use of individual metrics include managerial, firm, and industry characteristics that are excluded from Equation 1 on marketing-mix performance, and Equations 5 and 6 on metric effectiveness include type of marketing-mix decision dummy variables which are excluded from Equation 3. Our main rationale is that once we include the metric's effectiveness for making a particular type of decision, the latent utility for metric use (Equation 3) and the performance score (Equation 1) should not include dummy variables for type of decision because this information is encapsulated in metric effectiveness (θ_{idk}), which also appears in these two equations.

Descriptive Statistics

The average firm in our sample had 12,658 full-time employees, with a median size of 125. Fifty-six percent of respondents were top-level managers (i.e., S/VP and C-level), 28% of firms employed a CMO, and 57% of firms competed in mature or declining life stages. Rather than repeat complete details on the definitions, operational measures, descriptive statistics, and published sources of these variables from Mintz and Currim (2013), we refer the reader to Web Appendix Table 1 or to that paper.

In Figure 3.A (shown following the references), we provide model-free evidence that metric use depends on type of decision by displaying the percent of time that managers used a metric given the type of marketing-mix decision, ordered by the percent of time the metric was used for all decisions. The figure shows that percentages vary considerably between metrics and within metric by marketing decision. For example, the three most employed metrics for traditional advertising decisions (awareness, marketing expenditures on branding, and ROI) were different than the most employed metrics for pricing decisions (net profit, target volume, and market share).[11]

In Figure 3.B (shown following the references), we provide model-free evidence that performance scores vary by metric and decision by displaying the average performance score by type of marketing-mix decision when using the metric. The average marketing-mix performance score for all survey responses is 4.9 out of 7 possible points, and the average scores vary more within metric by type of decision than they vary across metrics. For example, the performance score when EVA is employed is 5.32 but ranges from 3.59 for traditional advertising to 6.38 for PR. In addition, the performance measure has considerable variation within and between subjects, which is inconsistent with demand effects where managers uniformly rate their decisions highly.[9] However, the figure also illustrates the need for using a model to separate the effectiveness of the metrics for different decisions because subjects used multiple metrics for each decision.

When combining panels A and B of Figure 3, the descriptive statistics show that metric use and performance need not align with each other. For example, target volume is frequently used, however, average performance scores tend to be lower when it is used. In contrast, EVA is infrequently used, but when it is used, average performance is relative large, except for traditional advertising.

Analyses of the data shows no indication of multicollinearity based on variance inflation factor scores well below 6 (Hair et al. 1998) and over 99% of pairwise correlation coefficients are less than .40 (e.g., Leeflang et al. 2000). Common method bias is not detected based on the Lindell and Whitney (2001) test where we adjusted the correlation matrix by the lowest positive pairwise correlation value to create a partial-correlation adjusted matrix, and no resulting pairwise correlation lost significance. The survey also included multiple response scales (i.e., nominal, continuous, and Likert scales), which should help lessen concerns about common method bias (e.g., Podsakoff et al. 2003). In addition, non-response bias is not found, based on the Armstrong and Overton (1977) test to compare early and late respondents scores on the included constructs. Further, in 26% (333 of 1,287) of the decisions, managers reported to employ zero to three metrics in their decisions, demonstrating that respondents were not reluctant to describe decisions or less likely to participate in the survey if they employed no or a very small amount of metrics.

Results

The model detailed earlier was estimated using MCMC methods. The algorithm ran for 200,000 iterations with the last 100,000 used to summarize the posterior moments of the parameters. Simulation studies were conducted to test the code, the recoverability of parameters, and the convergence properties of model parameters. Convergence of the actual data was assessed by examining the time series plots of selected parameters and re-estimating the model with different random starting points.[10] Web Appendix F provides further analysis to illustrate the importance of accounting for endogeneity and heterogeneity.

Hypothesis Tests

To test our proposed conceptual framework, we summarize our composite hypotheses with partial F-tests from an ANOVA model. The independent variables in this analysis are the hypothesized composite measures and the dependent variable is the posterior mean of the random effects for ex-post, metric effectiveness θ_{idk}. The posterior means are estimated from the full model, which is given by Equations 1 to 7. This approach is not Bayesian, but provides a convenient method to summarize the results and determine whether a composite variable has a significant impact on the effectiveness of a metric.

Table 4 (shown following the references) presents the effects tests for five nested models. Model 1 has main effects for individual metric (H_1) and marketing decision (H_2). Model 2 adds interactions between metric and decision (H_3). Model 3 adds manager, firm, and industry covariates (H_4). Model 4 adds interactions among the contextual covariates and metrics (H_5), and Model 5 adds interactions among the contextual covariates and type of marketing decisions (H_6). We find support for H_1 to H_5 at the .001 significance level but not for H_6. Consequently, these results provide support for our central proposition that metrics vary in their effectiveness. In addition, these results provide support for our central expectation, based on value chain theory, that the type of marketing-mix decision is an important driver of metric effectiveness. Further, these results provide support that the manager, firm, and industry decision setting also matter and are important to account for in models determining metric effectiveness. Contributions to theory based on our proposed conceptual model and the implications of the results of these hypotheses tests are discussed further in the Conclusion section.

We next examine the coefficients from our overall model detailed earlier. A Bayesian method for testing the null hypothesis that a regression coefficient is zero is to compute the posterior probability that the regression coefficients is greater than zero. If this probability is larger than .975 (positive effect) or less than .025 (negative effect), then the posterior distribution is shifted away from zero and the data favors the hypothesis that the regression coefficient is not zero. In our study, the prior mean of the regression coefficients is zero, which biases the results toward the null hypothesis. However, despite this, in our empirical analysis we reject the null hypotheses for many of the regression parameters (see Table 5 in the next section). Hence, we conclude that metric effectiveness varies by type of metric, type of marketing decision, and contextual covariates. Next, we discuss the results of these parameter estimates.

Parameter Estimates

An important managerial question to address related to this work is to provide guidance for which individual metrics when employed associate with better (worse) performance for a given type of marketing-mix decision or decision setting. As a by-product of our empirical model and estimation, we can examine such relationships as summarized below.

Influence of Type of Decision on the Effectiveness of Individual Metrics. In Table 5 (shown following the references), we provide the parameter estimates for how the type of decision influences a metric's effect on marketing-mix performance (a subset of the $\boldsymbol{\Phi}$ matrix in Equations 5, 6, and 7). The coefficients in the table should be viewed as the impact of the type of decision on the effectiveness of an individual metric on marketing-mix performance for the average manager, firm, and industry, as we mean-center the continuous control variables and employ effects coding for the discrete control variables. A positive (negative) coefficient indicates that the impact of the metric is beneficial (detrimental).

Since there are too many combinations of metrics and decisions to detail each result one-by-one, we summarize the main empirical findings as follows. First, when examining individual metrics (i.e., by looking at each row in the table), two metrics, awareness and willingness to recommend, are found to be close to "silver bullets" that are consistently associated with superior performance across different types of decisions when employed. However, in contrast, we find three metrics, total customers, target volume, and NPV, are "lead bullets" associated with worse performance for most types of marketing-mix decisions. Further discussion for the reasons and implications of these results are detailed in the Conclusion section. Second, we find certain metrics can have both a beneficial *and* detrimental association with performance, depending on the type of decision. For example, share of voice is highly effective when employed for PR, social media, and traditional advertising, and highly ineffective for price promotions.

Third, when examining the results for each type of decision (i.e., by looking at each individual column), we can suggest what are the "right" and "wrong" metrics[12] to employ for that decision. For example, for pricing decisions, the metrics EVA, preference, satisfaction, and willingness to recommend are found as "right" metrics, which are beneficial to performance, while likeability, ROS, and NPV are found as "wrong" metrics that are detrimental. Fourth, when looking broadly on the impact of financial and marketing metrics after adjusting for the control variables including past firm performance, we find that financial metrics are for a large part detrimental to performance for different types of marketing-mix decisions while marketing metrics have more of a mixed, beneficial, and detrimental effect depending on the individual metric. Finally, our results appear to have face validity. For example, likeability is most effective for social media and least effective for pricing. EVA is highly effective for NPD decisions where the development team is considering the value added of the new product, while it is detrimental for traditional advertising decisions.

Impact of the Managerial, Firm, and Industry Decision Setting on Effectiveness of Individual Metrics. In Web Appendix Table 2, we provide the results of our variables which account for the type of manager, firm, and industry (the remainder of the $\boldsymbol{\Phi}$ matrix). The presence of significant coefficients demonstrates that accounting for these variables is important as they do in fact matter to whether metrics have a beneficial or detrimental impact on marketing-mix performance. For example, we find quality is more effective for marketers with a greater quantitative orientation, while CLV is more effective for large firms in service industries that have CMOs. Consequently, not accounting for the type of manager, firm, and industry may lead to omitted variable biases or measurement errors when assessing the effectiveness of an individual metric. Though these results are interesting, we view them more as control variables and, accordingly, do not provide further discussion on their impact.

Metric Use. We report the estimated parameters for the manager, firm, and industry variables in the metric's latent utility, δ from Equation 3, in Web Appendix Table 3. The coefficients are the effects of these decision setting variables on the latent utility after adjusting for metric effectiveness. For example, we find top managers are more likely to use ROMI and NPV and those managers with greater metric training are more likely to use net profit, preference, and share of wallet. Since these variables are viewed more as control variables, we will not elaborate further on the specific relationships. Instead, we note that, since many of the relationships are significant, excluding them from the model would bias the other coefficients.

Impact of Ex-Ante Beliefs of Effectiveness of Metric Use. In Table 6 (shown following the references), we report the ρ_k multiplier scores from Equation 7 for the metric's latent utility. This parameter provides a model-based indicator of how a managers' ex-ante beliefs about the impact of a metric on marketing performance determines the metric's use in the decision, while accounting for managerial, firm, and industry characteristics. Larger values of ρ_k, for example $\rho_k > 1$, mean that for a given value of ex-ante effectiveness $\tilde{\theta}_{idk}$, the metric is more likely to be used if $\tilde{\theta}_{idk} > 0$, and less likely to be used if $\tilde{\theta}_{idk} < 0$. In this sense, ρ_k magnifies the ex-ante effectiveness of the metric in the use equation. By contrast, when $\rho_k < 1$, it attenuates the role of ex-ante expectations.

Table 6 lists the metrics in descending order based on the posterior means of ρ_k. We see that 7 out of 10 financial metrics have $\rho_k > 1$ and that 8 out of 12 marketing metrics have $\rho_k \leq 1$. Thus, we find that the ex-ante effectiveness of financial metrics tends to be magnified in the use equation while it is attenuated for marketing metrics. It may be that marketing metrics may be more relevant and effective in managing and guiding marketing-mix efforts toward its specific goals, but the firm is more interested and can better judge financial outcomes of marketing-mix efforts, and this creates pressure for managers to employ financial metrics when reporting the results of marketing decisions.

The last column in Table 6 contains the estimated standard deviation of the error shock for ex-ante effectiveness from Equation 6, i.e. $\sigma_{\zeta k}$. When the standard deviation is large, there is more uncertainty in the managers' ex-ante beliefs about metric effectiveness. Table 6 indicates that there is a negative relationship between ρ_k and $\sigma_{\zeta k}$; the correlation between these two parameters is –0.64. Consequently, we find that when there is more uncertainty in the ex-ante effectiveness of a metric, its effectiveness is attenuated in the decision of whether to use the metric.

Overall, marketing metrics tend to have larger standard deviations and lower multipliers. Hence, managers appear more uncertain about the ex-ante effectiveness of marketing as compared to financial metrics, and this attenuates the use of marketing metrics. For marketing metrics, the average $\sigma_{\zeta k}$ = 2.13 and average ρ_k = 0.76, compared to $\sigma_{\zeta k}$ = 1.45 and ρ_k = 1.61 for the financial metrics. Therefore, managers appear to be more confident in assessing whether a financial metric will be effective in any given decision and rely on that assessment when deciding whether to use the metric. We explore possible reasons for these findings in the Conclusion section.

Analyzing the Error Covariance Matrix from the Performance and Use. Our integrated model of metric effectiveness and use also allows us to analyze the covariance structure between the metrics used and marketing-mix performance. This allows us to examine which combinations of metrics share common characteristics in their use and relationships with performance. To summarize the covariance matrix of posterior means, instead of displaying the 23 by 23 covariance matrix (i.e., each of the 22 metrics and performance), we compute the correlation matrix and perform a factor analysis to uncover its structure. Keep in mind that the factor model is based on the correlation of the random errors after removing contextual covariates and type of marketing-mix decision. Table 7 (shown following the references) contains the results from a six-factor solution, using the rule of including a factor if its eigenvalue is greater than one. Factor loadings in bold face are larger than .4 in absolute value.

The first factor loads –0.84 on performance and above 0.5 on seven marketing metrics. This factor loading shows that these marketing metrics share common, unobserved similarities in metric usage, and its association with performance implies that when these marketing metrics are used more than what would be expected based on their effectiveness, the performance of the decision tends to underperform expectations. The second factor consists of share of wallet, consideration, CLV, marketing expenditures, and share of voice. Factor 3 loads on the financial variables ROI, NPV, EVA, ROMI, and net profit. Factor 4 loads on target volume and segment profit. Factors 5 and 6 load highly on only one variable each, ROS and total customers respectively. Consequently, the results of the factor analysis provide three major takeaways: (1) groups of metrics share common, unobserved sources of variation; (2) endogeneity lurks in metric choice and performance; and (3) managers can use these results to see which metrics are grouped together and find which metrics they could employ (i.e., from different factors) to diversify the information they utilize.

Conclusion

Normatively, individual metrics are employed to improve decisions. However, managers cannot employ every metric in every decision and metrics that managers employ can be irrelevant to the goal of the decision, which could negatively affect its performance (Moorman and Day 2016).

Hence, academics and practitioners are unsure of which metrics are more effective and perform better for different marketing-mix decisions, and have continuously encouraged further research on this topic. To accomplish this, we propose a behavioral framework and corresponding statistical model that integrates decision performance, metric use, and ex-ante expectations and ex-post realizations of metric effectiveness.

The primary theoretical contribution is to develop a conceptual model suggesting individual metrics will vary in their effectiveness and that the type of marketing-mix decision will be a driver of such variation of effectiveness. Guided by value chain theory, we examine the alignment or misalignment between the objectives of marketing-mix decisions, and the information individual metrics provide, to propose underlying expectations on what makes individual metrics effective. We control for managerial, firm, and industry characteristics based on decision maker, firm resource based, and contingency theories. Further, our focus is on the marketing-mix decision unit of analysis, the unit for most managerial decisions. This focus allows us to further our discipline's knowledge about managerial decision making and decision quality, which is important to both academic and managerial practice.

The primary methodological contribution is a new Bayesian model and estimation methodology which address selection bias and observed and unobserved heterogeneity, with multiple, binary endogenous regressors and weak-form rational expectations. To accomplish this, we use multiple equations and a parametric error structure that controls for slope and intercept endogeneity, the propensity for certain metrics to be used in conjunction with each other, and observed and unobserved heterogeneity. We believe this model structure and algorithmic development will be useful in applications beyond our own. For example, in finance, analysts employ a variety of metrics related to a company's profitability to make buy, hold, or sell recommendations. However, the metrics selected to make those decisions, i.e., a firm's ROA, financial leverage, forecasted EPS, etc., are not selected at random. Our model can be employed to determine which metrics are associated with successful stock picks.

Managerially, our model-based results help shed light on the current state of metric use and effectiveness, which is important to practice since it can help researchers and managers better understand, explain, and predict managerial behavior aimed at improving their firms' marketing-mix performance (e.g., Varadarajan 2010). First, we find that two customer-based mindset marketing metrics, awareness and willingness to recommend, are consistently beneficial for managers to employ across a number of marketing-mix decisions. In contrast, we find a consistent negative relationship when managers employ two financial metrics, target volume and NPV, across a number of marketing-mix decisions. This set of results are significant, as it provides evidence that managers need to consider and consistently employ such customer mindset metrics and not just financial based metrics in their marketing-mix decisions. Further, these results provide evidence supporting current efforts on making firms more customer-centric with their marketing-mix decision making.

Second, we find that marketing metrics *on average in our sample* are more effective than financial metrics when employed by managers making marketing-mix decisions. This finding does not mean financial metrics have no inherent value or are unimportant. Instead, it shows a disconnect between, on the one hand, normative recommendations to encourage and facilitate financial metric use or top management's desire for marketing managers to focus on financial metrics, and on the other hand, what managers are doing in practice. For example, while normatively, marketing managers should employ forward-looking financial metrics when making their marketing-mix decisions, this does not mean that this is occurring in practice, nor that such managers are knowledgeable, resourced, incentivized, or have enough foresight to use such metrics effectively. Further, some metrics can contain more valuable (or detrimental) information than others and some information used can be irrelevant to the goal of the decision, which could negatively affect the decision's outcome. Prior to this research, it was unknown which metrics, when employed by managers making a marketing-mix decision, are associated with better or worse decision outcomes. Consequently, it is important for more studies to investigate questions regarding the use and effectiveness of *individual* metrics, as it has a potential to generate interest in how we as a discipline can facilitate and incentivize metric use and effectiveness in order to bridge this disconnect.

Perhaps this finding of marketing metrics *on average in our sample* being more effective than financial metrics is because marketing metrics are easier metrics to influence for managers making marketing-mix decisions. For example, customer intent is easier to influence than behaviors, and financial metrics are far removed from marketing-mix decisions, so when financial metrics are employed, they are associated with worse outcomes. An additional possibility is that marketing metrics are more tactical and closely aligned to the goals of many marketing-mix decisions than financial metrics, so they are associated with better outcomes when employed. Perhaps calculating financial metrics is neither straightforward nor easy for individual marketing-mix decisions such as advertising, social media, NPD, distribution, etc., so when they are employed, they lead to worse performance outcomes. In addition, some financial metrics are only available after many marketing-mix decisions are made, making them useful for post mortems but less useful for managing individual decisions. Whichever the case, these are important issues that have been documented in our sample for the first time and future research can employ our work as a building block to try to better understand the rationale for our results.

However, we also find that managers *on average in our sample* appeared more uncertain in their assessments of the ex-ante effectiveness of marketing metrics, more hesitant to use them when they thought that they were effective, and less discerning in differentiating between specific metrics in their decisions of which one to use. This result supports normative desires for managers to better understand and employ financial metrics. A possible reason for this combination of results is that while marketing-mix decisions are more specific to the marketing function, financial metrics are easier for managers across the organization to understand. For example, ROI is a great way of reporting the results of a traditional advertising campaign since ROI is easily translatable across the organization for managers from a variety of functions to understand. However, as the purpose of a traditional advertising campaign is often to increase awareness, a measure of ROI may mask whether awareness was increased. Consequently, awareness may be necessary to manage the campaign. Yet, since managers feel pressured to employ and report financial metrics to others in the firm, they are more likely to employ them relative to their effectiveness, compared to marketing metrics, which although perhaps more effective, are less understood or accepted by non-marketing constituents in the firm.

Taken together, it appears there is a strong unmet need for academics and consultants to enhance the knowledge and use of various metrics in marketing-mix decisions. For financial metrics, even though there has been an increased desire for marketing accountability over the last two decades, our results show that we as a discipline have much work to do. We need to reduce the gap between normative metric recommendations based on inherent value and the actual use and effectiveness of metrics in practice. Hence, the challenge seems to be developing or applying metrics that link marketing-mix decisions to financial outcomes and motivating, facilitating, and training managers on metric use. For marketing metrics, the challenge appears to be convincing managers to employ such metrics and diversify their use of metrics to help mitigate the managers' a priori uncertainty of their effectiveness. We also caution that our results may be dependent on our empirical setting but expect the conceptual framework and model presented in the paper on metric use and effectiveness will be relevant to any marketing manager's decision setting.

We have identified three potential drawbacks to our current methodology; additional research on these topics would be useful. First, while efforts were made to obtain a representative sample of managers, our results are dependent on this sample of respondents. If the sampled managers contained a greater proportion of financially savvy respondents, we might find greater efficacy for financial metrics. Our results should be replicated across multiple samples. Second, while we evaluate the effectiveness and use of 24 individual metrics across 10 types of marketing-mix decisions, this analysis could be expanded to include additional metrics and types of decisions. Third, while we have argued that it appears necessary to rely on subjective measures of performance to examine the relationship between individual metrics and individual marketing-mix decisions, it may be possible to conduct field experiments to isolate the effect. Our model is flexible enough that a manager or researcher could just substitute their performance measures in place of ours to examine which metrics are more and less likely to be effective and used across the situations in which the decisions are made. Future research incorporating objective performance could substantiate recommendations for what are the "right metrics" for the "right decision." We hope such future research will build on our efforts.

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Footnotes

[1] In Web Appendix A, we contrast our "micro" approach for measuring metric effectiveness versus a "macro" approach.

[2] We note this decision is exogenous to the manager since the manager is tasked to determine whether a specific type of action, like raising price, increasing or decreasing internet advertising, or adjusting distribution is a good choice for the firm. Put differently, a manager cannot simply choose decision situations for which he or she knows *a priori* that the outcome will always be more favorable.

[3] The index j is an artifact of the survey since subjects can evaluate multiple decisions, while the index d identifies the actual marketing-mix decision.

[4] In exploratory analyses, we estimated a large number of additional models using different control variables in Equation 1, and only recent business performance was consistently significant, and it also had the largest standardized effect.

[5] Following Menon et al. (1999) the managers were told to select decisions "that were not so recent that performance evaluation was premature and not so long ago that memory about the decision and performance was fuzzy."

[6] Marketing metrics are defined as metrics that are based on a customer mindset while financial metrics are defined as metrics that are either monetary or readily converted to monetary-based outcomes (Mintz and Currim 2013).

[7] Mintz and Currim (2013) also ask managers to indicate which of three specific to a marketing-mix decision marketing metrics and which of three specific to a marketing-mix decision financial metrics they employed for each decision. However, we focus solely on the 24 total general metrics because these metrics were suited across all the different types of marketing-mix decisions, while specific to a marketing-mix decision metrics were only suited to each type of marketing-mix decision, which limits their applicability to other types of decisions.

[8] If the reader is interested in results of metric effectiveness for any of the performance measures individually (i.e., marketing, financial, overall, and relative to similar past activities), please feel free to contact the authors.

[9] Also, our measure of metric effectiveness is the relative change in performance for using the metric and is not sensitive to biases in the absolute level of the performance ratings (i.e., adding a constant to the ratings will not change our metric effectiveness).

[10] Unlike frequentist methods that integrate the likelihood function over random effects, Bayesian models are able to estimate random effects as a step in the MCMC algorithm. The distribution of the posterior means for each random effect is a nonparametric method of displaying their distribution of heterogeneity without assuming a specific family of distributions.

[11] Two of the metrics, stock prices/returns and Tobin's Q, were so rarely employed (less than 1% of the decisions) that we were forced to drop them from our analysis.

[12] We do not mean "right" and "wrong" as value judgement: all metrics have important roles to play. "Right" and "wrong" are relative to the other metrics being used in a particular context.

Figure 1. Conceptual Framework for how Metric Effectiveness is Influenced by the Decision Setting

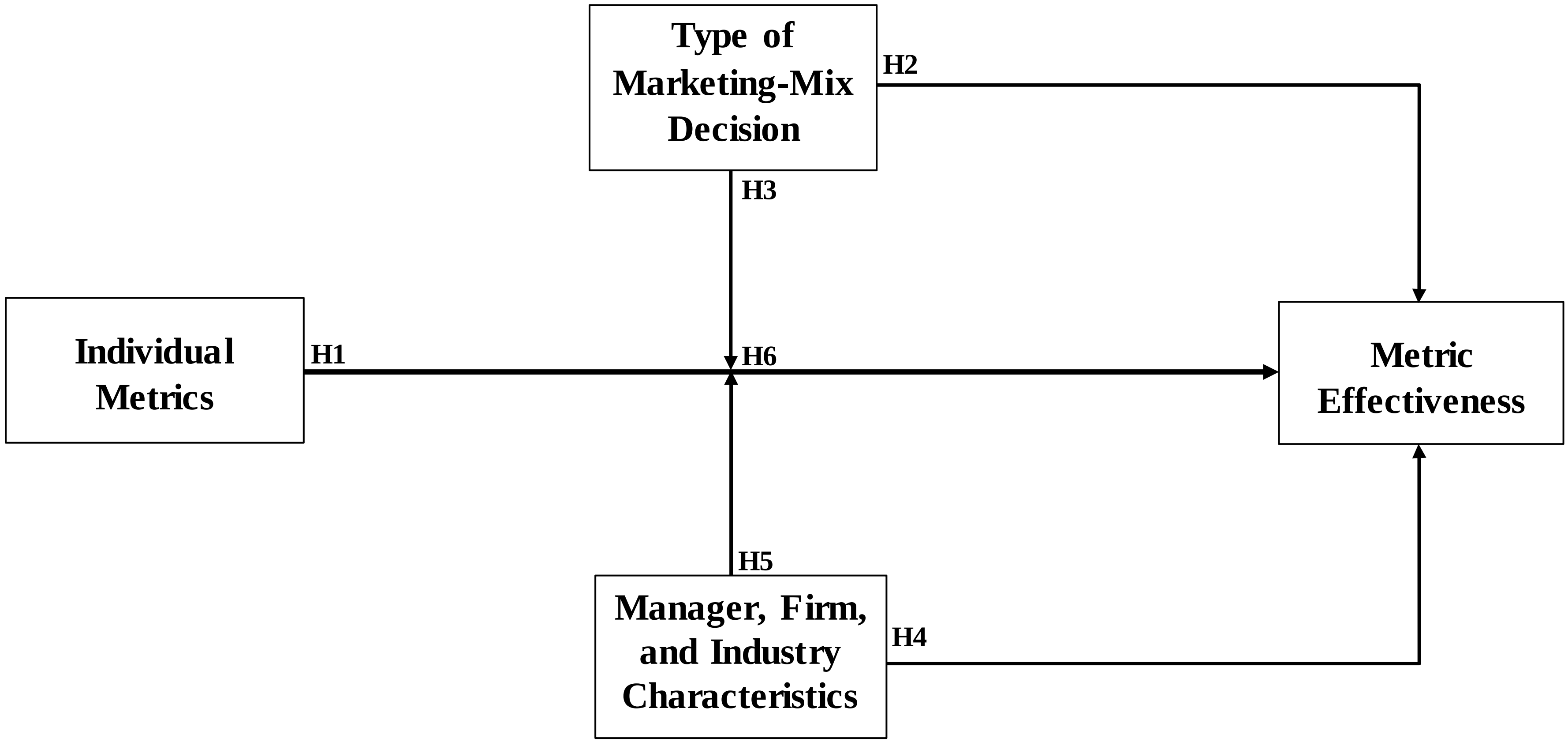


Figure 2. Behavioral Statistical Model for Metric Use and Effectiveness

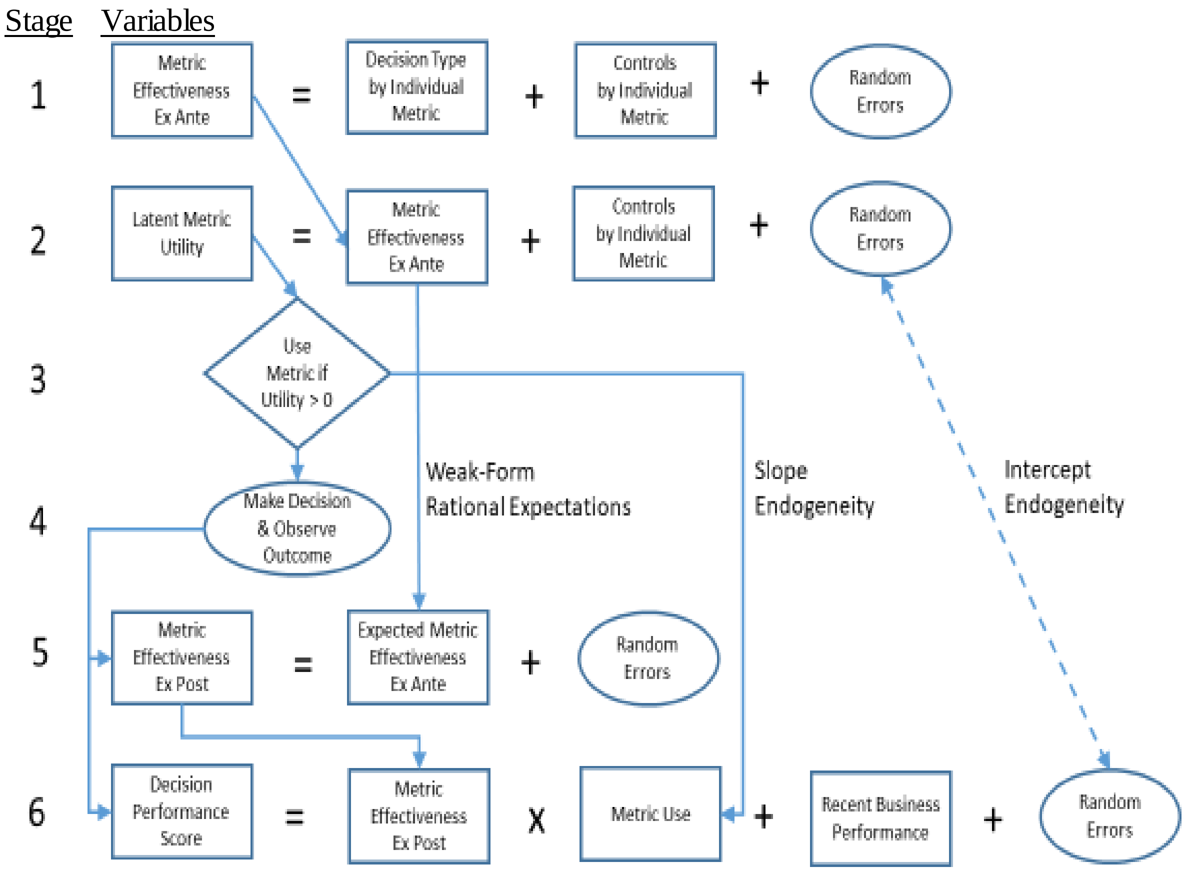


Figure 3. Descriptive Statistics of Metric Use and Effectiveness by Marketing-Mix Decision.
A. Proportion of times the metric was used given a decision type.
B. Average score of decisions if metric was used given a decision type.

Horizontal reference line is the overall mean.

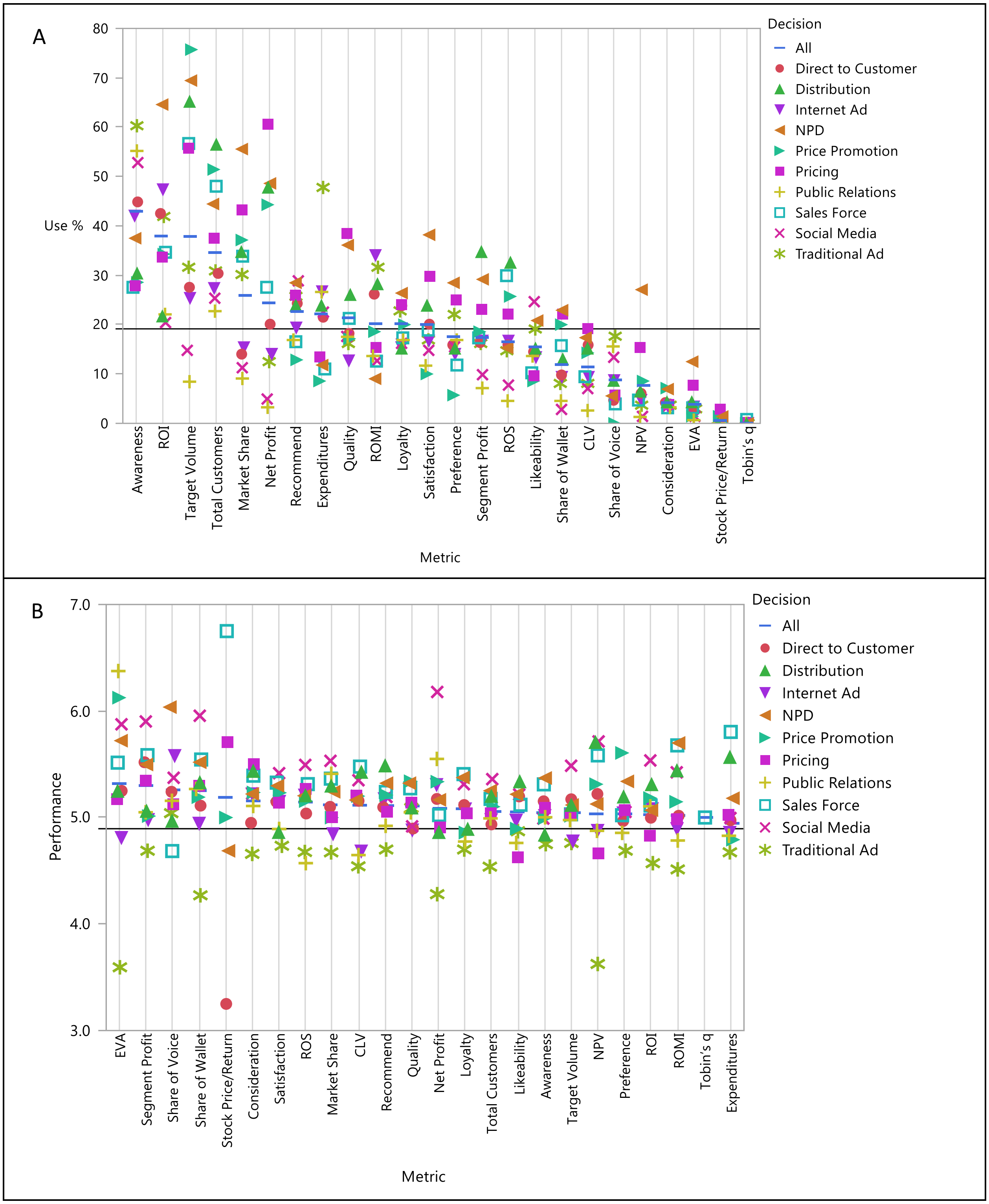


Table 1. Related Literature on Metric Use and Effectiveness by Marketing Managers

	Whether Paper Includes:						
Authors	**Drivers of Aggregate or Individual Metric Use**	**Links Aggregate or Individual Metric Use to Performance**	**Drivers of Aggregate or Individual Metric Effectiveness**	**Links Individual Metric Effectiveness and Use to Performance**	**Examines Multiple Marketing-Mix Decisions**	**Unit of Analysis is Marketing-Mix Decision Level**	**Summary**
Abramson et al. (2005)	No	Aggregate	No	No	No	No	Investigates whether access to decision aids improves marketing-mix decision outcomes
Ambler (2003)	No	No	No	No	Yes	No	Proposes metrics for managers to employ for different types of decisions
Atuahene-Gima and Murray (2004)	Aggregate	Aggregate	Aggregate	No	No	No	Investigates antecedents and consequences of marketing performance measurement systems
Bauer et al. (2013)	Aggregate	Aggregate	No	No	No	Yes	Examines antecedents and consequences of marketing managers using fast and frugal information processing techniques
Chng et al. (2015)	Aggregate	Aggregate	No	No	Yes	Yes	Investigates how past performance influences the total amount of information managers employ when making marketing decisions
Deshpandé and Zaltman (1982)	Aggregate	No	No	No	No	No	Investigates what makes managers more likely to use market researcher supplied information
Deshpandé and Zaltman (1984)	Aggregate	No	No	No	No	No	Investigates what affects market research suppliers' perceptions of managerial information use
Farris et al. (2010)	No	No	No	No	Yes	No	Provides list of metrics which are appropriate for different types of decisions
Frösén et al. (2016)	No	Aggregate	Aggregate	No	No	No	Examines how the relationship between market orientation, marketing performance measurement systems, and firm size influences firm profits
Glazer et al. (1992)	No	Aggregate	No	No	Yes	Yes	Via a marketing simulation game, examines whether providing additional information to managers improves performance
Glazer and Weiss (1993)	No	Aggregate	No	No	Yes	Yes	Via a marketing simulation game, investigates whether industry turbulence affects amount of information and how such overall information use is associated with performance
Homburg et al. (2012)	No	Aggregate	Aggregate	No	No	No	Investigates how the relationship between marketing performance measurement systems, the firm, and the industry affect firm performance

Hult et al. (2017)	6 Individual Metrics	No	No	No	No	No	Investigates the extent to which managers' perceptions of drivers of customers' satisfaction and loyalty align with actual customers
Lee et al. (1987)	Aggregate	No	No	No	No	No	Experiments on what makes managers more likely to use market researcher supplied information, based on decision maker's characteristics
Lehmann and Reibstein (2006)	Aggregate	No	No	No	Yes	No	Provides recommendations for which metrics managers should employ based on type of decision and manager
Menon and Varadarajan (1992)	Aggregate	No	Aggregate	No	No	No	Proposes theoretical model suggesting environment, task, firm, and manager characteristics affect knowledge utilization
Menon et al. (1999)	Aggregate	Aggregate	Aggregate	No	No	No	Investigates how firm resources and culture affect information use for marketing strategy performance measurement systems
Mintz and Currim (2013)	Aggregate	Aggregate	No	No	Yes	Yes	Develops a model on drivers of total metric use; links total metric use to marketing-mix performance
Mintz and Currim (2015)	No	Aggregate	Aggregate	No	Yes	Yes	Examines when total metric use is less beneficial to marketing-mix performance
Moorman (1995)	Aggregate	No	No	No	No	No	Proposes that organizational culture impacts information
Morgan et al. (2005)	1 Individual Metric	1 Individual Metric	1 Individual Metric	1 Individual Metric	No	No	Examines the drivers of the use of customer satisfaction data
O'Sullivan and Abela (2007)	No	Aggregate	No	No	No	No	Examines whether the ability to measure metrics affects firm performance
Perkins and Rao (1990)	Aggregate	No	No	No	No	No	Investigates how managerial experience affects information use
Sinkula (1994)	Aggregate	No	No	No	No	No	Proposes theoretical model on how organizations process market information
Sinkula et al. (1997)	Aggregate	No	No	No	No	No	Examines how organizational learning affects information generation and dissemination
Venkatesan (2017)	4 Individual Metrics	No	No	No	No	No	Proposes theoretical framework for how firms should manage customers by using four metrics
This Paper	24 Individual Metrics	24 Individual Metrics	24 Individual Metrics	24 Individual Metrics	Yes	Yes	Investigates the relationship between the effectiveness of an individual metric, its use, and the outcome of a marketing-mix decision

This is a review of papers on metric or information use by managers making marketing decisions. It does not include papers that link marketing-mix activities with financial metric outcomes but do not consider metric or information use by managers (e.g., see Edeling and Fischer 2016; Srinivasan and Hanssens 2009 for reviews).

Aggregate = examines total amount of metric or information use; Individual = examines individual metric use

Table 2. Manager, Firm, Industry, and Decision Characteristics Used in Models
"x" indicates variables in the marketing-mix performance model; "z" indicates variables in latent utility model for use; and "w" indicates variables in heterogeneity distribution for random, metric effectiveness.

	Model for			Theory/Justification (Source(s))
Model Variables	Performance (Equation 1)	Metric Use (Equation 3)	Metric Effectiveness (Equations 5 & 6)	
Individual Metric Use	x			Decision Making Theory (Abramson et al. 2005; Jaworski 1988; Menon et al. 1999)
Individual Metric Effectiveness	x	z		Selection Effects (Li and Tobias 2011)
Recent Business Performance	x	z	w	State Dependence / Resource Based Theory (Wernerfelt 1984; Kozlenkova et al. 2014)
Managerial Characteristics • Top vs. Mid-level Manager • Marketing Functional Area • Managerial Experience • Quantitative Orientation • Metric-based Compensation • Metric-based Training		z	w	Decision Maker's Perspective / Self-Efficacy Theory (Curren et al. 1992; Perkins and Rao 1990)
Firm Characteristics • Market Orientation • Strategic Orientation ○ Prospectors ○ Analyzers ○ Low-Cost Defenders ○ Differentiated Defenders • Organizational Involvement • Firm Size • Public vs. Private Owned • CMO Presence • B2B vs. B2C • Goods vs. Services		z	w	Resource Based Theory (Wernerfelt 1984; Kozlenkova et al. 2014)
Industry Characteristics • Product Life Cycle • Industry Concentration • Market Growth • Market Turbulence		z	w	Contingency Theory (Donaldson 2001; Homburg et al. 1999)
Marketing-mix Decision • Traditional Advertising • Digital Advertising • Direct to Consumer • Social Media • Price Promotions • Pricing • New Product Development • Sales Force • Distribution • PR/Sponsorships			w	Value Chain Theory (Lehmann and Reibstein 2006)

Table 3. Marketing-Mix Decisions and Metrics.

Variable	**Abbreviated Name**	**Variable**	**Abbreviated Name**
Type of Marketing-Mix Decision			
Direct to Customer	D2C	Pricing	Pricing
Distribution	Distribution	Public Relations or Sponsorships	PR
Internet Advertisement	Internet Ad	Sales Force	Sales Force
New Product Development	NPD	Social Media	Social Media
Price Promotion	Price Promo	Traditional Advertisement	Traditional Ad
Financial Metric		*Marketing Metric*	
Net Profit	Net Profit	Market Share	Market Share
Return on Investment	ROI	Awareness	Awareness
Return on Sales	ROS	Satisfaction	Satisfactions
Return on Marketing Investment	ROMI	Likeability	Likeability
Net Present Value	NPV	Preference	Preference
Economic Value Added	EVA	Loyalty	Loyalty
Marketing Expenditures (% on Brand Building Activities)	Expenditures	Willingness to Recommend	Recommend
Stock Prices / Stock Returns	Stock Prices/Returns	Perceived Product Quality	Quality
Tobin’s Q	Tobin's Q	Consideration Set	Consideration
Target Volume (Units or Sales)	Target Volume	Total Customers	Total Customers
Customer Segment Profitability	Segment Profit	Share of Customer Wallet	Share of Wallet
Customer Lifetime Value (CLV)	CLV	Share of Voice	Share of Voice

Table 4. F-Statistics for Effect Tests where the Dependent Variable is the Posterior Mean of Metric Effectiveness

Source	Hypothesis	DF	Model 1	Model 2	Model 3	Model 4	Model 5
Metric	H_1	21	231.35***	202.68***	205.36***	1176.86***	1174.45***
Marketing Decision	H_2	9	29.44***	32.81***	36.06***	1309.21***	162.76***
Metric x Decision	H_3	189		18.09***	18.33***	636.48***	635.18***
Covariates	H_4	21			15.76***	572.74***	387.87***
Covariates x Metric	H_5	441				2069.54***	2064.07***
Covariates x Decision	H_6	189					0.73

*** if p-value < 0.001; ** if 0.001 ≤ p-value < 0.01; * if 0.01 ≤ p-value < 0.05

Table 5. Type of Decision's Impact on Metric Effectiveness

Note: Bolded and italicized numbers indicate significant coefficient: P(Coefficient > 0) > 0.975 or P(Coefficient < 0) < 0.975.
Metrics are ordered by the average of the posterior means (overall mean) across all subjects and decisions.

Metric	Overall Mean	Traditional Ad	Internet Ad	Direct to Customer	Social Media	Price Promotion	Pricing	NPD	Sales Force	Dist-ribution	Public Relations
Awareness	1.123	***1.515***	***1.311***	***1.287***	***1.410***	***0.847***	0.514	***0.760***	***0.805***	0.486	***1.614***
Recommend	0.800	***0.393***	1.037	***1.054***	***0.822***	***0.905***	***0.790***	***0.790***	***0.882***	***1.272***	0.614
Satisfaction	0.745	0.225	0.238	0.319	0.002	0.510	***1.082***	***0.725***	0.582	***1.072***	-0.341
Likeability	0.429	0.028	0.096	-0.078	***0.707***	-0.113	***-0.765***	0.026	-0.202	0.098	0.140
Preference	0.371	0.217	0.160	0.479	0.273	-0.495	***1.306***	0.629	0.357	***-0.745***	0.520
Share of Wallet	0.348	-0.080	0.193	0.018	-0.696	***0.457***	***0.697***	***0.460***	***0.353***	0.034	-0.217
CLV	0.327	***-0.578***	***-0.498***	0.073	***-0.508***	0.058	0.253	0.002	-0.454	0.012	***-1.197***
Share of Voice	0.266	***0.834***	***0.576***	0.014	***1.105***	***-2.747***	***0.269***	0.026	***0.120***	***0.519***	***1.421***
Loyalty	0.256	***0.895***	***0.752***	***1.101***	0.630	***1.344***	0.623	0.693	0.712	0.079	0.843
Market Share	-0.001	-0.287	***-0.589***	***-0.712***	-0.697	-0.232	-0.095	-0.046	-0.195	-0.410	***-0.761***
Segment Profit	-0.006	-0.013	0.322	0.142	0.060	-0.095	0.193	0.149	0.331	0.712	***-0.311***
Quality	-0.011	-0.889	-0.953	-0.472	-0.181	-0.141	0.628	-0.108	0.483	0.434	-0.064
Expenditures	-0.039	***0.700***	0.381	0.188	0.290	-0.126	-0.143	-0.380	-0.158	-0.013	0.371
ROMI	-0.058	0.141	0.210	-0.033	***-0.576***	***-0.320***	***-0.587***	***-0.872***	***-0.448***	***-0.321***	***-0.382***
Consideration	-0.061	***-0.766***	0.593	-0.088	0.788	***1.080***	0.536	0.913	***0.695***	0.391	***0.127***
ROI	-0.175	-0.035	0.098	0.046	-0.356	-0.159	-0.205	0.162	-0.065	-0.391	-0.235
Total Customers	-0.336	***-0.703***	***-0.774***	***-0.769***	***-0.655***	-0.062	***-0.522***	***-0.413***	-0.136	-0.057	***-0.644***
ROS	-0.403	-0.223	-0.108	-0.073	-0.544	***0.199***	***-0.002***	-0.349	***0.374***	0.278	***-0.847***
Net Profit	-0.446	-0.676	-0.541	-0.444	***-1.023***	***-0.019***	***0.215***	-0.111	-0.243	-0.137	***-1.061***
Target Volume	-0.792	***-0.580***	***-0.665***	***-0.621***	***-0.901***	0.080	***-0.260***	***-0.111***	-0.110	***-0.209***	***-1.077***
NPV	-0.822	***-1.297***	***-0.747***	***-0.938***	***-1.479***	***-0.724***	***-0.470***	***-0.129***	***-1.050***	***-1.028***	***-1.275***
EVA	-0.947	***-0.304***	1.334	0.073	-0.252	-0.514	***1.203***	***2.457***	***1.114***	-0.204	0.228

Table 6. Metric Effectiveness Multiplier for Metric Use and Uncertainty in Ex-Ante Effectiveness

Metric	Type	Metric Effectiveness Multiplier in Use	Rational Expectations Error STD DEV
ROI	Financial	2.580	0.486
Net Profit	Financial	2.275	0.544
ROMI	Financial	2.064	0.856
Target Volume	Financial	1.999	0.521
ROS	Financial	1.721	0.929
NPV	Financial	1.695	1.150
Market Share	Marketing	1.668	0.635
Expenditures	Financial	1.617	0.686
Share of Wallet	Marketing	1.217	1.398
Total Customers	Marketing	1.177	0.975
Share of Voice	Marketing	1.048	1.476
Awareness	Marketing	0.954	0.710
CLV	Financial	0.842	1.913
Segment Profit	Financial	0.775	1.756
Consideration	Marketing	0.758	5.671
Likeability	Marketing	0.601	1.289
EVA	Financial	0.571	5.604
Loyalty	Marketing	0.461	2.035
Satisfaction	Marketing	0.377	2.379
Quality	Marketing	0.371	2.494
Recommend	Marketing	0.236	3.914
Preference	Marketing	0.227	2.539

Table 7. Factor Analysis of Error Correlation from Performance and Latent Utility for Use
Factors were rotated using a Varimax procedure to improve interpretability. Eigenvalues and communalities calculated using the rotated factor solution. Italicized, bold factors are above 0.4.

Variable	Factor 1	Factor 2	Factor 3	Factor 4	Factor 5	Factor 6	Communality
Performance	***-0.843***	-0.078	0.091	0.146	0.080	0.171	0.781
Likeability	***0.813***	0.037	0.332	0.188	0.083	0.012	0.814
Satisfaction	***0.803***	0.015	0.273	0.145	0.047	0.368	0.878
Recommend	***0.757***	0.318	0.028	0.365	0.173	-0.019	0.838
Awareness	***0.730***	0.157	0.171	0.080	0.021	-0.038	0.595
Loyalty	***0.702***	0.231	0.206	0.073	0.094	0.347	0.723
Preference	***0.665***	***0.422***	0.293	0.167	0.264	-0.043	0.806
Quality	***0.591***	0.317	0.188	0.047	0.361	0.260	0.686
Share of Wallet	0.163	***0.800***	0.302	0.127	-0.094	0.067	0.786
Consideration	0.157	***0.772***	-0.072	-0.012	0.098	0.016	0.636
CLV	0.089	***0.758***	0.277	0.101	-0.220	0.217	0.765
Expenditures	***0.416***	***0.578***	0.074	0.009	0.393	0.204	0.709
Share of Voice	0.200	***0.456***	0.362	0.243	-0.371	0.067	0.581
ROI	0.115	0.059	***0.851***	0.106	0.232	0.127	0.822
NPV	0.131	***0.547***	***0.746***	0.160	-0.008	-0.126	0.916
EVA	0.384	0.232	***0.665***	0.276	0.045	0.146	0.744
ROMI	***0.403***	0.101	***0.527***	0.146	0.348	0.252	0.656
Net Profit	0.260	0.200	***0.493***	***0.409***	0.111	0.161	0.556
Target Volume	0.075	0.003	0.261	***0.942***	0.065	0.187	1.000
Segment Profit	0.156	***0.538***	0.163	***0.550***	0.052	0.118	0.660
Market Share	0.190	0.381	0.156	0.385	0.213	0.203	0.440
ROS	0.186	-0.095	0.333	0.188	***0.821***	-0.036	0.866
Total Customers	0.020	0.196	0.123	0.253	-0.012	***0.780***	0.726
Percent Variance	22.545	16.120	13.848	9.029	6.655	5.641	

Web Appendix for "A Behavioral Model to Infer Metric Effectiveness in Managerial Marketing-Mix Decision Making"

Web Appendix A. Our Micro approach versus Macro approaches in the Literature

In Panel A of Web Appendix Figure 1, the researcher observes some measure of which metrics are being used in the firm as well as some aggregated measure of firm performance. Panel B represents the actual process in which metrics are used to make specific decisions; and then the summation of all those decisions (as well as others) results in the firm's overall performance. In other words, there is a hidden layer in macro analyses that involve micro-level specific decisions and outcomes, and these mediate the effect of marketing metrics on firm performance. Attempting to statistically identify the effect of one metric on one particular type o2f decision, which is the goal of the present research, seems problematic using aggregate data (e.g., see Katsikeas et al. 2016 review on marketing performance measures for a similar discussion). Further, trying to control for all confounding factors (e.g., the firm's mix of marketing, financial, and organizational decisions along with changes in the industry and economy) in cross-sectional or even in time series data to isolate the effect of one specific metric on one type of decision on aggregate firm performance would be a Herculean task. Panel C of Web Appendix Figure 1 represents how this research models metric use and effectiveness at the micro level.

Web Appendix B. Model's Contribution to Literature on Endogeneity

Our model of metric effectiveness addresses two sources of endogeneity. The first is the observation that the use of a particular metric may be influenced by the expected effectiveness of the metric. Managers are more likely to use metrics that they believe are more effective. The second source of endogeneity is when metric use is correlated with the error term in Equation (1). This may occur when additional explanatory variables are correlated with metric use but are omitted from the model. In a general context, Luan and Sudhir (2010) refer to the first source of endogeneity as "slope endogeneity" and the second as "intercept endogeneity."

The proposed model uses several equations and explicitly considers the relationship between metric use and metric effectiveness. In this sense, it is similar to the general approach suggested by Manchanda et al. (2004) to address slope endogeneity in sales response models. Specifically, slope endogeneity is addressed in our setting by making the decision of whether or not to use a specific metric, m_{idk}, a function of the model parameter $\tilde{\theta}_{idk}$, which represents the manager's ex-ante belief of metric effectiveness. However, the model also addresses intercept endogeneity via a correlated error structure between the metric use equation and the performance equation (see Equation (4) above and the dotted line in Figure 2). The extended modeling framework distinguishes our approach from instrumental variable/control function adjustments to a single equation. We show in the results section that the proposed model offers additional insights compared to the instrumental variable or control function methodology.

Our approach is most similar to that of Li and Tobias (2011) who use a three equation model to determine earnings, the heterogeneous return to schooling, and the level of schooling; their model also includes common parameters and a correlated error structure. However, our model differs from Li and Tobias (2011) in three important ways. First, we consider multiple explanatory variables (which metrics were used) as opposed to a single explanatory variable (level of education). As documented by Mintz and Currim (2013), decision makers often employ more than one metric to make a decision. Second, our explanatory variables are binary as opposed to continuous. The control function approach of Luan and Sudhir (2010) does not consider dichotomous regressors and while the semi-parametric approach of Park and Gupta (2012) considers multinomial regressors, as they note, their model is not identified for binary variables. Li and Tobias (2011) also assume students know how much more money they would earn for each additional year of education completed. Perfect foresight is an extreme assumption for students or managers. Rather, we assume the decision makers have rational expectations of the effectiveness of a particular metric, but that it may differ from the metric's actual performance. Thus, our third departure is allowing for the ex-ante expectation of metric effectiveness to differ from the ex-post realization of metric effectiveness. This issue has not been addressed in the literature on slope endogeneity. The addition of ex-ante expectations, multiple binary endogenous regressors, and a complicated error covariance structure necessitates a new method for estimating model parameters.

Web Appendix C. MCMC Algorithm

The appendix details the full conditional distribution for the MCMC algorithm. We use the notation "Ω|Rest" for the distribution of parameter Ω given all observables and all other parameters except Ω. It is convenient to rewrite manager i's utility in Equation (3) as a vector:

$$\boldsymbol{u}_i = \boldsymbol{\Delta}'\boldsymbol{z}_i + \boldsymbol{R}'\boldsymbol{\theta}_i + \boldsymbol{\nu}_j \text{ for } i = 1, \dots, n \qquad 8$$

where $\boldsymbol{\Delta} = [\boldsymbol{\delta}_1, \dots, \boldsymbol{\delta}_J]$, and $\boldsymbol{R} = diag[\rho_1, \dots, \rho_J]$, a matrix with 0 on the off-diagonals and ρ_j for the (j,j) element. The entire data for the latent utilities can be written by stacking the transpose of Equation (8):

$$\boldsymbol{U} = \boldsymbol{Z\Delta} + \boldsymbol{\Theta R} + \mathbf{E}_{\boldsymbol{U}} \qquad 9$$

where row i is $\mathbf{u}_i'$ for $\mathbf{U}$, $\mathbf{z}_i'$ for $\mathbf{Z}$, θ_i' for $\boldsymbol{\Theta}$, and $\boldsymbol{\nu}_i'$ for $\mathbf{E}_{\mathrm{U}}$. Similarly, Equation (5) can be compactly written for all observations:

$$\boldsymbol{\Theta} = \boldsymbol{W\Phi} + \mathbf{E}_{\boldsymbol{\Theta}} \qquad 10$$

where row i is $\mathbf{w}_i'$ for $\mathbf{W}$, and $\boldsymbol{\eta}_i'$ for $\mathbf{E}_{\boldsymbol{\Theta}}$.

Equation (1): Full Conditional of $\boldsymbol{\beta}$

$$\begin{aligned}
\boldsymbol{\beta}|\text{Rest} &\sim N(\boldsymbol{\mu}_{\beta n}, \boldsymbol{V}_{\beta n}) \\
\boldsymbol{V}_{\beta n} &= \left(\boldsymbol{V}_{\beta 0}^{-1} + \sigma^{-2}\sum_{i=1}^{n}\boldsymbol{x}_i\boldsymbol{x}_i'\right)^{-1} \\
\boldsymbol{\mu}_{\beta n} &= \boldsymbol{V}_{\beta n}\left(\boldsymbol{V}_{\beta 0}^{-1}\boldsymbol{\mu}_{\beta 0} + \sigma^{-2}\sum_{i=1}^{n}\boldsymbol{x}_i[y_i - \boldsymbol{m}_i'\boldsymbol{\theta}_i]\right)
\end{aligned} \qquad 11$$

Equations (1), (3), and (5): Full Conditional of $\boldsymbol{\theta}_i$

$$\begin{aligned}
\boldsymbol{\theta}_i|Rest &\sim N(\boldsymbol{\mu}_{\theta i}, \boldsymbol{V}_{\theta i}) \\
\boldsymbol{V}_{\theta i} &= (\boldsymbol{\Lambda}^{-1} + \sigma^{-2}\boldsymbol{m}_i\boldsymbol{m}_i' + \boldsymbol{R}'\boldsymbol{\Sigma}^{-1}\boldsymbol{R})^{-1} \\
\boldsymbol{\mu}_{\theta i} &= \boldsymbol{V}_{\theta i}(\boldsymbol{\Lambda}^{-1}\boldsymbol{\Phi}'\boldsymbol{w}_i + \sigma^{-2}\boldsymbol{m}_i[y_i - \boldsymbol{x}_i'\boldsymbol{\beta}] + \boldsymbol{R}'\boldsymbol{\Sigma}^{-1}[\boldsymbol{u}_i - \boldsymbol{\Delta}'\boldsymbol{z}_i])
\end{aligned} \qquad 12$$

Equation (1): Full conditional of σ^2

$$\begin{array}{lcc} \sigma^2 & \sim & IG(r_{\sigma n}/2, s_{\sigma n}/2) \\ r_{\sigma n} & = & r_{\sigma 0} + n \\ s_{\sigma n} & = & s_{\sigma 0} + \sum_{i=1}^{n} \left(y_i - \boldsymbol{x}_i^{'}\boldsymbol{\beta} + \boldsymbol{m}_i^{'}\boldsymbol{\theta}_i\right)^2 \end{array} \qquad 13$$

Equations (2) and (3): Impute the Latent Utility u_i

We sequentially generate u_{ij} from truncated, conditional normal distributions. Define $\mathbf{u}_{i(j)}$ to be the vector of latent utilities $\mathbf{u}_i$ with row j deleted; $\boldsymbol{\mu}_i = \boldsymbol{\Delta}^{'}\boldsymbol{z}_i + R'\theta_i$; μ_{ij} to be row j of $\boldsymbol{\mu}_i$; $\boldsymbol{\mu}_{i(j)}$ to be $\boldsymbol{\mu}_i$ with row j deleted; $\boldsymbol{\Sigma}_{jj}$ to be the (j,j) element of $\boldsymbol{\Sigma}$; $\boldsymbol{\Sigma}_{(jj)}$ to be $\boldsymbol{\Sigma}$ with row j and column j deleted; and $\boldsymbol{\Sigma}_{j(j)}$ to be row j of $\boldsymbol{\Sigma}$ with column j deleted. For j = 1, …, J sequentially generate

$$\begin{array}{lcc} u_{ij}|Rest & \sim & N\left(\mu_{ij|(j)}, \Sigma_{j|(j)}\right)\chi\left[\left(2m_{ij} - 1\right)u_{ij} > 0\right] \\ \mu_{ij|(j)} & = & \mu_{ij} + \boldsymbol{\Sigma}_{j(j)}\boldsymbol{\Sigma}_{(jj)}^{-1}\left[\boldsymbol{u}_{i(j)} - \boldsymbol{\mu}_{i(j)}\right] \\ \Sigma_{j|(j)} & = & \Sigma_{jj} - \boldsymbol{\Sigma}_{j(j)}\boldsymbol{\Sigma}_{(jj)}^{-1}\boldsymbol{\Sigma}_{j(j)}^{'} \end{array} \qquad 14$$

We use the normal, inverse cdf transform to generate from the truncated normal distribution. In particular, let F be the univariate, normal cumulative distribution function (cdf) with means and variances as in Equation (14). If $m_{ij} = 1$, then u_{ij} is positive. The cumulative, truncated normal cdf for u_{ij} is: G(u) = [F(u) – F(0)] / [1 – F(0)]. If $m_{ij} = 0$, then u_{ij} is negative, and its cumulative distribution function if G(u) = F(u)/F(0). Then $G(u_{ij})$ has a uniform distribution. Therefore, to generate u_{ij} first generate a uniform random variable ξ and invert $G(u_{ij}) = \xi$:

$$u_{ij} = \begin{cases} F^{-1}[F(0) + \xi\{1 - F(0)\}] & \text{if} \quad m_{ij} > 0 \\ F^{-1}[\xi F(0)] & \text{if} \quad m_{ij} \le 0. \end{cases}$$

Equations (3) and (9): Full conditional of Δ

$$\begin{array}{lcc} \mathrm{vec}(\boldsymbol{\Delta}')|\mathrm{Rest} & \sim & N(\boldsymbol{\mu}_{\Delta n}, \boldsymbol{V}_{\Delta n}) \\ \boldsymbol{V}_{\Delta n} & = & [\boldsymbol{V}_{\Delta 0}^{-1} + \boldsymbol{Z}'\boldsymbol{Z}\otimes\boldsymbol{\Sigma}^{-1}]^{-1} \\ \boldsymbol{\mu}_{\Delta n} & = & \boldsymbol{V}_{\Delta n}\{\boldsymbol{V}_{\Delta 0}^{-1}\boldsymbol{\mu}_{\Delta 0} + (\boldsymbol{Z}'\otimes\boldsymbol{\Sigma}^{-1})\mathrm{vec}[(\boldsymbol{U} - \boldsymbol{\Theta}\boldsymbol{R})']\} \end{array} \qquad 15$$

where the Kronecker product is $\otimes$, and "vec" stacks the columns of the matrix into a vector.

Equations (3) and (9): Full Conditional of ρ_j

Define $\boldsymbol{\rho} = (\rho_1,\ldots,\rho_J)'$ and $\mathbf{A}_i = \text{diag}(\boldsymbol{\theta}_i)$, the matrix with zero off-diagonal elements and $\boldsymbol{\theta}_i$ on the diagonal. The full conditional is:

$$\begin{aligned}
\boldsymbol{\rho}|\text{Rest} &\sim N\left(\boldsymbol{\mu}_{\rho n}, \boldsymbol{V}_{\rho n}\right)\prod_{j=1}^{J}\chi[\rho_j > 0] \\
\boldsymbol{V}_{\rho n} &= \left[\boldsymbol{V}_{\rho 0}^{-1} + \sum_{i=1}^{n}\mathbf{A}_i'\boldsymbol{\Sigma}^{-1}\mathbf{A}_i\right]^{-1} \\
\boldsymbol{\mu}_{\rho n} &= \boldsymbol{V}_{\rho n}\left[\boldsymbol{V}_{\rho 0}^{-1}\boldsymbol{\mu}_{\rho 0} + \sum_{i=1}^{n}\mathbf{A}_i'\boldsymbol{\Sigma}^{-1}(\mathbf{u}_i - \boldsymbol{\Delta}'\boldsymbol{z}_i)\right].
\end{aligned} \tag{16}$$

These coefficients are constrained to be positive. Define $\boldsymbol{\rho} = (\rho_1,\ldots,\rho_J)'$ and $\boldsymbol{\rho}_{(j)}$ to be $\boldsymbol{\rho}$ without the row j. Next, we sequentially generate each ρ_j from their conditional normal distribution in order to include the truncation. Define $\boldsymbol{\rho}_{(j)}$ and $\boldsymbol{\mu}_{(j)}$ to be $\boldsymbol{\rho}$ and $\boldsymbol{\mu}_{\rho n}$ without the row j. Define V_{jj} to be the (j,j) element of $\boldsymbol{V}_{\rho n}$; μ_j as the j[th] element of $\mu_{\rho n}$; $\mathbf{V}_{(jj)}$ to be $\boldsymbol{V}_{\rho n}$ after removing row j and column j; and $V_{j(j)}$ to be row j of $\boldsymbol{V}_{\rho n}$ after deleting column j. For j = 1, …, J sequentially generate ρ_j from conditional normal distributions:

$$\begin{aligned}
\rho_j|Rest &\sim N\left(\mu_{j|(j)}, V_{j|(j)}\right)\chi(\rho_j > 0) \\
\mu_{j|(j)} &= \mu_j + \boldsymbol{V}_{j(j)}\boldsymbol{V}_{(jj)}^{-1}\left[\boldsymbol{\rho}_{(j)} - \boldsymbol{\mu}_{(j)}\right] \\
V_{j|(j)} &= V_{jj} - \boldsymbol{V}_{j(j)}\boldsymbol{V}_{(jj)}^{-1}\boldsymbol{V}_{j(j)}'.
\end{aligned} \tag{17}$$

We use the inverse cdf transform to generate the truncated normal random variables:

$$\rho_j = F^{-1}[F(0) + \xi\{1 - F(0)\}]$$

where ξ is a uniform random variables and F is the normal cdf for Equations (16) and (17).

Equations (3) and (9): Full Conditional of Σ

The algorithm for generating $\boldsymbol{\Sigma}$ adapts the parameter expansion missing data procedure from Talhouk et al. (2012). The first step is to generate the "missing" variance parameters:

$$d_j^2 \sim IG\left(\frac{J+1}{2}, \frac{\Sigma^{jj}}{2}\right) \text{ for } j = 1, \ldots, J \tag{8}$$

where Σ^{jj} is the (j,j) element of $\boldsymbol{\Sigma}^{-1}$. Define the matrix $\mathbf{D} = \text{diag}(d_1, \ldots, d_J)$ with zeros on the off-diagonals and d_j in element (j,j). Set $\mathbf{b_i} = \mathbf{Du_i}$ and $\mathbf{B}$ as the stacked vector of $\mathbf{b}_i$. The covariance matrix of $\mathbf{b}_i$ is $\boldsymbol{\Omega} = \mathbf{D\Sigma D}$, and the variances are no longer equal to one. The key point of the method is that given the prior for $\boldsymbol{\Sigma}$ in Barnard et al. (2000) and the definition of $\mathbf{D}$ in Equation (18), the full conditional distribution of $\boldsymbol{\Omega}$ given $\mathbf{D}$ is inverted Wishart with known parameters:

$$\begin{aligned}
\boldsymbol{\Omega}|\text{Rest} &\sim IW(f_{\Omega n}, \boldsymbol{G}_{\Omega n}^{-1}) \\
f_{\Omega n} &= J - 1 + n \\
\boldsymbol{G}_{\Omega n}^{-1} &= \boldsymbol{I}_J + (\boldsymbol{B} - \boldsymbol{Z\Delta D} - \boldsymbol{\Theta RD})'(\boldsymbol{B} - \boldsymbol{Z\Delta D} - \boldsymbol{\Theta RD})
\end{aligned} \tag{9}$$

where $\mathbf{I}_J$ is a J by J identity matrix. Finally, we obtain the correlation matrix $\boldsymbol{\Sigma}$ from the "covariance" matrix $\boldsymbol{\Omega}$ by dividing by the "standard deviations" $\tau_j = \Omega_{jj}^{1/2}$ where Ω_{jj} is the (j,j) element of $\boldsymbol{\Omega}$: $\boldsymbol{\Sigma} = \mathbf{T}^{-1}\boldsymbol{\Omega}\mathbf{T}^{-1}$ where $\mathbf{T} = \text{diag}(\tau_1, \ldots, \tau_J)$.

Equations (5) and (10): Full Conditional of Φ

$$\begin{aligned}
\text{vec}(\boldsymbol{\Phi}')|\text{Rest} &\sim N(\boldsymbol{\mu}_{\Phi n}, \boldsymbol{V}_{\Phi n}) \\
\boldsymbol{V}_{\Phi n} &= [\boldsymbol{V}_{\Phi 0}^{-1} + \boldsymbol{W}'\boldsymbol{W} \otimes \boldsymbol{\Lambda}^{-1}]^{-1} \\
\boldsymbol{\mu}_{\Phi n} &= \boldsymbol{V}_{\Phi n}[\boldsymbol{V}_{\Phi 0}^{-1}\boldsymbol{\mu}_{\Phi 0} + (\boldsymbol{W}' \otimes \boldsymbol{\Lambda}^{-1})\text{vec}(\boldsymbol{\Theta}')]
\end{aligned} \tag{10}$$

Equations (5) and (10): Full conditional of Λ

$$\begin{aligned}
\boldsymbol{\Lambda}|\text{Rest} &\sim IW(f_{\Lambda n}, \boldsymbol{G}_{\Lambda n}^{-1}) \\
f_{\Lambda n} &= f_{\Lambda 0} + n \\
\boldsymbol{G}_{\Lambda n}^{-1} &= \boldsymbol{G}_{\Lambda 0}^{-1} + (\boldsymbol{\Theta} - \boldsymbol{W\Phi})'(\boldsymbol{\Theta} - \boldsymbol{W\Phi})
\end{aligned} \tag{11}$$

Web Appendix D. Identification of the Model

The reduced form model substitutes Equation (5) into Equation (1). Together with Equation (7), we obtain:

$$
\begin{aligned}
y_{ij} &= \boldsymbol{m}_{ij}'\boldsymbol{\Phi}'\boldsymbol{w}_{id} + \boldsymbol{m}_{ij}'\boldsymbol{\eta}_{id} + \boldsymbol{x}_{ij}'\boldsymbol{\beta} + \varepsilon_{ij} \\
u_{ijk} &= \rho_k \mathbf{w}_{id}'\boldsymbol{\phi}_k + \rho_k \zeta_{ik} + \boldsymbol{z}_{ij}'\boldsymbol{\delta}_k + \nu_{idk} \\
m_{idk} &= 1 \text{ if } u_{idk} > 0 \text{ and } m_{idk} = 0 \text{ if } u_{idk} \leq 0.
\end{aligned} \tag{12}
$$

where $\boldsymbol{m}_{ij} = (m_{ij1}, \ldots, m_{ijK})'$ is the vector of metric indicators. The performance outcome equation for y_{ij} and the exclusion restrictions in the covariates identify the coefficients $\boldsymbol{\beta}$ and $\boldsymbol{\Phi}$ and the error variances σ^2_Y and $\boldsymbol{\Lambda}$. The metric use equations identify the coefficients $\boldsymbol{\delta}$ and the error correlation $\boldsymbol{\Sigma}_U$. The identification of $\boldsymbol{\Phi}$ from the performance outcome equation then identifies its multiplier ρ_k in the metric utility equation. Since ρ_k is identified, then the variances $\sigma^2_{\zeta k}$ of the ex-ante shocks ζ_{ik} are identified. In particular, if one defines $\rho^*_k = a\rho_k$; $\Phi^* = \Phi/a$, and $\zeta^*_{ik} = \zeta_{ik}/a$ where a is a non-zero constant, then $\rho^*_k \boldsymbol{\Phi}^* + \rho^*_k \zeta^*_{ik} = \rho_k \boldsymbol{\Phi} + \rho_k \zeta_{ik}$, and the utility equation is left unchanged. However, we cannot arbitrarily redefine $\boldsymbol{\Phi}$ in the utility equation without changing the density function in the performance equation. Therefore, ρ_k and $\sigma^2_{\zeta k}$ are identified. Simulation studies conducted by the authors, and available upon request, confirm the models ability to obtain identified parameter estimates.

Web Appendix E. Exclusion Restrictions

For model identification, exclusion restrictions are necessary on which variables appear in each equation. Equation (1) includes the focal parameters Metric Use and Metric Effectiveness as well as the firm's recent business performance as a fixed effect. It is included under the theory that "a rising tide lifts all boats"; if a firm is enjoying good business performance, then the individual marketing-mix decisions are more likely to be better. In addition to Metric Effectiveness, Equation (3) includes managerial, firm, and industry characteristics that are excluded from Equation (1); an empirical justification for this is given when we discuss the results. We have referred to this set of variables as the "control variables" since there are theoretical reasons, cited in Table 3, to believe they may influence metric use above and beyond the focal variable Metric Effectiveness.

============== Table 2 ==================

Equations (5) and (6) on metric effectiveness includes the firm's recent business performance, the control variables, and variables indicating which type of marketing-mix decision is being made, which are excluded from Equations (1) and (3). As detailed in Li and Tobias (2011, p. 347), "what is most necessary for identification purposes is the existence of some variable affecting" the effectiveness of metric k for decision d and subject i, $\tilde{\theta}_{idk}$, that is conditionally uncorrelated with metric use and the decision outcome. The marketing-mix decision variables serve this role in Equations (5) and (6). Once we include the metric's effectiveness for making a particular type of decision, the latent utility for metric use (Equation 3) and the performance score (Equation 1) should not include dummy variables for type of decision because this information is encapsulated in metric effectiveness, which also appears in these two equations. Mathematically, if all of the independent variables appeared in all of the equations, the model would not be identified since metric effectiveness appears in the latent utility for metric use and decision performance, and use appears in decision performance. By definition, our measure of metric effectiveness depends on decision, so including indicator variables for decision in Equations (5) and (6), but not Equations (1) and (3) is appropriate.

Web Appendix F. Endogeneity and Heterogeneity Analysis

Additional analyses were conducted to illustrate the importance of endogeneity and heterogeneity. First, aggregate level models without the hierarchical Bayes components, Equations (5) and (6), were estimated with and without corrections for endogeneity. The posterior means for the metric effectiveness parameters are presented in Web Appendix Table 4; note that unlike in Table 5 in the manuscript, the results are by metric, not metric-by-decision. The first column in Web Appendix Table 4 represents results by just regressing decision outcome on the binary indicators for which metric was used. The second column contains the results when slope endogeneity is corrected with a "use" equation analogous to Equation (3) and intercept endogeneity is modeled through a correlated error structure between the two equations. Comparing the two columns, we see that share of voice was significant in the OLS analysis but is no longer significant after correcting for endogeneity; target volume and total customers are significant in the endogeneity corrected model but not in the OLS analysis; and awareness switches from positive and significant in the OLS analysis to negative and significant in the corrected model. If endogeneity were not present, we would not see changes in the parameter estimates. Consequently, if we did not model observed and unobserved heterogeneity, we would draw very different conclusions about metric effectiveness.

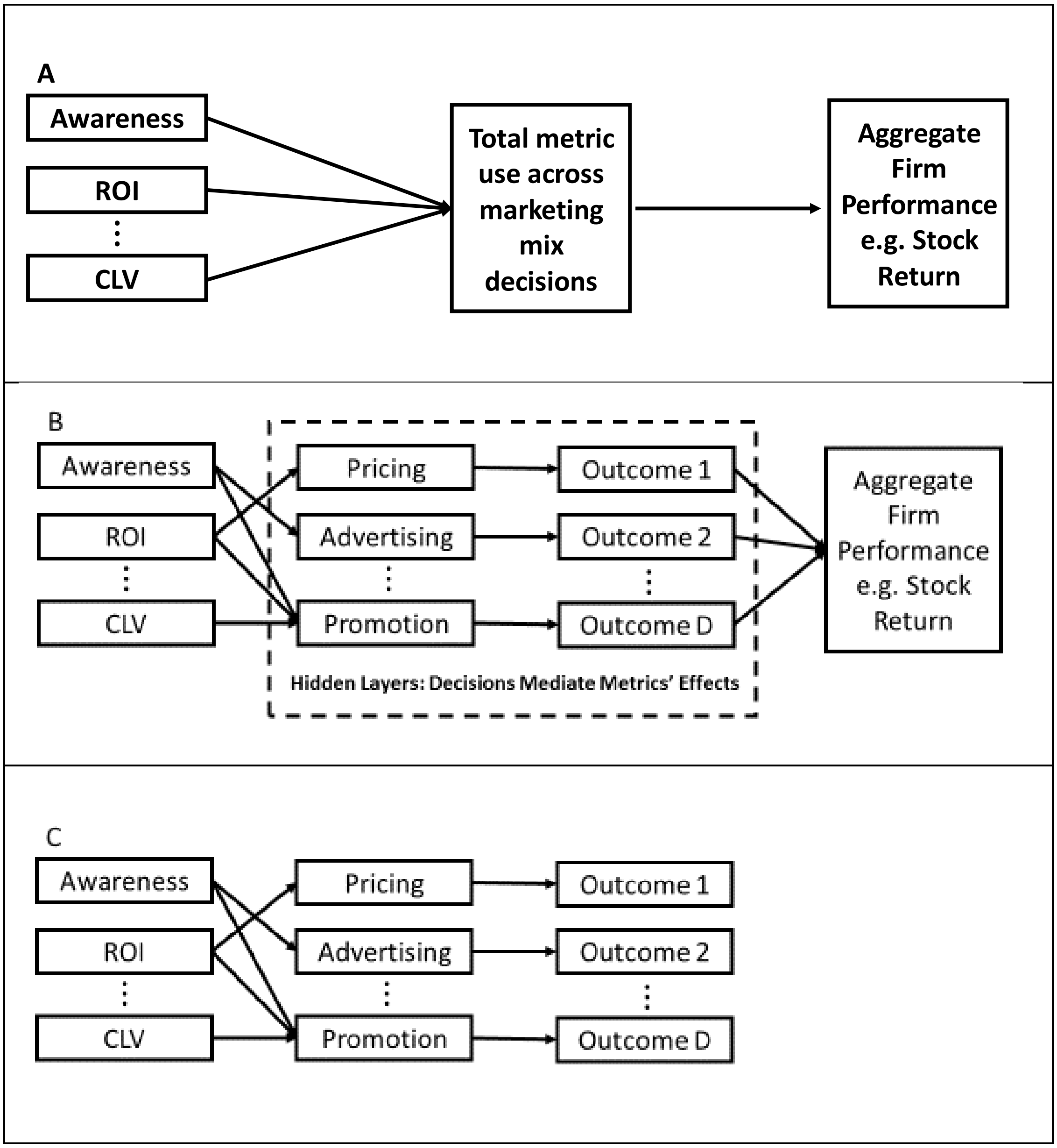
The estimated error covariances between the performance equation and the latent utility for metric use, $\sigma_y \Sigma_{YU}$ from Equation (4), indicate that metric use is endogenous in the full model. This vector captures the covariance between the performance equation (1) and the use equation (3) (the dotted line in Figure 2); if there is no covariance between the outcome and use equation, then there is no intercept endogeneity. The covariance between the error terms for performance and the latent utility for brand building marketing expenditures, awareness, satisfaction, likeability, preference, willingness to recommend, loyalty, and quality are significantly negative. The negative covariance between the error terms for the performance and the utility for marketing metrics implies endogenous selection effects, which would lead to biased estimates in the performance equations if the covariance was incorrectly assumed to be 0. Because these covariances are negative, the metric effectiveness measures would be biased towards zero: i.e., without adjusting for selection bias, metrics would seem to be less significant.

Web Appendix Figure 1. Research Models.

A. Firm level model where metric use and aggregate firm performance are observed.

B. Individual marketing-mix decisions and their outcomes mediate the effects of metrics on aggregate firm performance.

C. Proposed metric research model with observed metric use, decisions, and outcomes at the manager by decision level analysis.



Web Appendix Table 1. Definition of Constructs and Operational Measures

Construct Basis	Definition and Operational Measures	α	Mean	St. Dev.
Market Orientation (Deshpandé and Farley 1998; Kohli and Jaworski 1990; Verhoef and Leeflang 2009)	**Definition**: *The extent to which a firm measures, monitors, and communicates customer needs and experiences throughout the firm and whether the firm's strategy is based on this information.* **Measures**: How strongly do you agree or disagree with each of the following statements: (1 = strongly disagree, 7 = strongly agree) • Our business objectives are driven primarily by customer satisfaction • We constantly monitor our level of commitment and orientation to serving customer needs • We freely communicate information about our successful and unsuccessful customer experiences throughout all business functions • Our strategy for competitive advantage is based on our understanding of customer needs • We measure customer satisfaction systematically and frequently • We have routine or regular measures for customer service • We are more customer focused than our competitors • I believe this business exists primarily to serve customers	0.86	5.03	1.14
Strategic Orientation (Olson et al. 2005; Slater and Olson 2000)	**Definition**: *The strategy which a firm employs to compete in an industry or market, categorized based on two dominant frameworks of strategic orientation, the Miles and Snow (1978) typology which focuses on the firm's intended rate of product-market change, and the Porter (1980) typology, which focuses on the firm's differentiation or cost advantage.* **Measures**: Please select one of the following descriptions that best characterizes your organization: ☐ *Prospectors:* These firms are frequently the first-to-market with new product or service concepts. They do not hesitate to enter new market segments in which there appears to be an opportunity. These firms concentrate on offering products that push performance boundaries. Their proposition is an offer of the most innovative product, whether it is based on substantial performance improvement or cost reduction.	N/A	0.29	---
	☐ *Analyzers:* These firms are seldom first-in with new products or services or first to enter emerging market segments. However, by monitoring market activity, they can be early followers with a better targeting strategy, increased customer benefits, or lower costs.		0.24	---
	☐ *Low-Cost Defenders:* These firms attempt to maintain a relatively stable domain by aggressively protecting their product market position. They rarely are at the forefront of product of service development; instead, they focus on producing goods or services as efficiently as possible. In general, these firms focus on increasing share in existing markets by providing products at the best prices.		0.12	---
	☐ *Differentiated Defenders:* These firms attempt to maintain a relatively stable domain by aggressively protecting their product market position. They rarely are at the forefront of product or service development; instead, they focus on providing superior service and/or product quality. Their prices are typically higher than the industry average.		0.35	---
Organizational Involvement (Noble and Mokwa 1999)	**Definition**: *The extent to which a firm's marketing-mix decision or action is based on involvement of a wide range of managers across functions.* **Measures**: How strongly do you agree or disagree with each of the following statements: (1 = strongly disagree, 7 = strongly agree) • This marketing action was a real company-wide effort • People from all over the organization were involved in this marketing action • A wide range of departments or functions in the company got involved in this marketing action	0.94	3.80	1.70
Metric-based Compensation	**Definition**: *The importance of metrics in a manager's compensation package.* **Measures**: Please indicate how important each metric type is related to your compensation package: (1= not at all important, 7 = extremely important) • Overall Metrics • Marketing Metrics • Financial Metrics	0.82	4.90	1.50
Metric-based Training	**Definition**: *A manager's level of training on the use of metrics.* **Measures**: Please indicate your level of training with metrics (can be through work or educational experiences): (1= much less than average amount of training, 7 = much more than average amount of training) • Overall Metrics	0.94	4.45	1.68

	• Marketing Metrics • Financial Metrics			
Functional Area (Finkelstein et al. 2009)	**Definition**: *Whether a manager works in the marketing department.* **Measures**: Please indicate your job title: CEO/Owner, CMO, C-Level (Other than Marketing), SVP/VP of Marketing, SVP/VP Sales, SVP/VP (Other than Marketing and Sales), Director of Marketing, Director of Sales, Brand Manager, Marketing Manager, Product Manager, Sales Manager, Other (Please list)	N/A	0.54	---
Managerial Level (Finkelstein et al. 2009)	**Definition**: *Whether a manager is (a) VP-level or higher (e.g., SVP, C-level or Owner) or (b) lower than VP-level (e.g., Director, Manager).* **Measures**: Please indicate your job title: CEO/Owner, CMO, C-Level (Other than Marketing), SVP/VP of Marketing, SVP/VP Sales, SVP/VP (Other than Marketing and Sales), Director of Marketing, Director of Sales, Brand Manager, Marketing Manager, Product Manager, Sales Manager, Other (Please list)	N/A	0.58	---
Managerial Experience	**Definition**: *A manager's experience in number of years as a manager, at the firm, and in the current position.* **Measures**: How many years of managerial experience do you have? How many years have you been working for this company? How many years have you been working at your current position?	0.68	9.54	5.68
Quantitative Background	**Definition:** *A manager's qualitative/quantitative orientation based on education and work experience.* **Measures:** Please rate your qualitative/quantitative background: (1 = entirely qualitative, 7 = entirely quantitative) • Overall orientation • Educational Background • Work Experience Background	0.85	4.31	1.11
Firm Size	**Definition**: *The number of full-time employees in a firm.* **Measure**: Approximately how many full-time employees does your firm have?	N/A	5.35	---
Type of Ownership (Verhoef and Leeflang 2009)	**Definition**: *Whether a firm is publicly traded or privately held.* **Measure**: Is your firm publicly traded?	N/A	0.22	---
CMO Presence	**Definition:** *Whether a firm employs a Chief Marketing Officer (CMO).* **Measure:** Does your firm employ a Chief Marketing Officer (CMO)?	N/A	0.29	---
Recent Business Performance (Jaworski and Kohli 1993)	**Definition:** A *business unit's overall performance last year, relative to its own expectations and its competitors' performance.* **Measures:** To what extent did the overall performance of the business unit meet expectations last year: (1=poor, 7=excellent) To what extent did the overall performance of your business unit relative to your major competitors meet expectations last year: (1=poor, 7=excellent)	0.84	5.34	1.30
B2B vs. B2C (Verhoef and Leeflang 2009)	**Definition**: *The extent to which a manager's sales come from B2B or B2C markets.* **Measure**: Please indicate the extent to which your sales come from B2B or B2C markets: (1 = mostly B2B, 7 = mostly B2C)	N/A	2.91	---
Goods vs. Services (Verhoef and Leeflang 2009)	**Definition**: *The extent to which a manager's sales come from goods or services markets.* **Measure**: Please indicate the extent to which your sales come from goods or services markets: (1 = mostly goods, 7 = mostly services)	N/A	4.68	---
Product Life Cycle (Deshpandé and Zaltman 1982)	**Definition:** *The stage of the product life cycle.* **Measure:** At which one of the following stages would you place your product? (shown in a product life cycle diagram, introductory, growth, maturity, decline)	N/A	0.55	---
Industry Concentration (Kuester et al. 1999)	**Definition:** *The percentage of sales the four largest businesses competing in a market control.* **Measure:** Approximately what percentage of sales does the largest 4 competing businesses in your market control? • 0-50%, 51-100%	N/A	0.43	---
Market Growth (Homburg, Workman, and Krohmer 1999)	**Definition:** *The average annual growth or decline of the company and the industry over the last three years.* **Measure:** Over the last three years, what was the average annual market growth or decline for your company? Over the last three years, what was the average annual market growth or decline for your industry?	0.66	5.23	1.87
Market Turbulence (Miller et al. 1998)	**Definition:** *The rate at which products or services become obsolete, the ease of forecasting consumer preferences, and how often a firm needs to change its marketing and production/service technology to keep up with competitors and/or consumer preferences.*	0.63	4.29	1.07

	Measures: How strongly do you agree or disagree with each of the following statements (1 = strongly disagree, 7 = strongly agree): ® = reverse scored • Products/services become obsolete very slowly in your firm's principal industry ® • Your firm seldom needs to change its marketing practices to keep up with competitors ® • Consumer demand and preferences are very easy to forecast in your firm's principal industry ® • Your firm must frequently change its production/service technology to keep up with competitors and/or consumer preferences			
Marketing-mix Decision (Menon et al. 1999)	**Definition:** *A major marketing-mix decision undertaken not so recently that performance evaluation is premature and not so long ago that memory of the decision and its performance is fuzzy.* **Measures:** Please indicate which types of major marketing decisions you have undertaken (or implemented) that (1) were not so recent that performance evaluation is premature and (2) not so long ago that memory about the decision and performance is fuzzy: • Traditional Advertising (i.e., TV, Magazine, Radio, etc.) • Internet Advertising (i.e., Banner Ads, Display Ads, SEO, etc.) • Direct to Consumer (i.e., Emails, CRM, Direct mail, etc.) • Social Media (i.e., Twitter, Facebook, MySpace, etc.) • Price Promotions • Pricing • New Product Development • Sales Force • Distribution • PR/Sponsorships	N/A	0.11 0.12 0.17 0.11 0.10 0.05 0.08 0.11 0.04 0.12	--- --- --- --- --- --- --- --- --- ---
Metrics Use (Ambler 2003; Ambler et al. 2004; Barwise and Farley 2004; Du et al. 2007; Farris et al. 2010; Hoffman and Fodor 2010; Lehmann and Reibstein 2006; Pauwels et al. 2009; Srinivasan et al. 2010)	**Metric Use Definition:** *A metric is defined to be used in a marketing-mix decision if a manager employed the metric as a decision aid when making the marketing-mix decision.* **Measure:** Please indicate if you used any of the following MARKETING or FINANCIAL metrics when making your marketing-mix decision: See Table 3 for the list of metrics.	N/A	---	---
Marketing-mix Activity Performance (Jaworski and Kohli 1993; Moorman and Rust 1999; Ramaswami et al. 2009; Verhoef and Leeflang 2009)	**Definition:** *The performance of a marketing-mix activity is defined based on a firm's stated marketing, financial, and overall outcomes, relative to a firm's stated objectives and to similar prior decisions.* **Measures:** Relative to your firm's stated objectives, how is the last major marketing activity undertaken performing overall? (1=much worse, 7=much better) Relative to similar prior marketing activities you've undertaken, how is the last major marketing activity undertaken performing? (1=much worse, 7=much better; N/A if unsure or never undertook activity) Relative to your firm's stated objectives, how is the last major marketing activity undertaken performing on: (1=much worse, and, 7=much better; N/A if unsure) • Customer satisfaction • Profitability • Customer loyalty • Sales • Market share • ROI	0.94	4.90	1.06

Note: The first 3 columns in the table are taken from (Mintz and Currim 2013)

Web Appendix Table 2. Managerial, Firm and Industry Characteristics' Impact on Metric Effectiveness

Note: Bolded and italicized numbers indicated significant coefficient: P(Coefficient > 0) > 0.975 or P(Coefficient < 0) < 0.975

Metric	Metric Comp	Metric Training	Quant	Marketer	Top Manager	Work Exper	Firm Size (log)	Public Firm	B2C	Services	Business Perform
Awareness	-0.022	-0.015	-0.087	0.001	***-0.216***	0.148	-0.035	0.051	0.011	***-0.263***	-0.070
Recommend	***-0.097***	***0.437***	-0.100	***-0.356***	***-0.222***	-0.112	-0.158	-0.113	-0.149	-0.154	0.225
Satisfaction	***-0.490***	0.002	-0.490	-0.235	***0.466***	-0.113	0.253	-0.312	0.127	-0.019	-0.306
Likeability	-0.211	***0.367***	-0.164	0.199	0.163	-0.360	***0.291***	***-0.548***	***0.243***	-0.060	***-0.429***
Preference	***0.181***	-0.401	***0.344***	0.225	-0.207	0.292	***0.305***	***-0.405***	-0.201	0.002	-0.355
Share of Wallet	***0.132***	***-0.445***	***-0.304***	0.051	***-0.120***	-0.366	-0.100	-0.219	-0.165	***-0.176***	0.036
CLV	0.057	-0.075	-0.077	0.623	0.342	***-0.090***	***0.504***	***-1.157***	0.152	***0.348***	0.217
Share of Voice	-0.440	0.012	***0.054***	-0.184	***0.210***	0.238	-0.035	0.289	-0.056	0.081	***0.463***
Loyalty	-0.033	-0.078	0.353	***-0.141***	-0.146	-0.068	***-0.360***	***0.785***	0.179	***0.333***	0.149
Market Share	-0.345	0.214	0.030	-0.114	-0.099	0.055	0.198	***-0.382***	0.134	-0.195	-0.040
Segment Profit	0.002	0.078	0.169	0.274	***0.509***	0.042	***0.392***	0.269	***0.180***	0.228	-0.104
Quality	0.204	-0.257	***0.420***	***0.338***	0.173	0.074	-0.016	-0.307	-0.084	0.079	0.072
Expenditures	0.045	-0.020	-0.190	-0.069	-0.008	-0.072	-0.208	***0.318***	0.085	-0.082	***-0.171***
ROMI	-0.061	0.173	-0.064	***-0.619***	-0.453	***0.117***	0.268	-0.258	0.174	***0.421***	0.018
Consideration	***0.177***	-0.590	0.263	1.057	***0.488***	0.067	***0.386***	-0.440	***-0.522***	***0.032***	***0.103***
ROI	0.272	-0.064	0.217	0.229	0.024	-0.144	-0.112	0.099	-0.047	0.051	0.022
Total Customers	***0.133***	0.122	0.040	0.000	-0.032	0.166	0.194	-0.194	***-0.213***	0.111	-0.147
ROS	-0.056	0.060	***-0.262***	0.030	-0.156	0.103	***-0.087***	***0.154***	-0.200	0.007	***0.237***
Net Profit	0.019	***-0.376***	***0.227***	0.115	-0.094	-0.117	0.061	-0.132	-0.105	***0.197***	***0.282***
Target Volume	-0.025	0.039	0.288	0.048	***0.258***	-0.012	-0.238	0.311	0.203	-0.292	0.164
NPV	0.149	***0.312***	***-1.258***	-0.584	-0.495	-0.328	0.021	0.059	***-0.060***	***0.381***	-0.194
EVA	0.273	-0.282	***0.756***	***-0.718***	***-1.288***	1.071	***-0.196***	1.149	***0.269***	-0.608	-0.181

Web Appendix Table 2 Continued.

Metric	CMO	Market Orientation	Market Turbulence	Analyzers	Low Cost Defender	Diff Defender	Life Cycle	Market Conc	Growth	Org Involv
Awareness	-0.068	0.007	0.033	0.143	-0.006	-0.128	-0.073	***-0.231***	-0.001	***0.263***
Recommend	-0.003	-0.110	***0.172***	0.035	0.408	-0.010	0.061	***-0.212***	0.047	-0.213
Satisfaction	-0.139	0.184	0.067	0.305	-0.690	0.428	***-0.143***	0.068	0.190	0.039
Likeability	-0.234	0.091	0.366	0.172	-0.048	-0.148	0.343	***0.376***	***0.244***	0.116
Preference	0.178	0.067	-0.116	-0.289	0.734	***-0.570***	-0.211	-0.214	-0.205	-0.149
Share of Wallet	-0.027	-0.145	-0.130	***0.596***	-0.927	-0.305	0.421	0.079	-0.003	0.058
CLV	***0.210***	0.041	***0.364***	-0.291	0.151	0.329	-0.044	0.063	-0.155	0.000
Share of Voice	-0.024	***-0.750***	-0.113	-0.560	-0.014	0.703	-0.141	0.104	0.204	0.398
Loyalty	0.073	-0.069	***-0.277***	-0.029	0.116	0.378	-0.188	0.249	***0.316***	***0.330***
Market Share	-0.261	0.194	-0.060	-0.034	***-0.675***	0.211	-0.005	-0.117	0.162	-0.036
Segment Profit	-0.053	0.228	-0.208	0.251	0.074	-0.077	-0.289	0.216	-0.003	-0.088
Quality	0.059	0.036	***-0.139***	0.096	-0.099	-0.140	0.063	0.037	-0.247	-0.265
Expenditures	0.041	***0.000***	0.089	0.366	-0.146	0.213	0.051	***0.085***	0.006	-0.184
ROMI	***-0.045***	***-0.517***	-0.110	0.007	***-1.105***	0.279	0.048	***0.145***	0.127	0.190
Consideration	***0.961***	***0.619***	***0.246***	0.896	***1.337***	***-1.544***	-0.395	***0.132***	-0.104	-0.161
ROI	0.201	0.084	0.102	***-0.152***	0.127	0.076	***0.162***	-0.085	0.087	***-0.220***
Total Customers	-0.252	-0.011	-0.083	-0.188	0.253	0.167	0.006	-0.209	0.042	0.120
ROS	0.140	-0.329	-0.032	0.221	-0.052	-0.245	-0.216	0.045	0.004	0.042
Net Profit	-0.099	***-0.419***	0.133	0.257	***0.358***	***-0.309***	0.147	0.016	0.074	0.049
Target Volume	0.206	0.073	0.002	-0.084	0.319	0.104	-0.148	-0.005	-0.058	***0.233***
NPV	***-0.179***	***0.130***	-0.232	***0.037***	***-1.279***	***0.076***	0.430	0.577	-0.183	***0.494***
EVA	***0.781***	***1.542***	***1.092***	***-1.212***	***2.901***	-0.493	***-0.659***	***-1.602***	0.264	***-0.173***

Web Appendix Table 3. Managerial, Firm and Industry Characteristics' Impact on Metric Use

Note: Bolded and italicized numbers indicated significant coefficient: P(Coefficient > 0) > 0.975 or P(Coefficient < 0) < 0.975.

Metric	Intercept	Metric Comp	Metric Training	Quant	Marketer	Top Manager	Work Exper	Firm Size (log)	Public Firm	B2C	Services	Business Perform
Net Profit	0.910	0.348	***0.805***	-0.306	-0.530	0.268	0.234	-0.363	0.589	***0.528***	***-0.818***	-0.501
ROI	***0.904***	-0.419	0.380	***-0.531***	-0.599	0.018	0.267	0.197	0.050	0.152	-0.304	-0.050
ROS	-0.629	***0.700***	0.174	0.442	-0.201	0.434	-0.104	0.282	-0.186	0.359	-0.168	-0.388
ROMI	-0.091	***0.610***	-0.144	0.285	***1.493***	***0.960***	-0.128	***-0.925***	0.797	-0.227	***-0.999***	-0.165
NPV	-1.022	0.260	-0.291	***2.128***	0.768	***1.017***	0.117	-0.049	0.722	0.078	***-0.977***	0.546
EVA	***-6.490***	***0.897***	0.424	-0.169	0.209	0.166	0.061	0.780	***-1.131***	-0.026	0.153	0.209
Expenditures	-0.381	0.138	0.274	0.242	0.316	0.052	0.235	0.114	-0.440	-0.164	-0.042	***0.476***
Target Volume	***1.509***	0.326	0.234	-0.482	-0.229	-0.393	-0.031	0.421	-0.493	-0.333	0.254	-0.339
Segment Profit	***-0.469***	0.346	0.114	0.014	-0.330	-0.363	-0.084	-0.353	-0.050	-0.030	***-0.442***	0.118
CLV	***-1.348***	0.018	0.554	0.194	-0.479	-0.140	0.234	-0.387	***0.978***	0.046	-0.384	***-0.605***
Market Share	***0.690***	***0.833***	-0.146	-0.109	-0.021	0.286	-0.127	-0.049	***0.678***	-0.238	-0.072	0.129
Awareness	-0.272	***0.244***	0.112	-0.001	-0.128	0.052	-0.148	-0.035	-0.004	-0.042	0.207	0.183
Satisfaction	-0.094	***0.462***	-0.020	0.162	0.049	-0.145	0.159	-0.198	***0.354***	0.066	-0.071	0.012
Likeability	-0.305	0.231	-0.207	-0.007	-0.137	-0.069	0.218	-0.300	0.278	-0.046	-0.138	***0.292***
Preference	-0.060	0.105	***0.176***	-0.087	0.005	0.123	-0.012	***-0.229***	***0.301***	0.075	-0.123	0.136
Recommend	-0.067	***0.145***	0.079	-0.031	-0.014	-0.004	0.137	-0.132	0.087	***0.160***	0.019	-0.077
Loyalty	***-0.393***	0.185	0.065	-0.147	0.100	0.078	0.078	0.052	-0.173	0.024	***-0.239***	-0.156
Quality	0.015	0.061	0.107	-0.192	-0.082	0.007	-0.039	-0.187	***0.312***	0.067	-0.160	0.009
Consideration	***-8.154***	-0.522	0.873	***-0.985***	-0.229	0.641	0.198	-0.728	0.551	***0.963***	-0.151	0.548
Total Customers	***1.174***	0.079	0.118	0.003	-0.070	0.134	-0.186	-0.361	0.305	***0.522***	-0.201	0.136
Share of Wallet	***-1.635***	-0.005	***0.871***	***0.501***	-0.188	0.597	***0.561***	0.485	0.440	0.138	0.146	0.170
Share of Voice	***-2.000***	***0.767***	0.302	-0.407	0.230	-0.084	-0.298	0.081	-0.185	0.205	-0.319	-0.402

Web Appendix Table 3 Continued.

Metric	CMO	Market Orientation	Market Turbulence	Analyzers	Low Cost Defender	Diff Defender	Life Cycle	Market Conc	Growth	Org Involv
Net Profit	0.267	***1.031***	-0.367	-0.383	-0.464	0.587	-0.438	0.122	-0.211	0.097
ROI	-0.499	-0.033	-0.268	0.488	0.181	-0.468	-0.368	0.353	-0.220	***0.706***
ROS	-0.319	***0.667***	0.086	-0.108	0.916	-0.081	0.347	0.028	0.073	-0.021
ROMI	0.462	***0.871***	0.106	0.318	***2.342***	-0.592	-0.148	-0.361	-0.152	-0.361
NPV	0.599	-0.110	0.725	0.227	***2.171***	0.016	-0.706	-0.597	0.377	-0.532
EVA	-0.475	***-0.944***	0.009	1.201	***-2.688***	1.032	0.214	***1.049***	0.288	0.244
Expenditures	0.026	0.109	-0.026	-0.685	0.579	-0.324	-0.055	0.059	-0.149	0.263
Target Volume	-0.323	-0.272	0.017	0.062	-0.278	-0.378	***0.402***	0.004	0.231	-0.276
Segment Profit	0.154	-0.063	0.142	-0.094	0.445	-0.149	0.387	-0.165	0.070	0.233
CLV	-0.132	0.149	***-0.381***	***0.591***	-0.013	-0.703	-0.154	-0.009	0.323	0.089
Market Share	***0.526***	-0.262	0.056	0.343	1.106	-0.523	-0.002	0.339	-0.291	0.249
Awareness	0.020	0.199	-0.083	-0.064	0.098	-0.042	-0.031	***0.286***	-0.102	***-0.254***
Satisfaction	0.002	0.195	0.025	-0.188	***0.536***	-0.146	-0.077	0.138	-0.054	0.136
Likeability	0.243	0.163	-0.173	-0.361	***0.507***	-0.147	-0.161	-0.139	***-0.278***	0.090
Preference	-0.050	0.142	0.091	-0.030	0.127	0.013	0.039	0.047	-0.081	0.090
Recommend	-0.015	***0.190***	-0.004	-0.180	0.093	-0.024	-0.122	0.089	-0.017	0.097
Loyalty	-0.021	***0.328***	0.142	0.022	0.123	-0.277	0.169	-0.008	-0.106	-0.036
Quality	-0.052	***0.213***	0.045	0.148	-0.033	-0.024	0.019	0.021	0.004	***0.285***
Consideration	-0.999	-0.033	1.167	-0.201	***-2.520***	0.694	0.752	0.192	-0.500	***0.529***
Total Customers	***0.470***	0.117	0.041	0.115	0.196	-0.296	-0.111	***0.346***	0.016	-0.023
Share of Wallet	0.100	-0.078	0.033	-0.433	***1.447***	0.284	***-0.515***	0.117	0.071	0.120
Share of Voice	0.134	0.824	0.238	***0.858***	0.111	-0.791	0.215	0.023	***-0.482***	-0.380

Web Appendix Table 4. Posterior Means of Metric Effectiveness in Models without Heterogeneity

Metric	*OLS No Endogeneity*	*Endogeneity*
Net Profit	0.00	0.07
Return on Investment (ROI)	0.04	0.71
Return on Sales (ROS)	0.09	0.35
Return on Mktg. Investment (ROMI)	0.02	-0.09
Net Present Value (NPV)	-0.21	-0.31
Economic Value Added (EVA)	0.05	-0.24
Mktg. Expend. on Branding	***-0.17***	***-0.69***
Target Volume	0.09	***0.81***
Segment Profitability	***0.28***	***0.51***
Customer Lifetime Value (CLV)	0.10	0.01
Market Share	0.00	-0.31
Awareness	***0.13***	***-0.71***
Satisfaction	0.10	-0.31
Likeability	-0.03	-0.28
Preference	-0.08	-0.37
Willingness to Recommend	0.07	-0.41
Loyalty	0.01	-0.13
Quality	0.06	0.14
Consideration Set	0.08	0.09
Total Customers	0.05	***0.76***
Share of Wallet	0.18	-0.09
Share of Voice	***0.27***	-0.41

Note: Bolded and italicized numbers indicate significant coefficient

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