The Right Metrics for Marketing-Mix Decisions

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Abstract

This study addresses the following question: For a given managerial, firm, and industry setting, which individual metrics are effective for making marketing-mix decisions that improve perceived performance outcomes? We articulate the key managerial takeaways based on testing a multi-stage behavioral framework that links decision context, metrics selection, and performance outcomes. Our statistical model adjusts for potential endogeneity bias in estimating metric effectiveness due to selection effects and differs from past literature in that managers can strategically choose metrics based on their ex-ante expected effectiveness. The key findings of our analysis of 439 managers making 1,287 decisions are that customer-mindset marketing metrics such as awareness and willingness to recommend are the most effective metrics for managers to employ while financial metrics such as target volume and net present value are the least effective. However, relative to financial metrics, managers are more uncertain about the ex-ante effectiveness of customer-mindset marketing metrics, which attenuates their use. A second study on 142 managers helps provide detailed underlying rationale for these key results. The implications of metric effectiveness for dashboards and automated decision systems based on machine learning systems are discussed.

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

1. Introduction

Selecting the right metrics for managers to employ when making a marketing-mix decision is critical for marketing practice (Lehmann, 2004). In aggregate, managerial metric use has been found to improve decision quality (Farris, Bendle, Pfeifer, & Reibstein, 2010), accountability (Rust, Ambler, Carpenter, Kumar, & Srivastava, 2004), and organizational performance (O'Sullivan & Abela, 2007). However, managers rarely have a shortage of metrics to employ when making a marketing-mix decision; rather they have difficulty deciding which metrics to employ for a particular decision (Lehmann & Reibstein, 2006). In addition, many managers may find themselves under pressure from managers of other functional units such as finance and operations to employ the wrong metrics (Mintz & Currim, 2013). This can result in managers employing a flurry of metrics, and quick fixes to strategic decisions, instead of a careful selection of specific metrics for a particular marketing-mix decision. Further, some metrics contain more valuable or irrelevant information for the goal of the decision, which could positively or negatively affect the decision's outcome if they are employed (Glazer, Steckel, & Winer, 1992). As a result, some managers may be reducing the performance outcome of the marketing-mix decision by not employing the best or effective metrics for the decision or employing the wrong metrics (Morgan & Piercy, 1998).

To overcome such difficulties, pressures, and challenges, practitioners (e.g., Marketing Science Institute Research Priorities 1998-2020; Institute for the Study of Business Markets B-to-B Marketing Trends 2008-2014) and marketing scholars (e.g., Lehmann, 2004; Wind, 2009) have continuously advocated research to identify which metrics managers should employ to improve their marketing-mix decisions. However, despite such calls, there is a large discrepancy in the literature on the number of studies focused on marketing-mix effectiveness (e.g., see Hanssens, 2015 for a review) relative to the number of studies focused on which metrics are associated with an increase in marketing-mix decision performance outcomes when employed by managers. Further, because the use of financial metrics should help managers justify marketing-mix decisions to non-marketing top executives (Lehmann, 2004) and thus help marketing's stature in the firm (Verhoef & Leeflang, 2009), there has been a strong desire among scholars and top executives to move from marketing to financial metrics for assessing marketing-mix decisions (Farris, Hanssens, Lenskold, & Reibstein, 2015).

Yet, as summarized in Web Appendix Table 1, little to no empirical research has provided an assessment of the relative effectiveness of the *individual* financial and marketing metrics managers employ for their specific marketing-mix decisions. As a result, there remains an important gap in the metrics literature between proposing metrics based on normative theories and providing insight into which specific metrics are effective for particular decisions in practice.

In this paper, we address these gaps by empirically examining the relationship between the use of a metric for a specific marketing-mix decision and that decision's perceived performance outcome. Our main objective is to provide practical guidelines to managers on which metrics will be effective or ineffective when making a specific marketing-mix decision. We focus on the following three central research questions: (i) What is the relationship between a specific metric employed for a particular marketing-mix decision and that decision's perceived performance outcome? (ii) What drives this effect? and (iii) How do we empirically model this relationship after accounting for endogeneity due to selection effects and controlling for heterogeneous managers across different decision settings?

To answer these research questions, we first develop a generalized behavioral framework based on extant theories and literature. In this framework, we propose underlying rationale for why an individual metric may vary in its effectiveness, why a manager may strategically choose to employ or not employ the metric, and how such expectations interrelate. We then test the framework on data from a survey of 439 managers (Mintz & Currim, 2013) who report the metrics employed and the perceived performance outcomes of 1,287 specific marketing-mix decisions. The data are unique in that the unit of analysis is a manager employing metrics for a specific marketing-mix decision and then rating the outcome of this specific marketing-mix decision, based on a self-reported eight-item composite performance measure. This is in contrast to studies that use aggregate measures of firm performance, which result from a multiplicity of decisions by a firm for several products, and thus are unable to link metric effectiveness, use, and performance at the decision and setting level (see Web Appendix A for details).[1]

The proposed behavioral framework and use of cross-sectional empirical data also requires an updated statistical methodology. We propose a new hierarchical Bayes (HB) model to empirically test this framework, which allows metric effectiveness to vary across the overall population of managers based on the type of marketing decision and covariates for the manager, firm, and industry characteristics of the setting in which the decision is made. The proposed model corrects for two sources of selection bias: unobserved factors that can impact both metric use and metric effectiveness, and strategic behavior due to managers selecting metrics that they perceive a priori to be more effective. The methodology also allows us to employ a one-shot survey to infer ex-ante and ex-post metric effectiveness instead of multiple waves of data collection, which is infeasible for most researchers.

Our empirical results should help managers make better quality decisions by employing metrics associated with improved performance outcomes, tailored to their managerial, firm,

[1] In fact, stock return and firm value (Tobin's q), two financial-market metrics often employed in the marketing-finance interface academic literature were reported to be used by managers in our sample so infrequently (less than 1%) that we had to drop the two metrics from our analyses.

industry, and marketing-mix decision setting. For example, using Ailawadi, Neslin, and Lehmann (2003) taxonomy of metrics, we find customer-mindset marketing metrics such as awareness, willingness to recommend, and satisfaction are the three metrics in our sample consistently associated with improved marketing-mix performance outcomes, while financial-market and product-market financial metrics such as target volume, net present value (NPV), and return on marketing investments (ROMI) are the three metrics consistently associated with worse marketing-mix performance outcomes. Other metrics are better suited for some decisions and disadvantageous for others. Thus, we find that just employing financial metrics does not lead to greater perceived marketing-mix outcomes.

Further, we find that financial-market and product-market financial metrics such as target volume, NPV, and ROMI which are salient for top executives, appear ex-ante to be the metrics that managers making marketing decisions are more certain about. However, based on our results, such metrics may not be the most effective for assessing the performance of marketing-mix decisions. Instead, in our sample, the most consistently beneficial metrics for managers to employ may be under-used and less salient customer-mindset based ones, such as awareness and willingness to recommend. Consequently, our findings provide evidence of a potential disconnect between the metrics typically employed and those found to be most effective, in a manner similar to how *Moneyball* (Lewis, 2004) details the ways the Oakland Athletics baseball team used new, under-utilized metrics (i.e., on-base percentage and slugging percentage) to improve their team's performance.[2] However, as detailed in the Discussion, reducing managerial ex-ante uncertainty of customer-mindset metrics found to be most effective remains a significant challenge to their use.

[2] We thank the AE and an anonymous reviewer for this suggestion.

In addition, our results can help firms build better dashboards and automated marketing-mix decision systems using machine learning algorithms. For example, such tools should employ effective customer-mindset metrics shown to be associated with improved performance outcomes, contingent on the manager, firm, industry, and type of marketing-mix decision. However, because our analysis detects considerable endogeneity bias due to managers using metrics that they ex-ante expect to be more effective, we document that it is also important for dashboards and automated marketing decision tools to account for the two types of selection effects controlled for in our model or else risk substantially biasing their metric recommendations by ignoring such selection effects. Next, we define our core constructs and summarize our conceptual and statistical model.

2. Theory

2.1. Definition of Main Constructs

Our unit of analysis for this study is a manager making a *particular* marketing-mix decision (i.e., a *specific* traditional advertising, social media, or new product development decision). *Metrics* help managers quantify trends or characteristics to assist in diagnosing, benchmarking, monitoring, and assessing current and forthcoming marketing-mix efforts (Farris et al., 2010). *Metric use* is defined as whether a manager uses a metric, for consideration, benchmarking, monitoring, or assessing a specific marketing-mix decision, by considering the trends or characteristics that individual metrics provide. *Marketing-mix decision performance* is defined as the performance outcomes of that particular decision as evaluated by the manager.

Our main focus is on *metric effectiveness,* which is defined as a *latent* variable that measures the association between a manager using a certain metric in a specific marketing-mix decision and that decision's performance outcome. We operationalize metric effectiveness as the regression coefficient from regressing individual metric use (IV) onto marketing-mix decision performance (DV). Since the IV of metric use either takes a zero or one value for each individual metric (i.e., either the manager did or did not employ the metric), the regression coefficient is the effect of using the metric on performance, hence metric effectiveness. In other words, we do not specifically ask respondents "how effective is each metric to their decision," but rather infer metric effectiveness statistically based on measuring the effect of whether a manager employed a given metric for a specific marketing-mix decision and the performance outcome of this decision, while accounting for a number of estimation issues. Web Appendix B provides details on a survey confirming metric effectiveness as an appropriate label for this latent variable.

2.2. Conceptual Overview

We propose the following six-stage parsimonious (as if) conceptual model in Figure 1 that articulates the transition process from metric use in a decision to the performance of the decision, aimed at inferring the effectiveness of an individual metric. The model is derived based on a dozen formal and dozens more informal managerial interviews, in addition to a literature review of managerial and individual decision-making processes. Table 1 provides the full list of antecedent variables of metric effectiveness, metric use, and marketing-mix performance.

Table 2 summarizes the six-stages. To begin the process, managers are assumed to possess some initial, ex-ante belief on each individual metric's effectiveness (e.g., ROMI) prior to deciding whether to use it for a specific type of marketing-mix decision (e.g., price promotion) (Stage 1). This ex-ante belief of the metric's effectiveness is expected to be a function of the type of marketing-mix decision, and the characteristics of the decision setting (the set of W antecedent variables in Table 1): the manager (e.g., top-level marketer with quantitative background), firm (e.g., large, market-oriented firm), and industry (e.g., growing with high market competition).

Subsequently, when managers are tasked with making a specific type of marketing-mix decision (e.g., price promotion) they form a latent utility for each metric (e.g., ROMI) based on their ex-ante belief of effectiveness and their specific decision setting (the set of Z antecedent variables in Table 1) (Stage 2), and decide to use the metric if its utility for their decision setting exceeds zero (Stage 3). More than one metric may satisfy this condition, and managers may employ multiple metrics. In theory, metric effectiveness and metric utility could be the same in our model since metric utility is a function of ex-ante metric effectiveness. However, there may be unobserved institutional factors, such as pressure from top managers, that encourages those making marketing-mix decisions to use a particular metric, even if the managers do not believe the metric is effective. Thus, we assume that metric effectiveness does not by itself completely determine metric utility or metric use.

Next, the manager is assumed to execute or make the marketing-mix decision, using the metrics whose utility exceeded zero and evaluates or observes the decision's outcome (Stage 4). The execution and evaluation of the outcome in Stage 4 is known to the manager but not directly observed by the researchers. Based on the decision's outcome, managers update their beliefs about the metrics' effectiveness that they used in the decision to obtain their ex-post metric effectiveness (Stage 5). Finally, after the decision has been made and its outcomes determined, managers report their evaluation of the decision's performance to us on the survey (Stage 6). We assume that the reported performance depends on metric use, ex-post metric effectiveness, and other covariates (the set of X antecedent variables in Table 1; i.e., recent business performance). This parsimonious process representation has similarities to how decision makers (e.g., managers and consumers) have been continuously posited in the literature to employ new information in a Bayesian setting to update their prior beliefs in order to form posterior beliefs.

To determine how closely the proposed conceptual model mirrors managers' decision-making process, we conducted a second study of 142 managers recruited via a Precision Sample panel of managers (see Web Appendix B). In this study, paid managerial respondents, who needed to have a title in marketing (of at least a mid-level marketing manager) and had to have made recent marketing decisions for their firms, were found to provide strong support for each aspect of the six-stage conceptual model posited above. For example, around 80% of managers indicated that they strongly agreed, agreed, or somewhat agreed that the characteristics of the decision setting were important factors influencing their (i) beliefs of a metric's a priori effectiveness, (ii) use of a metric, and (iii) updating of beliefs of a metric's a priori effectiveness.

Three central expectations, as summarized in Table 1, guide this conceptual framework. First, we expect metric effectiveness (column 3) to depend on the alignment between the information provided by the metric and the goal or objective of the marketing-mix decision being made (the last row). This expectation follows value chain theory (e.g., Lehmann & Reibstein, 2006), which suggests that different marketing-mix decisions have divergent goals and objectives (Ambler, 2003; Farris et al., 2010). Second, we expect the effectiveness and use of an individual metric (columns 2 and 3) may be related to characteristics of the decision setting, (i.e., manager, firm, and industry factors; rows 3, 4, and 5). However, since we consider such characteristics of the decision setting as control rather than main variables, we refer the reader to Table 1 and Mintz and Currim (2013), where details on the individual theories/justification for the inclusion of such characteristics are provided, such as decision maker (e.g., Perkins & Rao, 1990), self-efficacy (e.g., Bandura, 1982), resource-based (e.g., Wernerfelt, 1984), and contingency (e.g., Donaldson, 2001) theories. Third, we expect some managers may strategically employ an individual metric for a marketing-mix decision (Farris et al., 2010). For example, managers often decide on whether to employ a metric for a marketing-mix decision based on their ex-ante perception of the effectiveness of the metric; a result supported in our second survey with around 95% of the 142 managers strongly agreeing, agreeing, or somewhat agreeing that they employ metrics for their marketing-mix decisions based on their *a priori* belief of the metric's effectiveness (Web Appendix B). This is also why we assume that differences between metric effectiveness and metric utility or use will exist. Next, we describe our statistical model.

3. Statistical Model

3.1. Methodological Challenges

The conceptual model presented above produces a number of methodological challenges. First and foremost, selection effects occur, as metrics are not randomly assigned to managers and marketing-mix decisions, and may be strategically picked by managers and their firms based on their expectations about the metric's effectiveness for a marketing-mix decision. Intercept endogeneity (Heckman, 1979) results when unobserved factors simultaneously impact the stochastic term of the metrics' random utilities (Stage 2) for metric use and decision performance (Stage 6), creating correlation between the two error terms, as represented by the bidirectional arrow between ν and ε in Figure 1. Slope endogeneity (Manchanda, Rossi, & Chintagunta, 2004) occurs because metric use (Stage 3) and reported decision performance (Stage 6) both depend on metric effectiveness. Our methodology generalizes the full-information approach of Li and Tobias (2011) for intercept and slope endogeneity. For further discussion on the model's contribution to the endogeneity literature, we refer the reader to Web Appendix C.

In addition to selection effects, managers have heterogeneous preferences for metrics. Not controlling for observed and unobserved heterogeneity can result in aggregation bias. We employ hierarchical Bayes (HB) methods to estimate the heterogeneity in metric effectiveness across managers and marketing-mix decisions. Finally, the conceptual model employs ex-ante expectations about metric effectiveness in selecting metrics and ex-post evaluations of decision performance after making the marketing-mix decision. In order to measure ex-ante and ex-post metric effectiveness with one survey, we assume weak-form rationality (Pesaran & Weale, 2006), which posits that the ex-ante and ex-post expectations of metric effectiveness are constant across the population of managers but individuals managers are allowed to revise their beliefs with experience.

3.2. Model Specification

To statistically test the conceptual model introduced in Section 2.2., and summarized in Figure 1 and Table 2, we now detail the HB model stage by stage.

3.2.1. Stage 1. Ex-Ante Metric Effectiveness. In Stage 1, $\tilde{\theta}_{idk}$ is manager's *i* ex-ante beliefs about the effectiveness of metric *k* (e.g., ROMI) for marketing-mix decision *d* (e.g., price promotion). As we will see in Equation 7, "metric effectiveness" is measured as the effect of using the metric on the performance of the marketing-mix decision. Ex-ante metric effectiveness varies across the population of managers according to:

$$\tilde{\theta}_{idk} = \boldsymbol{w}'_{id}\boldsymbol{\phi}_k + \zeta_{ik} \qquad 1$$

where $\boldsymbol{w}_{id}$ is a vector of the exogenous covariates (Table 1) and the type of marketing decision, and $\boldsymbol{\phi}_k$ is a vector of regression coefficients for metric *k*. The ex-ante random errors $\{\zeta_{ik}\}$, which capture the unobserved heterogeneity in managers' ex-ante beliefs, have a normal distribution with mean 0 and standard deviation $\sigma_{\zeta k}$. They are mutually independent and are associated with each subject and metric but not decision in order to identify the model, as will be shown below.

3.2.2. Stage 2. Metric Use Equations. Manager *i* forms a latent utility in Stage 2 for metric *k* based on his or her ex-ante belief about metric effectiveness for decision type *d*:

$$u_{idk} = \rho_k\tilde{\theta}_{idk} + \boldsymbol{z}_i'\boldsymbol{\delta}_k + \nu_{idk} \qquad 2$$

where ρ_k is a positive scale factor for ex-ante metric effectiveness, $\boldsymbol{z}_i$ are exogenous, decision context covariates (Table 1) with regression coefficients $\boldsymbol{\delta}_k$, which includes the intercept, and $\{\nu_{idk}\}$are random error. Conceptually, the intercept is the marginal utility of employing the metric minus the marginal cost of the metric. However, as described as a limitation in the Discussion section, we do not have cost information in the survey, so we are unable to disentangle the two. The intercept can also reflect standard, measurement properties, such as reliability and validity: a metric with better validity may have a larger positive intercept than metrics with inferior validity, all else being equal. While the covariates $\boldsymbol{z}_i$ and $\boldsymbol{w}_{id}$ share the same managerial, firm, and industry independent variables, $\boldsymbol{w}_{id}$ includes the type of marketing-mix decision while $\boldsymbol{z}_i$ excludes it to identify the model (Table 1). The type of marketing-mix decision impacts metric utility through the ex-ante metric effectiveness beliefs $\tilde{\theta}_{idk}$. Further rationale for this exclusion restriction is described in Web Appendix D. The random shocks $\{\nu_{idk}\}$ are normally distributed with mean zero and variance one, which identifies the multivariate probit model. To allow for the possibility of groups of metrics often being selected to be employed together (e.g., Fischer & Himme, 2017), the vector $\boldsymbol{\nu}_{id} = (\nu_{id1}, \ldots, \nu_{idK})'$ has correlation matrix $\boldsymbol{\Sigma}_U$.

The parameters $\{\rho_k\}$ scale the ex-ante beliefs and are restricted to be positive to identify the model. They amplify ($\rho_k > 1$) or attenuate ($\rho_k < 1$) the ex-ante metric effectiveness in metric use. The scaling varies by metric to represent a selection propensity. For instance, managers may use return on investment (ROI) more frequently than warranted by their beliefs about ROI's effectiveness for the decision, for example, because of institutional or salience reasons such as upper-management requirements or since these metrics are more well-known. Then the scale factor ρ_k would be greater than one and boost ex-ante metric effectiveness. Conversely, managers may view a metric such as customer preferences for the brand as being highly effective, but select it less often than its ex-ante effectiveness because it is too expensive to obtain (Sridhar, Naik, & Kelkar, 2017). Then the scale factor ρ_k would be less than one and down-weight ex-ante metric effectiveness.

By substituting Equation 1 into Equation 2, we obtain the reduced form of the metric use utility:

$$u_{idk} = \rho_k[\boldsymbol{w}'_{id}\boldsymbol{\phi}_k + \zeta_{ik}] + \boldsymbol{z}_i'\boldsymbol{\delta}_k + \nu_{idk}. \quad 3$$

The ex-ante shocks $\{\zeta_{ik}\}$ can be viewed as random effects and are identified by the within-subject correlations due to managers making multiple marketing-mix decisions. They would not be well separated from the errors terms $\{\nu_{idk}\}$ 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. The multivariate probit model assumes that the unobserved heterogeneity $\{\nu_{idk}\}$ is correlated across metrics. The model is not identified if the random shocks $\{\zeta_{ik}\}$ also have a full covariance matrix (a result confirmed via simulation studies); hence, we assume they are independent.

3.2.3. Stage 3. Select Metrics to Use. Managers select subsets of the K metrics with positive latent utility in Stage 3:

$$m_{idk} = 1 \text{ if } u_{idk} > 0, \text{and } m_{idk} = 0 \text{ if } u_{idk} \leq 0. \quad 4$$

where 1 indicates metric k was selected and 0 indicates metric k was not selected for decision d. The correlated error terms for the latent utilities (Equation 2) results in a multivariate probit model for the observed choices. Managers can strategically select metrics because their ex-ante beliefs about metric effectiveness $\tilde{\theta}_{idk}$ appear in the random utility of Equation 2. Managers are more likely to select a metric if they expect it to increase their performance. Since their multiplier ρ_k is positive, managers are forward-looking and are more likely to select metrics they view as being more effective.

3.2.4. Stages 4 and 5. Ex-Post Metric Effectiveness Heterogeneity. Managers observe the outcome of their marketing decision in Stage 4 and revise their ex-ante beliefs about metric effectiveness after observing the outcome of the marketing decision in Stage 5. The ex-post effectiveness θ_{idk} for manager i, metric k, and decision d is conditional on ex-ante effectiveness, $\tilde{\theta}_{idk}$:

$$\theta_{idk}|\tilde{\theta}_{idk} = \mu_{idk} + \eta_{idk}. \tag{5}$$

The conditional mean μ_{idk} describes observed heterogeneity, and the random errors $\{\eta_{idk}\}$ describe unobserved heterogeneity. The multivariate normal random shock for the K metrics have mean zero and covariance matrix $\boldsymbol{\Lambda}$.

Next, we use the weak form of rational expectations (Pesaran & Weale, 2006) to relate the ex-ante and ex-post beliefs. Weak-form rational expectations posits that ex-ante and ex-post expectations across the population are equal and allows for heterogeneous beliefs and updating of beliefs. Each manager has their beliefs, which can change with new information. However, these idiosyncratic beliefs average out across the population because information about metric effectiveness is diffused across the population of managers. For instance, a manager who uses ROMI can update their beliefs about its effectiveness, but individual experiences are not sufficiently informative to change the average beliefs across all managers. Weak-form rational expectations assumes that the ex-ante and ex-post expectation in Equations 1 and 5 are equal, so ex-post metric effectiveness becomes:

$$\theta_{idk}|\tilde{\theta}_{idk} = \boldsymbol{w}'_{id}\boldsymbol{\phi}_k + \eta_{idk}. \tag{6}$$

where unobserved heterogeneity $\{\eta_{idk}\}$ is correlated across metrics. Implicitly, the random errors in the ex-ante and ex-post metric effectiveness equations have to be independent for the means to be equal, as can be seen from the conditional distribution of a multivariate normal distribution.

3.2.5. Stage 6. Marketing-Mix Performance Equation. Finally, manager i provides an overall performance evaluation y_{id} for decision type d (e.g., how the price promotion performed when using ROMI) in Stage 6:

$$y_{id} = \sum_{\boldsymbol{k=1}}^{\boldsymbol{K}} m_{idk}\theta_{idk} + \boldsymbol{x}_i'\boldsymbol{\beta} + \varepsilon_{id} \qquad 7$$

where m_{idk} is the observed indicator of metric use (e.g., whether ROMI was or not used) from Equation 4, θ_{idk} is the ex-post metric effectiveness in Equation 6, $\boldsymbol{x}_i$ 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 (see Table 1).[3] The survey elicits the subjects' overall performance of the marketing-mix decision, y_{id}, after respondents had made their decision and observed its outcome; subjects did not rate individual metrics for effectiveness relative to the decision. This approach is similar to metric conjoint analysis where subjects do not rate individual attribute levels but give overall ratings for products with different attribute levels. A concern is that managers may systematically report higher performance, y_{id}, than actual performance, which would bias the intercept. However, our measures of metric effectiveness are slopes, which are less affected by biased reporting (see Web Appendix E).

The normally distributed random shocks $\{\varepsilon_{id}\}$ are mutually independent and have mean 0 and standard deviation σ_Y. These random shocks are correlated with those for metric use

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

(Equation 2) and are independent of the ex-ante and ex-post effectiveness (Equations 1 and 6). The full correlation matrix Σ and covariance matrix Ξ for the random shocks ε_{id} for latent metric utility and ν_{id} for decision performance rating (Equations 2 and 7) are:

$$\mathbf{\Sigma} = \begin{bmatrix} 1 & \mathbf{\Sigma}_{YU} \\ \mathbf{\Sigma}_{UY} & \mathbf{\Sigma}_{U} \end{bmatrix} \text{ and } \mathbf{\Xi} = \begin{bmatrix} \sigma_Y^2 & \sigma_Y \mathbf{\Sigma}_{YU} \\ \sigma_Y \mathbf{\Sigma}_{UY} & \mathbf{\Sigma}_{U} \end{bmatrix} \qquad 8$$

where $\boldsymbol{\Sigma}_U$ is the K x K correlation matrix of the error terms for latent metric utility in Equation 2, $\boldsymbol{\Sigma}_{UY}$ is a K vector of correlations between ε_{id} and ν_{idk} where the correlations depend on the metric and not on the type of decision, $\mathbf{\Sigma}_{YU} = \mathbf{\Sigma}'_{UY}$, and σ_Y is the error standard deviation for the performance Equation 7. In our study, Σ and Ξ are 23 x 23 matrices (i.e., 22 individual metrics and performance). If Σ_{UY} is non-zero, then metric selection is endogenous. This patterned covariance matrix is nonstandard, and we apply Lenk and Orme (2009) to extend the estimation method of Talhouk, Doucet, and Murphy (2012).

Slope endogeneity occurs because metric effectiveness determines both metric use (Equations 2 and 4) and the performance rating (Equation 7). The presence of ex-ante metric effectiveness in Equation 2 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 $\boldsymbol{w}$ in Equations 1 and 6, $\boldsymbol{z}$ in Equation 2, and $\boldsymbol{x}$ in Equation 7 have exclusion restrictions (see Table 1 and Web Appendix D) to identify the model by exogenous variation.

3.2.6. Priors and Conditional Distributions. Bayesian inference requires prior distributions for the unknown parameters, and we use standard specifications, except the correlation and covariance matrices in Equation 8, which use the prior of Barnard, McCulloch, and Meng (2000) and the MCMC method of Talhouk et al. (2012). Web Appendix F presents the details of the prior distributions and details the full conditional distributions for the MCMC algorithm. Web Appendix G provides identification details and includes a description via reduced form models to show that metric effectiveness is a theoretical construct that can be measured from the manifest variables of use and performance. Simulation studies, reported in Web Appendix H, confirm the model's ability to obtain identified parameter estimates by Bayesian analysis. In Table 2, we summarize the model equations associated with each of the six stages described above.

4. Data

4.1. Data Collection and Variables

We test our model on 1,287 marketing-mix decisions reported by 439 U.S. managers from Mintz and Currim (2013). Mintz and Currim (2013) and Mintz and Currim (2015) use the same data to examine drivers of *overall* metric use and how such use of metrics relates with marketing-mix performance. In contrast, the goal of the current paper is to delineate which *individual* metrics, when employed by managers making a specific marketing-mix decision, are associated with better or worse decision outcomes, while accounting for endogeneity due to selection effects and controlling for heterogeneous managers, their ex-ante beliefs on metrics, and the managerial, firm, and industry decision setting.

Respondents were obtained via two different strata: (i) LinkedIn-based professional organizations (81%) and (ii) MBA alumni of a U.S. west coast university (19%). The sample was convenience-based and varied on firm size, industries, and recent performance since the study was targeting a wide assortment of firms. Target respondents were managers who held job titles of at least a mid-level manager (i.e., brand/marketing manager or higher) or a top-level executive involved in marketing-mix decisions (i.e., S/VPs and C-suite executives).

The questionnaire consisted of two sections. In the first section, managers reported up to 10 marketing-mix decisions they had recently made, the individual metrics employed for each decision, and each decision's performance outcomes. Table 3 lists the 10 marketing-mix decisions and the 24 metrics.[4] Subjects reported between 1 and 10 decisions, with the average subject reporting 2.9 marketing-mix decisions. The mean number of general metrics used per decision is 4.5 with a standard deviation of 3.7.

After indicating which metrics managers employed for a specific marketing-mix decision, they assessed the performance outcomes of this decision. Secondary data or other objective data are not available at the marketing-mix decision level of analysis from a large number of firms. Further, attempting to statistically identify the effect of one metric on one particular type of decision, the goal of the present research, is extremely problematic with aggregate firm-level data (e.g., see Katsikeas, Morgan, Leonidou, & Hult, 2016 for a review of marketing performance measures and Web Appendix A for a similar discussion). Consequently, we employ an eight-item subjective measure of marketing-mix performance taken from previous works (e.g., Jaworski & Kohli, 1993; Moorman & Rust, 1999; Verhoef & Leeflang, 2009). This composite performance measure is based on the decision's stated marketing (e.g., customer satisfaction, loyalty, and market share), financial (e.g., sales, profitability, and ROI), and overall outcomes, relative to a firm's stated objectives and to similar prior decisions. 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. In fact, 75% of the decisions were rated less than 5.8 out of 7 points, which provides evidence against ego self-preservation or demand effects. For further

[4] Mintz and Currim (2013) also asked managers to indicate which of three specific marketing metrics and which of three specific financial metrics they employed for each marketing-mix 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 marketing-mix decision metrics were only suited to each type of marketing-mix decision, which limits their applicability to other types of decisions.

empirical, theoretical, and statistical rationale for our marketing-mix performance measure, we refer the reader to Web Appendices A and E.

In the second section of the survey, managers answered questions on managerial, firm, and industry characteristics, with the vast majority of these questions taken directly or slightly adapted from prior published studies (see Web Appendix Table 2). To assess the quality of our data, a number of procedures are implemented in the design of the questionnaire, and a number of tests are performed with support found assuring the data is of reasonable quality (see Web Appendix I).

In summary, the data employed enables us to conduct one of the first large scale managerial studies to empirically test metric effectiveness at the marketing-mix decision level. However, the data also has its share of limitations, for example, we are unable to obtain the cost of creating and using a metric, differentiate between a manager's first and repeated use of a metric, or collect objective measures of performance outcomes at the marketing-mix decision level. Nevertheless, despite such limitations, the data is rich enough for us to infer which metrics are most and least effective for managers to employ for a given type of manager, decision, firm, and industry.

4.2. Descriptive Statistics

The average firm in our sample had 12,658 full-time employees and a median size of 125 employees. Top-level managers (i.e., S/VP and C-level managers) represent 56% of respondents, and marketers accounted for 54% of respondents. For further descriptive statistics of the sample, we refer the reader to Web Appendix Table 2 and Mintz and Currim (2013).

Figure 2 provides model-free evidence that metric use depends on type of decision by displaying the percent of time that managers employed a metric given the type of marketing-mix decision, ordered by the percent of time the metric was used for all decisions. 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). Further, 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.

Figure 3 graphs estimated ordinary least squares (OLS) coefficients or effects from regressing the DV performance onto binary indicators (dummy variables) for metric use. Each type of decision has a separate OLS regression. The figure shows that metric effectiveness deviates from its use, and that its effectiveness varies across marketing-mix decisions. For example, ROI is the second most used metric after awareness, but it is the eleventh most effective metric; ROI is frequently used but not particularly associated with better decision performance. In addition, Figure 3 shows that metric effectiveness depends on the type of decision. For instance, awareness is most effective when managers employ it for traditional advertising decisions and least effective when managers employ it for distribution decisions. Further, Figure 3 shows that the performance measure has considerable variation within and between subjects, which is inconsistent with demand effects where managers uniformly rate their decisions highly.

Figures 2 and 3 supports our central thesis that metric use and effectiveness depends on type of marketing-mix decision. However, this model-free evidence may not align with our model estimates for a number of reasons. First, it ignores covariates that effect the use and effectiveness of metrics. Second, it ignores the heterogeneity across managers. Finally, it ignores selection biases from measuring metric effectiveness for metrics that were used in the marketing-mix decision. Consequently, to better analyze the data, we need to employ our proposed econometric model to correct for selection effects and to account for heterogeneity when estimating parameters. In Web Appendix Table 3 and Web Appendix Figure 2, we provide additional details on the empirical correlations among performance and metric choice.

5. Results

The model detailed earlier was estimated using MCMC methods. The algorithm ran for 200,000 iterations with the last 100,000 used to estimate posterior parameters. Simulation studies were conducted to test the code, recoverability of parameters, and 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.

5.1. Influence of Type of Decision on the Effectiveness of Individual Metrics

Figure 4 and Table 4 provide the parameter estimates for how the type of marketing-mix decision influences a metric's effect on marketing-mix performance (Equations 1 and 6). The coefficients in the figure and table should be viewed as the impact of the type of marketing-mix decision on the effectiveness of an individual metric 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 use of the metric has a beneficial (detrimental) impact on the marketing decision outcome. The "Mean" column is the average of the coefficients across decisions within a metric.

Since there are too many combinations of metrics and decision settings to detail each result individually, we summarize the main empirical findings as follows. When examining individual metrics (rows in the table), two customer-mindset marketing metrics (awareness and willingness to recommend), when employed, are consistently associated with better performance outcomes across different types of decisions. Further, based on mean scores across all types of decisions in our sample, these two metrics appear to have the average greatest positive effect on marketing-mix decision performance outcomes. Interestingly, these metrics are the “bookends” on the customer purchase journey, where a customer initially learns about a product or brand and provides an after-purchase, post-evaluation recommendation to others. On the other hand, three financial-market and product-market financial metrics (target volume, NPV and ROMI) are associated with worse performance outcomes for most types of marketing-mix decisions. Therefore, we find that when financial-market and product-market financial metrics such as target volume, NPV and ROMI are employed for most types of marketing-mix decisions, performance outcomes of such decisions are, on average, relatively worse.

Results for the remainder of metrics are more nuanced, with metrics performing better or worse for different marketing-mix decisions depending on the alignment between the information provided by the metric and the goal of a type of marketing-mix decision, while their mean effect is insignificant overall across all types of decisions. For example, we find share of voice is highly effective when employed for PR, social media, and traditional advertising decisions, which are decisions where the metric is more aligned with the decisions’ goals; and highly ineffective for price promotion decisions, which is a decision where the metric is less aligned with the decision’s goals. These results are important as they enable us to identify which metrics are associated with better and worse outcomes for different types of marketing-mix decisions, and provide recommendations to managers on the metrics they should and should not employ when making these types of decisions. For instance, based on our results, managers making pricing decisions should employ metrics such as economic value added (EVA), preference, satisfaction, and willingness to recommend, which are associated with better decision outcomes, and not employ metrics such as likeability, return on sales (ROS), and NPV, which are associated with worse decision outcomes.

Further, when looking more broadly at the impact of financial and marketing metrics, we find that financial-market and product-market financial metrics, when employed, in large part have a negative relationship with the performance outcomes of several types of marketing-mix decisions (see Figure 4). For example, we find that when managers employ NPV, target volume, net profit, and ROMI when making their marketing-mix decisions, the performance outcomes of these decisions are for the most part either significantly worse or not significantly improved. Conversely, when managers employ a number of customer-mindset marketing metrics, such as awareness, willingness to recommend, loyalty, satisfaction, and share of wallet, the decision performance outcomes are generally improved, although not always significantly. This result is important because incorrect metric use of less effective financial-market and product-market financial metrics can damage the performance outcomes of marketing-mix decisions. Employment of the wrong metrics can also lead to erroneous strategies and tactical efforts aimed at improving erroneous metrics.

5.2. Impact of Managerial, Firm, and Industry Characteristics on Individual Metric Effectiveness

In Web Appendix Table 4, we provide the results of individual metric effectiveness based on the type of manager, firm, and industry (Equations 1 and 6). The presence of significant coefficients demonstrates that accounting for these variables is important as they do matter to whether metrics have a beneficial or detrimental impact on marketing-mix performance outcomes. For example, we find when top-level managers employ satisfaction and customer segment profitability, their performance outcomes are significantly improved in comparison to when mid-level managers employ such metrics. However, when top-level managers employ EVA and share of wallet, their performance outcomes are significantly worse than mid-level managers. Further, we find quality is more effective for marketers (vs. non-marketers) with a greater quantitative orientation, while customer lifetime value (CLV) is more effective for larger firms in service (vs. goods) industries that have chief marketing officers (CMOs). Although these results are interesting, we view the manager, firm, and industry characteristics more as control variables and, therefore, because of space constraints do not provide further discussion on their impact here.

5.3. Impact of Managerial, Firm, and Industry Characteristics on Individual Metric Use

We report in Web Appendix Table 5 the estimated parameters for the manager, firm, and industry variables on the metric's latent utility from Equation 2. The coefficients are the effects of these decision-setting variables on the latent utility after adjusting for metric effectiveness. For example, we find top-level managers are more likely to use financial measures such as ROMI and NPV than mid-level managers, marketing managers are more likely to use ROMI than non-marketers, and those managers with greater metric training are more likely to use net profit, preference, and share of wallet than managers with less metric training. Again, since these decision setting variables are viewed more as control variables, we do 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 and could lead to measurement errors when assessing the effectiveness and use of an individual metric.

5.4. Impact of Ex-Ante Beliefs of Effectiveness of Metric Use

In Table 5, we report the ρ_k multiplier scores from Equation 2 for the metric's latent utility, in descending order based on the posterior means of ρ_k. This parameter provides a model-based indicator of how a managers' ex-ante beliefs about the impact of a metric on marketing performance outcomes determines the metric's use in the decision. Larger values of ρ_k (e.g., $\rho_k > 1$), 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, $\rho_k > 1$ magnifies the role of ex-ante effectiveness of the metric in the use equation, while $\rho_k < 1$ attenuates its role.

We find that 7 out of 10 financial metrics have ρ_k multiplier scores of > 1, while 8 out of 12 marketing metrics have ρ_k multiplier scores of < 1. When examining the 8 specific marketing metrics with ρ_k multiplier scores of < 1, most of these metrics are customer-mindset marketing metrics, such as preferences, quality, loyalty, and satisfaction with the product, service, or brand. Further, managers tend to have greater uncertainty about the ex-ante beliefs about these marketing customer-mindset metrics' effectiveness, based on their estimated standard deviation of the error shock for ex-ante effectiveness from Equation 1 (last column in Table 5), even though most of these marketing metrics were found in Section 5.1 to be effective metrics that managers should employ for their marketing-mix decisions. In contrast, when examining the 7 out of 10 financial-market and product-market financial metrics, with ρ_k multiplier scores of > 1, most of these metrics were found in Section 5.1 to be less effective metrics that managers should not employ for their marketing-mix decisions.

Thus, it appears that managers are more uncertain about the ex-ante effectiveness of customer-mindset marketing metrics compared to financial-market and product-market financial metrics, and this attenuates the use of the more effective customer-mindset metrics in their marketing-mix decisions — a concerning result. In contrast, managers appear to be more confident in assessing whether a less effective financial-market and product-market financial metric will be effective and rely on that confidence when deciding to use the metric – another concerning result. Consequently, the ex-ante effectiveness of less effective financial metrics tends to be magnified in the use equation while it is attenuated for the more effective customer-mindset marketing metrics. This means that less effective financial-market and product-market financial metrics are being employed by managers more frequently than would be expected because of managers' higher ex-ante beliefs of effectiveness, while more effective customer-mindset marketing metrics are being employed less frequently than would be expected because of managers' lower ex-ante beliefs of effectiveness. We expand on this aspect in the Discussion.

Web Appendix Table 6 displays the estimated covariances. There are selection effects if the covariances between the error terms of the latent utilities in Equation 2 and the performance outcome in Equation 7 are not zero. Eight of the 22 covariances between performance and metric utility are significantly negative. This negative correlation for these metrics imply that unobserved factors that contribute to metric use (positive random errors in metric utility, Equation 2) tend to reduce decision outcomes (negative random errors in performance, Equation 7). One important possibility is that managers may be pressured to employ some metrics, even if they would not normally select them under their own volition. Further, many of the error terms for metric utility are correlated, which means they are more likely (unlikely) to be used (not used) together for positive (negative) correlations than if they were independent.

5.5. Model Comparisons

A valid concern is the necessity of our proposed model, which is rather complex, to control for endogeneity and heterogeneity. For example, one could assume that managers' metric use reveals their perception of metric effectiveness and, consequently, we could estimate a model that links use of metrics and that specific marketing-mix decision's performance outcomes based solely on Equation 7 (which ignores endogenous selection effects). Therefore, we estimate five reduced versions of the model that remove (i) slope endogeneity, (ii) intercept endogeneity, and (iii) both intercept and slope endogeneity, and test two additional models that are homogeneous, which introduce aggregate bias if heterogeneity is present. The average metric effectiveness of each model is reported in Web Appendix Table 7. As reported in Web Appendix J, the key result of the additional models is that they demonstrate that failing to appropriately account for both heterogeneity and endogeneity leads to materially different conclusions about metric effectiveness. Consequently, this additional analysis demonstrates that the full model which accounts for selection effects and heterogeneity is preferred to reduced models that ignore some or all of these important features.

6. Discussion

To address the important gap between the normative value and empirical effectiveness of metrics, we developed a behavioral framework and corresponding statistical model to assess the use and effectiveness of individual metrics when employed for specific marketing-mix decisions by using self-reported perceived decision outcomes. The behavioral framework posits that individual metrics will vary in their effectiveness by type of marketing-mix decision and across managers and decision settings, and that managers will strategically select metrics they ex-ante believe to be more effective in such settings.

The primary contribution of this research is to improve managerial practice. The model-based results provide several key managerial takeaways on metric use and metric effectiveness. First, we find three customer-mindset marketing metrics – awareness, willingness to recommend, and satisfaction – are consistently effective for managers to employ across most marketing-mix decisions. These metrics, when employed, are consistently found to significantly improve marketing-mix decision outcomes. Conversely, we find that three financial-market and product-market financial metrics – target volume, NPV, and ROMI – are consistently detrimental to employ across such decisions. These results suggest that managers need to consistently employ the more effective customer-mindset marketing metrics and not just the less effective financial-market and product-market financial metrics in their marketing-mix decisions. Further, these results provide evidence supporting current efforts to make firms more customer-centric in their marketing-mix decision-making. Second, we find that financial-market and product-market financial metrics are, on average, less effective when employed by managers when making their marketing-mix decisions than customer-mindset marketing metrics. This finding does not mean financial metrics have no inherent value or are unimportant. Instead, these empirical results show disconnects between, on the one hand, normative recommendations to encourage and facilitate financial-market and product-market financial metrics, and, on the other hand, actual practice. Prior to this research, it was unknown which metrics were used and were associated with better or worse decision outcomes for individual marketing-mix decisions.

Further, admittedly, this empirical finding that marketing customer-mindset metrics tend to be more effective than financial-market and product-market financial metrics was unexpected and not the original intent of the study. Thus, to gain a better understanding of the underlying reasons for these findings, we asked the 142 managers in our second study specifically about their thoughts regarding this result. Aggregated responses based on a pre-set list of reasons indicate that managers believe that marketing metrics such as awareness, satisfaction, and market share are viewed to be more effective than financial metrics such as net profit, ROI, and sales because marketing metrics are more (i) available, (ii) related to the goals of the decisions, (iii) likely to demonstrate improvements in decision outcomes, and (iv) easily understood. In addition, key individual insightful comments (via text-entry responses) included that “marketing metrics have a more broad goal of building long term profitability that financial metrics can’t necessarily accurately measure,” and “I think marketing metrics help you to better pinpoint the habits and preferences of your targeted demographic; which will enable a business owner to sustain and improve their financial gains.”

Third, we also find that managers in our sample, on average, appeared more uncertain in their assessments of the ex-ante effectiveness of customer-mindset marketing-based metrics, more hesitant to use them even 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-market and product-market financial metrics. A possible reason for this combination of results is that while marketing-mix decisions are more specific to the marketing function, financial-market and product-market financial metrics are more salient and easier for managers across the organization to understand. While proponents of the use of financial metrics in the marketing literature have normatively suggested the importance of financial metrics and empirically shown that financial-market and product-market financial metrics can be linked to marketing decisions (including via organizational pressure to use such metrics), no prior work has compared the effectiveness of these types of metrics for marketing-mix decisions as we have done in this study.

Taken together, the three key results noted above demonstrate that the most salient metrics are not often the most effective. If managers continue to pursue and over-use less effective financial-market and product-market financial metrics and under-use more effective customer-mindset metrics, the result will be less effective marketing-mix decisions. Of course, improvement of marketing-mix decisions is the ultimate goal of the marketing discipline, and this should be more important for managers to accomplish than appeasing managers outside of marketing in incorrect ways. Further, our results demonstrate that there is a strong unmet need for academics and consultants to enhance the knowledge and use of various metrics in marketing-mix decisions, and to increase the saliency of those metrics that are more effective. For financial-market and product-market 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 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 customer-mindset marketing-based 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.

In addition, our research, using self-reported decision outcomes, also contributes to managerial practice by allowing firms to examine which metrics are significantly associated with better or worse marketing-mix performance when employed for their specific managerial, firm, industry, and type of decision context. For example, by combining results from Table 4 and Web Appendix Table 4, we find that quantitative oriented managers working for market-oriented firms who are making sales force or price promotion decisions should employ ROS since this metric is associated with improved performance when employed in each of these settings. Conversely, quantitative-oriented managers working in firms with a low-cost defender strategic orientation making traditional advertisement decisions should focus less on consideration sets, since this metric is associated with worse performance when employed in such a setting.

Further, with the increasing use of automated marketing decisions, these results can help provide a starting point for which metrics should be employed for certain decisions, which can subsequently be improved upon. For example, 67% of marketing leaders currently use a marketing automation platform, and an additional 21% plan to use a marketing automation platform in the next two years (HubSpot, 2019). In addition, a report by Forrester found that

94% of marketers believe a "solution that provides continuous, autonomous optimization across channels would be appealing to them" is valuable to their organization, while 91% said a "tool that enables their teams to review, analyze, and act upon customer and marketing data in a continuous and real-time fashion would be valuable for their organization" (Forrester, 2017). However, less is known about which metrics firms should employ to review, analyze, and act upon when using these marketing automation platforms. This is an important disconnect, as in our second sample of 142 managers, we find about 70% of managers desire to include effective metrics for their automated marketing-mix decisions in the near future. Thus, the identification of the effectiveness of metrics for specific managerial, firm, industry, and type of decision contexts is crucial in the development of automated decision systems based on machine learning algorithms.

The managerial contributions of our work are enabled by a new, HB model that addresses selection bias due to intercept and slope endogeneity with multiple, binary endogenous regressors. The model employs weak-form rational expectations to permit estimation of ex-ante and ex-post beliefs about metric effectiveness from data collected after managers made the marketing-mix decision without requiring multiple waves of data collection (i.e., before and after the decisions were made). We believe this model structure and algorithmic development will be useful in applications beyond marketing metrics. 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 (a firm's return on assets, financial leverage, forecasted earnings per share, etc.), are not selected at random. Our model can be employed to determine which metrics are associated with successful stock picks. Additional applications in judgement and decision-making, and consumer and choice behavior, which attempt to link the individual pieces of information decision makers employ in their decisions with that decision's subsequent outcome, would also benefit from the proposed model structure and algorithmic development.

Finally, we identify several limitations of our work which create avenues for future research. First, our results should be replicated across multiple samples. Second, we limit our analysis to 24 metrics. Managers in practice are able to select from a much larger number of metrics. Third, some of the metrics included in our study may be more or less relevant to managers' businesses, which is why we correct for a large number of industry, firm, and managerial characteristics in our model and empirical analyses. Fourth, the cost of creating and using a metric is relevant, and as is the difference in the process between first and repeated metric use based on inertia from the past. However, we did not collect this data. Fifth, if data become available, our model is flexible enough that a manager or researcher could substitute their objective performance measures in place of ours to examine which metrics are more and less likely to be effective and used across the settings in which the decisions are made. Sixth, we recommend future research to examine how the chain-links between different individual metrics can improve performance of marketing-mix decisions based on execution levers (e.g., everyday low pricing) to strategic decisions (e.g., pricing) to value (e.g., customer satisfaction), which was infeasible in this work, but where our results can help inform such efforts.

Despite these limitations, this research is the first to conduct a large-scale empirical investigation on the relationship among metric effectiveness, metric use, and marketing-mix decision performance. It proposes a new Bayesian statistical framework that corrects for two sources of selection bias and overcomes a number of additional methodological challenges, and utilizes a dataset containing information on which of 24 metrics 439 managers employed for their 1,287 marketing-mix decisions across a large number of decision settings (firms, industries, and decisions) that also includes the self-reported performance outcomes of these decisions. In addition, it provides several notable managerial takeaways on which metrics are most and least effective for a given decision context and identifies a number of potential avenues for future research to expand on. We hope such future research will build on our efforts.

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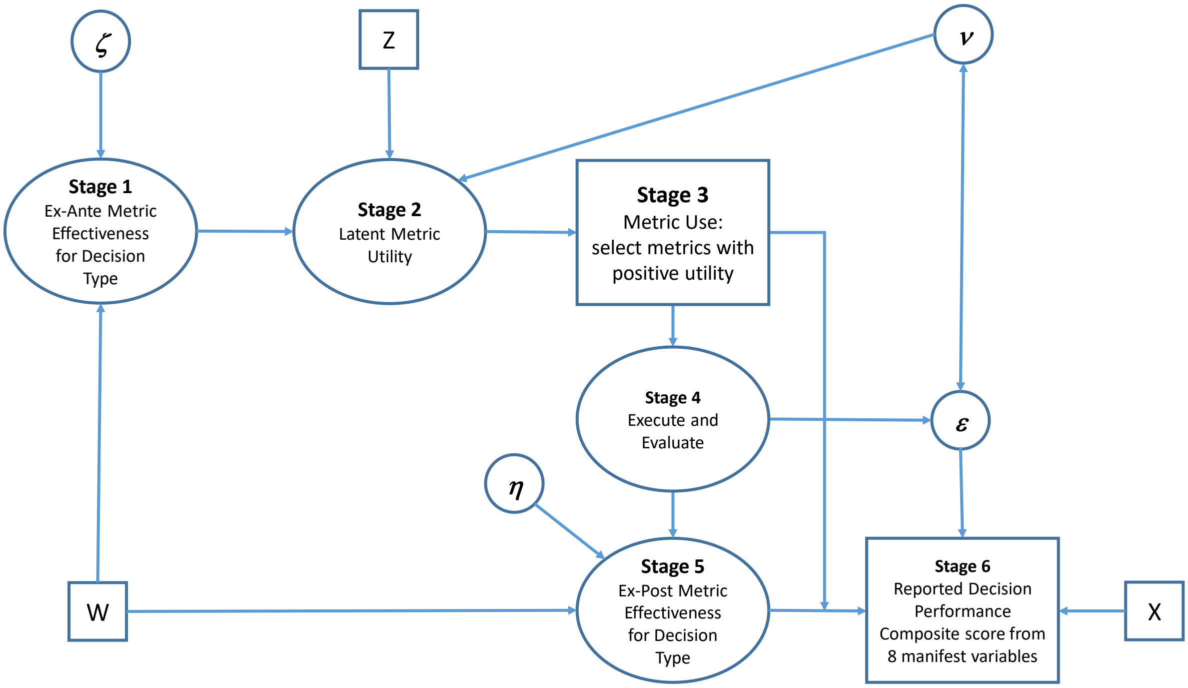
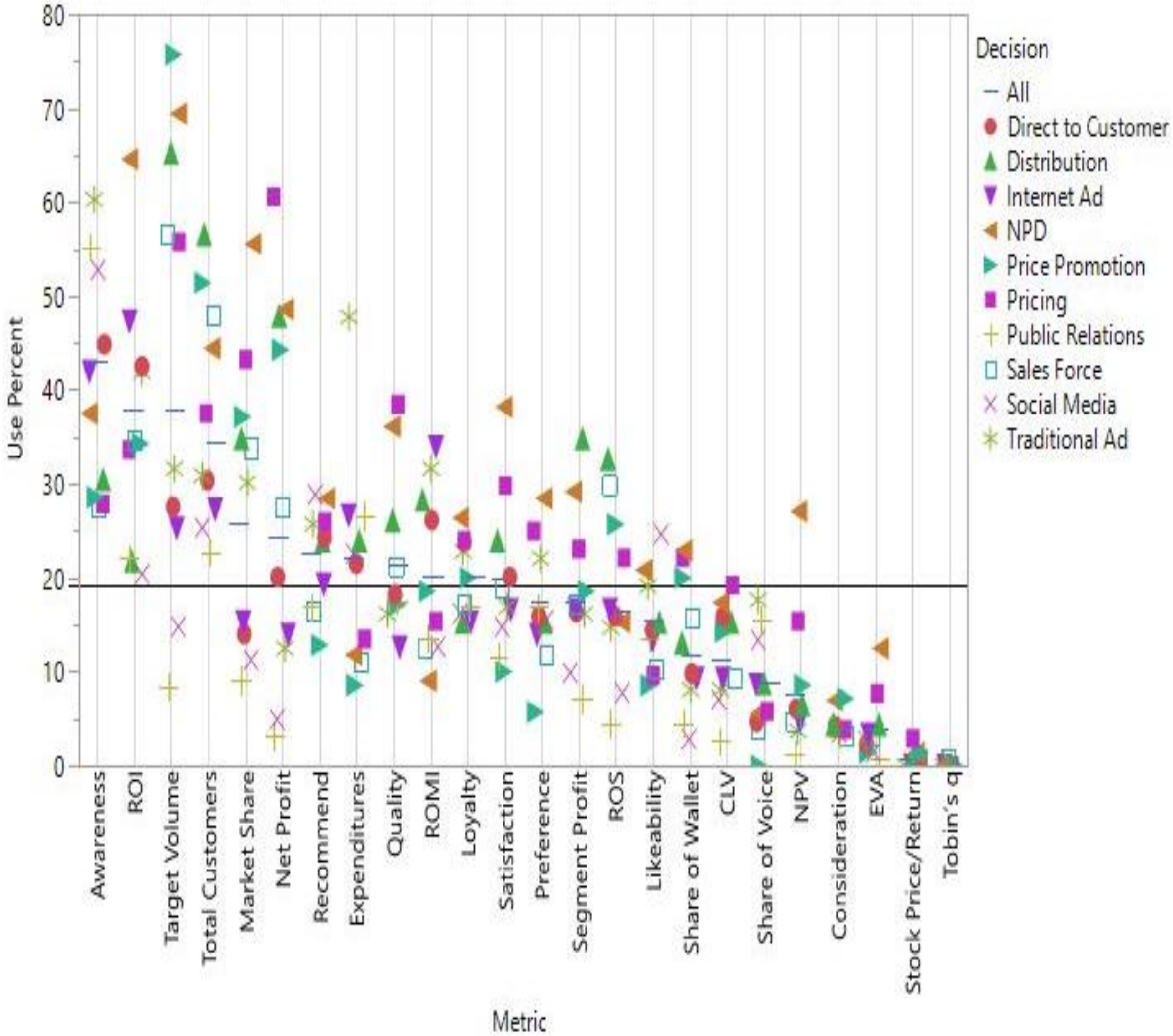
Figure 1. Conceptual Model for Metric Effectivness and Use and Decision Performance.



<u>Notes</u>:

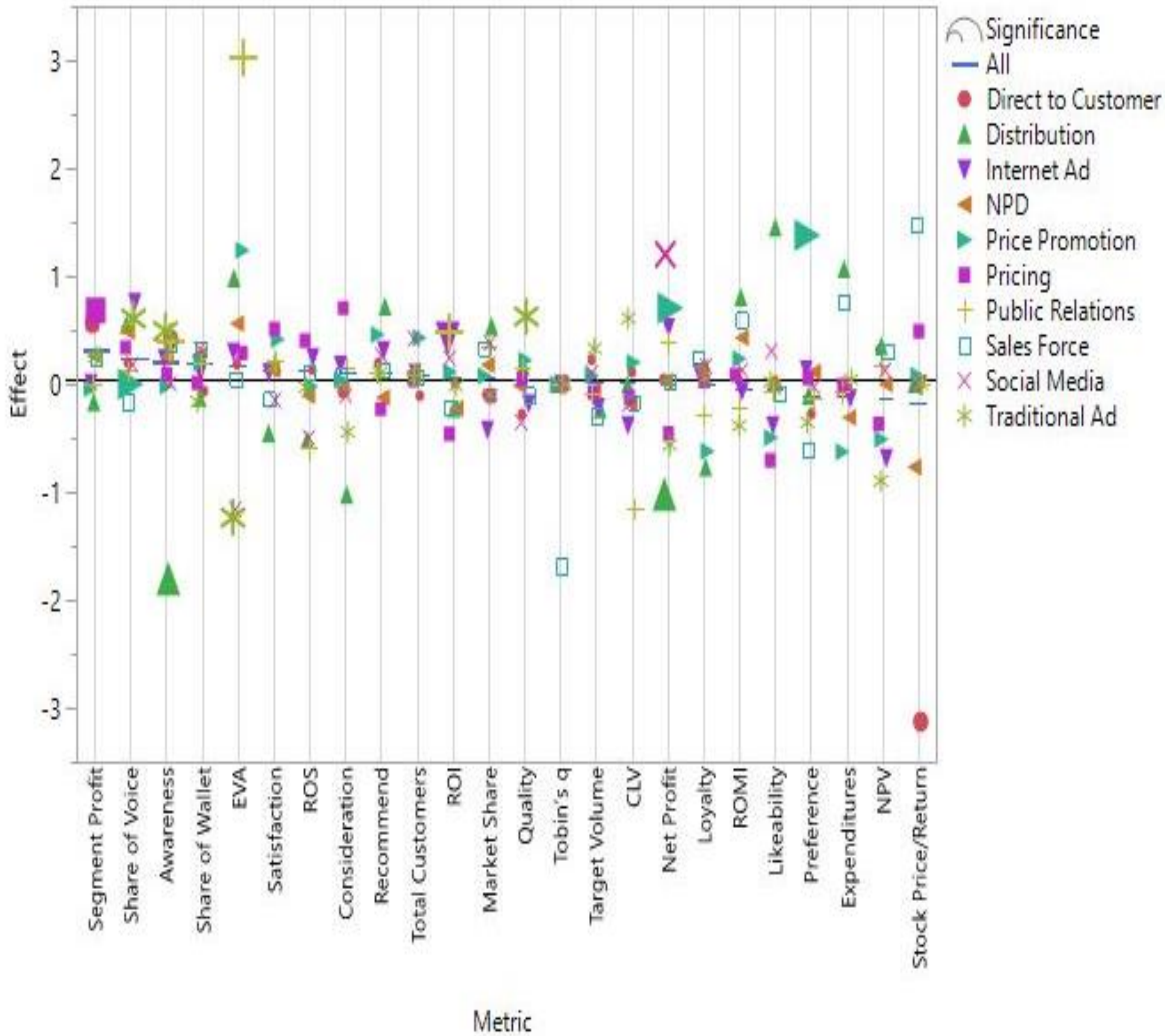
1. Rectangles are observed variables, and ovals are latent variables.
2. The reported decision performance is a composite score based on eight survey items. We represent these manifest variables with one rectangle instead of eight.
3. W, X, and Z are observed covariates noted in Table 1.
4. ζ, ν, η, and ε are random errors.
5. Intercept endogeneity is due to the correlation between the ν and ε random errors, which is indicated by the bidirectional arrow.
6. Slope endogeneity results from metric use and decision performance depending on metric effectiveness.
7. Weak-form rationality equates the expected values of ex-ante and ex-post metric effectiveness.

Figure 2. Descriptive Statistics of Metric Use by Marketing-Mix Decision.



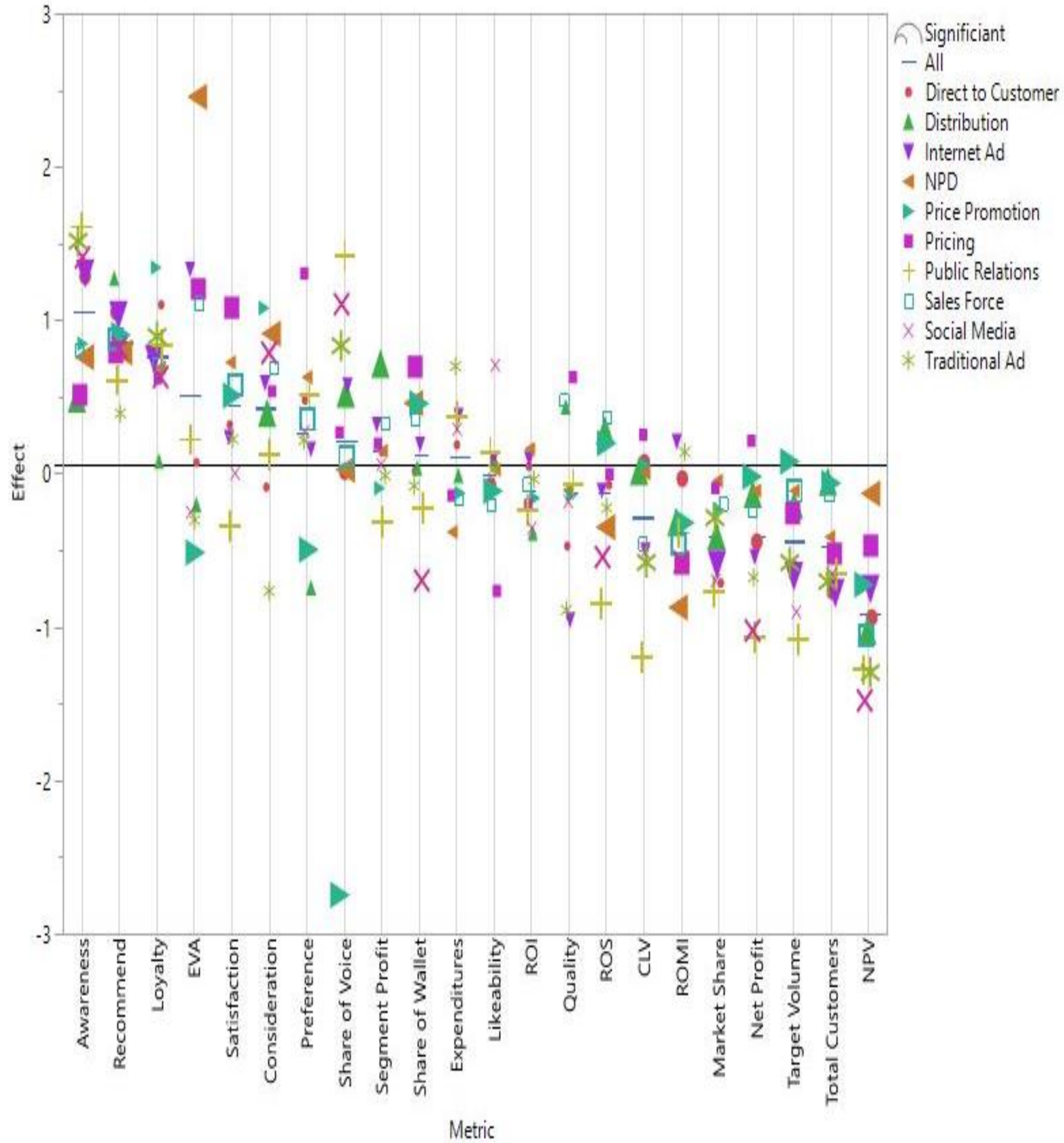
"All" is the percent of time the metric was used for all decisions, and the metrics are ordered by "All." The percentages in Figure 2 do not sum to 100 because each manager uses multiple metrics for each decision. The average percentage is 19.2%: a randomly selected measure has a 0.192 chance of being used in a randomly selected decision. The figure shows that the percentages of metric use vary considerably between metrics and within metric by marketing decision.

Figure 3. Descriptive Statistics of Metric Effectiveness by Marketing-Mix Decision.



Estimated OLS coefficients or effects from regressing the DV performance onto binary indicators (dummy variables) for metric use are shown. Each type of decision has a separate OLS regression. Symbol size is inversely proportion to the coefficient's p-value. Horizontal reference lines are the overall average. "All" is an aggregate regression that pools all of the data and ignores decision type. The metrics are sorted by "All." If a metric, such as Tobin's Q, was never used with a decision, then its effect is 0. The figure demonstrates that that metric effectiveness deviates from its use, and that its effectiveness varies across marketing-mix decisions.

Figure 4. Coefficients for Expected Metric Effectiveness by Decision.



Notes:

1. Large symbols in indicate significant coefficients where the posterior distribution of the coefficient is above zero or below zero with probability 0.925, respectively.
2. "All" is the average of the coefficients of for a metrics across the decision.
3. Metrics are ordered by "All."
4. The solid horizontal line is the average of all coefficients.

Table 1. Manager, Firm, Industry, and Decision Characteristics Employed in Models

Model Variables	Model for Performance (y) (Equation 7)	Model for Metric Use (m) (Equation 2)	Model for Metric Effectiveness (θ) (Equations 1 & 6)	Theory/Justification (Source(s))
<u>Individual Metric Use</u>	x			Decision Making Theory (Abramson, Currim, & Sarin, 2005; Jaworski, 1988; Menon, Bharadwaj, Adidam, & Edison, 1999)
<u>Recent Business Performance</u>	x	z	w	State Dependence / Resource Based Theory (Wernerfelt, 1984)
<u>Managerial Characteristics</u> • 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, Folkes, & Steckel, 1992; Perkins & Rao, 1990)

<u>Firm Characteristics</u>
• Market Orientation
• Strategic Orientation
  o Prospectors
  o Analyzers
  o Low-Cost Defenders
  o 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)

<u>Industry Characteristics</u> • Product Life Cycle • Industry Concentration • Market Growth • Market Turbulence		z	w	Contingency Theory (Donaldson, 2001)
<u>Marketing-mix Decision</u> • 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 & Reibstein, 2006)

"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.

Table 2. Model Summary that Coordinates Behavior in Figure 1 with Equations in Text

Variable	Stage	Equation	Number
Ex-ante Metric Effectiveness (Estimated)	1	$\tilde{\theta}_{idk} = \boldsymbol{w}'_{id}\boldsymbol{\phi}_k + \zeta_{ik}$	1
Latent Metric Utility (Estimated)	2	$u_{idk} = \rho_k \tilde{\theta}_{idk} + \boldsymbol{z}'_i \boldsymbol{\delta}_k + \nu_{idk}$ $\rho_k > 0$	2
Metric Choice (Observed)	3	$m_{idk} = \begin{cases} 1 & \text{if} \quad u_{idk} > 0 \\ 0 & \text{if} \quad u_{idk} \leq 0 \end{cases}$	4
Execute and Evaluate (Unobserved)	4	Unobserved and reflected in Stages 5 and 6	
Ex-post Metric Effectiveness (Estimated)	5	$\theta_{idk} \mid \tilde{\theta}_{idk} = \boldsymbol{w}'_{id}\boldsymbol{\phi}_k + \eta_{idk}$	6
Reported Decision Performance Rating (Observed)	6	$y_{id} = \sum_{\boldsymbol{k=1}}^{\boldsymbol{K}} m_{idk}\theta_{idk} + \boldsymbol{x}'_i\boldsymbol{\beta} + \varepsilon_{id}$	7
Random Errors	$\{\zeta_{ik}\}$,$\{\nu_{idk}\}$, $\{\eta_{idk}\}$, $\{\varepsilon_{id}\}$ and normally distributed with mean 0 and independent across subjects i		
ζ_{ik}	Independent over metrics k, and independent of $\{\nu_{idk}\}$,$\{\eta_{idk}\}$, and $\{\varepsilon_{id}\}$. The standard deviation ζ_{ik} of is $\sigma_{\zeta k}$.		
$\boldsymbol{\nu}_{id} = (\nu_{id1}, \ldots, \nu_{idK})'$	Correlated over metrics k with correlation Σ_U and correlated with ε_{id}, with correlation Σ_{UY}, and independent of $\{\zeta_{ik}\}$ and $\{\eta_{idk}\}$		
$\boldsymbol{\eta}_{id} = (\eta_{id1}, \ldots, \eta_{idK})'$	Correlated over metrics k and independent of $\{\zeta_{ik}\}$,$\{\nu_{idk}\}$, and $\{\varepsilon_{id}\}$. The covariance of $\boldsymbol{\eta}_{id}$ is $\boldsymbol{\Lambda}$.		
ε_{id}	Mutually independent over decision d with standard deviation σ_y; correlated (Σ_{YU}) with $\boldsymbol{\nu}_{id}$, and independent of ζ_{ik} and $\boldsymbol{\eta}_{id}$		
Exclusion Restrictions for IVS	$\boldsymbol{x}_i \subset \boldsymbol{z}_i \subset \boldsymbol{w}_{id}$		

Indices: subject i, marketing-mix decision of type d, and metric k.

Table 2 employs some notation on variables defined in Table 1.

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

*Indicates metric rarely used by managers (<1%), so we were forced to drop it from the analysis.

Table 4. Type of Decision's Impact on Metric Effectiveness

Metric	Mean	Trad. Ad	Internet Ad	Direct to Customer	Social Media	Price Promo	Pricing	NPD	Sales Force	Dist-ribution	Public Relations
Awareness	***1.055***	***1.515***	***1.311***	***1.287***	***1.410***	***0.847***	0.514	***0.760***	***0.805***	0.486	***1.614***
Recommend	***0.856***	***0.393***	1.037	***1.054***	***0.822***	***0.905***	***0.790***	***0.790***	***0.882***	***1.272***	0.614
Loyalty	***0.767***	***0.895***	***0.752***	***1.101***	0.630	***1.344***	0.623	0.693	0.712	0.079	0.843
EVA	0.513	***-0.304***	1.334	0.073	-0.252	-0.514	***1.203***	***2.457***	***1.114***	-0.204	0.228
Satisfaction	0.441	0.225	0.238	0.319	0.002	0.510	***1.082***	***0.725***	0.582	***1.072***	-0.341
Consideration	0.427	***-0.766***	0.593	-0.088	0.788	***1.080***	0.536	0.913	***0.695***	0.391	***0.127***
Preference	0.270	0.217	0.160	0.479	0.273	-0.495	***1.306***	0.629	0.357	***-0.745***	0.520
Share of Voice	0.214	***0.834***	***0.576***	0.014	***1.105***	***-2.747***	***0.269***	0.026	***0.120***	***0.519***	***1.421***
Segment Profit	0.149	-0.013	0.322	0.142	0.060	-0.095	0.193	0.149	0.331	0.712	***-0.311***
Share of Wallet	0.122	-0.080	0.193	0.018	-0.696	***0.457***	***0.697***	***0.460***	***0.353***	0.034	-0.217
Expenditures	0.111	***0.700***	0.381	0.188	0.290	-0.126	-0.143	-0.380	-0.158	-0.013	0.371
Likeability	-0.006	0.028	0.096	-0.078	***0.707***	-0.113	***-0.765***	0.026	-0.202	0.098	0.140
ROI	-0.114	-0.035	0.098	0.046	-0.356	-0.159	-0.205	0.162	-0.065	-0.391	-0.235
Quality	-0.126	-0.889	-0.953	-0.472	-0.181	-0.141	0.628	-0.108	0.483	0.434	-0.064
ROS	-0.129	-0.223	-0.108	-0.073	-0.544	***0.199***	***-0.002***	-0.349	***0.374***	0.278	***-0.847***
CLV	-0.284	***-0.578***	***-0.498***	0.073	***-0.508***	0.058	0.253	0.002	-0.454	0.012	***-1.197***
ROMI	-0.319	0.141	0.210	-0.033	***-0.576***	***-0.320***	***-0.587***	***-0.872***	***-0.448***	***-0.321***	***-0.382***
Market Share	***-0.402***	-0.287	***-0.589***	***-0.712***	-0.697	-0.232	-0.095	-0.046	-0.195	-0.410	***-0.761***
Net Profit	-0.404	-0.676	-0.541	-0.444	***-1.023***	***-0.019***	***0.215***	-0.111	-0.243	-0.137	***-1.061***
Target Volume	***-0.445***	***-0.580***	***-0.665***	***-0.621***	***-0.901***	0.080	***-0.260***	***-0.111***	-0.110	***-0.209***	***-1.077***
Total Customers	***-0.474***	***-0.703***	***-0.774***	***-0.769***	***-0.655***	-0.062	***-0.522***	***-0.413***	-0.136	-0.057	***-0.644***
NPV	***-0.914***	***-1.297***	***-0.747***	***-0.938***	***-1.479***	***-0.724***	***-0.470***	***-0.129***	***-1.050***	***-1.028***	***-1.275***
Number of Decisions (sum)	1,287 (in total)	136	150	214	142	70	104	144	127	46	154

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.

Table 5. 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

Web Appendix for "The Right Metrics for the Right Decision"

Table of Contents

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

In Panel A of Web Appendix Figure 1, the researcher observes aggregate measures of metric use by a firm as well as aggregated measures of firm performance, such as stock return or Tobin's Q or a combination thereof. 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 of marketing-mix decision, which is the goal of the present research, seems problematic using aggregate data (e.g., see Katsikeas, Morgan, Leonidou, & Hult [2016] review on marketing performance measures for a similar discussion). Another challenge is firms do not use a uniform standard for disclosing metric use (e.g., see Marketing Accountability Standards Board). Studies using aggregated data that rely on informants at firms can result in distorted information, especially for large firms, because subjects may not be fully informed about metric use throughout the firm and how frequently they are used for different marketing decisions. 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 marketing-mix 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. Details of Subsequent Survey of 142 Managers

We conducted a second survey data collection to provide (a) conceptual validation of our conceptual model, (b) decomposition of the meaning of metric effectiveness from a managerial point of view, (c) manager-based insights and reasons to help explain our results, and (d) link our work with potential machine learning applications for marketing-mix decision making. The survey was conducted in November 2019 and responses were recruited via a Precision Sample panel of managers. To assess data quality, we included quality control checks before, during, and after managers completed the survey: using attention checks, multiple questions about managerial qualifications, conducting analysis for patterned responses and completion times, and use of multiple response scales (nominal, constant sum, Likert scales). Respondents in this panel are only paid for quality submissions, and are paid relatively well for completing a 15 minute survey. Thus, respondents know they need to pass quality assurance checks to receive their compensation from the panel company. Further, our survey did not ask for sensitive data or questions where there was a correct or incorrect answer, which helped motivate them to provide truthful answers. Funding to pay for these managers was provided by one of the co-author's research support accounts.

Our final dataset consisted of responses by 142 managers. 39% of the managers in our sample were top-level managers in their firm (S/VP or C-level), and the gender ratio was equally split (50/50). The average firm size was 2,162 employees (median of 76), the majority of firms were privately held (77%), and firms competed in a wide variety of industries, with the largest sample from the services industry (30% of managers).

The results of the additional analysis provides, first, conceptual validation of our model, i.e., that managers (i) use, (ii) believe metrics are effective (dependent variables), and (iii) update beliefs based on our independent variables (characteristics of the firm, manager, industry, and type of marketing-mix decision [10 decisions representing 4Ps]). For example, we find 79% of managers somewhat agree, agree, or strongly agree with all aspects of our conceptual model in each of the 12 different questions that asked these managers whether manager, firm, and industry characteristics influence their (i) beliefs of a metric's a priori effectiveness, (ii) use of a metric, and (iii) update of beliefs about a metric's effectiveness based on results of previous marketing-mix decisions. This analysis is based on asking managers' 22 questions on the extent their "perception of the effectiveness (not use) of an individual metric, prior to making my marketing-mix decision, is based on xxx [characteristic]", on a 1-7 scale, where we vary the phrasing per stage of the conceptual model being asked, and based on the firm, managerial, industry, or decision characteristic. Further, we find strong support that managers decide on which metrics to use based on the metrics perceived a priori effectiveness (94% of managers somewhat agreed, agreed or strongly agreed). This is based on asking managers the extent that their "decision on which individual metrics to use is based on: how effective or important I perceive this metric to be for this specific marketing-mix decision," on a 1-7 scale with $\geq$5 = somewhat agreed or greater. Thus, based on this additional analysis, we find additional conceptual validation of our model beyond the theory-based reasons discussed in the theory section.

Second, in the new study when we specifically asked managers about the metrics they employ on their dashboards, we found about 75% of managers somewhat agree, agree, or strongly agree that they have ability to (i) use their own metrics on their dashboards, (ii) adjust metrics on their dashboards based on performance and effectiveness, and (iii) revise beliefs on which metrics to use and place on their dashboards based on performance and effectiveness. Hence, these findings provide further evidence that managers have a priori beliefs about a metric’s effectiveness, can choose which metrics to employ for their marketing-mix decisions, and continually update their beliefs based on prior decisions.

Third, the new study helped provide further decomposition of the meaning of the term “metric effectiveness.” In the analysis, we found that that the three main aspects managers consider for a metric to be effective is whether the metric employed (i) relates to goals of marketing-mix decisions, (ii) demonstrates improved marketing-mix decision outcomes, and (iii) has an ability to have its results documented, in comparison to ease of computation, ease of understanding, availability, usefulness to post mortems, and level of certainty. Further, the additional analysis confirmed the construct or label “effectiveness” as the most appropriate label for “a metric that you employ for a marketing-mix decision, and the outcome of the decision is positive,” which was selected about 19% more often than the next highest label, “valuable.”

Fourth, we asked the 142 managers in our new study the main reasons they believed customer-mindset marketing-based metrics could be more effective than financial metrics. This was useful because managers indicated in aggregated responses, based on a pre-set list of reasons, that they believed that marketing metrics such as awareness, satisfaction, and market share are viewed to be more effective than financial metrics such as net profit, ROI, and sales, since they are more (i) available, (ii) related to the goals of the decisions, (iii) likely to demonstrate improvements in decision outcomes and (iv) easily understood. Other options included: able to document results, relates to goals, ease of computation, level of certainty, and usefulness for post mortems. In addition, key individual insightful comments (via text-entry responses) were that “marketing metrics have a more broad goal of building long term profitability that financial metrics can't necessarily accurately measure.” “I think marketing metrics help you to better pinpoint the habits and preferences of your targeted demographic;

which will enable a business owner to sustain and improve their financial gains." "The biggest thing is understanding the story being told by the metrics. And I think marketing metric can be easier to read the story." and "Marketing metrics are more people focused."

Fifth, we were interested in examining whether we could link our results with the automated dashboard and marketing-mix allocation decision tools increasingly being employed by firms. Thus, we ask managers "what is your likelihood of basing the metrics you would use in automated marketing decisions in the future on metrics that are found to be most effective in the past?", on a 1-7 scale. The results find support of such a link: the majority (about 70%) of managers are interested in basing their automated marketing-mix decisions on metrics they found to be effective. Hence, by incorporating our results on metric effectiveness, automated dashboard and marketing-mix allocation tools can be better designed to focus on those metrics which are found to be most effective for a given manager, firm, industry, and type of marketing-mix decision.

Web Appendix C. 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, Rossi, and Chintagunta (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 2 in paper and the dotted line in Figure 1). 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 D. Exclusion Restrictions

For model identification, exclusion restrictions are necessary on which variables appear in each equation. Equation 7 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 2 includes managerial, firm, and industry characteristics that are excluded from Equation 7; 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 1, to believe they may influence metric use above and beyond the focal variable Metric Effectiveness.

Equations 1 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 3 and 7. 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. Once we include the metric's effectiveness for making a particular type of decision, the latent utility for metric use (Equation 2) and the performance score (Equation 7) 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 1 and 5, but not Equations 2 and 7 is appropriate.

Web Appendix E. Empirical, Theoretical, and Statistical Rationale for Performance Measure

After indicating which metrics managers employed for a specific marketing-mix decision, they assessed the performance outcomes of this decision. Ideally, there would be an objective measure of decision outcomes such as return on investment (ROI) or return on assets (ROA) 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 these financial metrics, for the calculation to be comparable between respondents, and for the methodology to be consistently applied to all types of marketing-mix decisions (e.g., pricing, distribution, sales force, etc.) (see also Wilden & Gudergan, 2015, pp. 188–189). Thus, any claim of objectivity would likely be illusory. Secondary data or other objective data are not available at the marketing-mix decision level of analysis from a large number of firms. Attempting to statistically identify the effect of one metric on one particular type of decision, the goal of the present research, is extremely problematic with aggregate firm-level data (e.g., see Katsikeas, Morgan, Leonidou, & Hult, 2016 review on marketing performance measures and Web Appendix A for a similar discussion).

Consequently, we decided to employ a composite eight-item subjective measure of marketing-mix performance taken from previous published works (e.g., Jaworski & Kohli, 1993; Moorman & Rust, 1999; Verhoef & Leeflang, 2009). This corresponding measure of marketing-mix performance, based on the decision’s stated marketing (customer satisfaction, loyalty, market share), financial (sales, profitability, ROI), and overall outcomes, relative to a firm’s stated objectives and to similar prior decisions, enables us to capture different types of performance to develop a well-diversified overall performance measure. Further, this combination of performance outcomes provides us a comprehensive composite subjective measure of performance and avoids task demand affects since subjects provided an overall score for their marketing-mix performance and not individual scores rating the effectiveness of each metric. This approach further reduces potential biases associated with using only a single measure or type of performance and task demand biases that can occur when subjects rate individual attributes (Kahneman, 2011). In addition, the composite performance score is the average of eight items and has a Cronbach alpha of 0.94, demonstrating very good internal consistency among the eight reflective items and indicating that managers rated their marketing-mix performance similarly across the different performance measures.

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. In fact, 75% of the decisions were rated less than 5.8 out of 7 points, and the average performance score had a mean of 4.9, which provides evidence against ego self-preservation, demand effects, or a reluctance by managers to report marketing-mix decisions with poorer performance. While we recognize the subjectivity of our dependent measure, studies by Germann, Lilien, Fiedler, and Kraus (2014), Germann, Lilien, and Rangaswamy (2013), and O'Sullivan and Abela (2007) were able to test a subset of their samples using both subjective and objective measures, and in each case obtained similar results. Additionally, our measure of metric effectiveness is a slope parameter, so it is insensitive to systematic bias in performance ratings. If managers tend to over-rate their performance, the intercept will be biased upwards, but not the slope.

Web Appendix F. 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. There are *N* subjects; subject *i* reports n_i marketing decisions, and *M* is the total number of observations. There are *K* metrics, and *D* types of marketing decisions.

The ex-ante and ex-post metric effectiveness in Equations 1 and 6 can be compactly written for all subjects by stacking the transposes of the Equations 1 and 6 into matrices:

$$\begin{aligned} \widetilde{\mathbf{\Theta}} &= \boldsymbol{W\Phi} + \mathbf{E}_{\widetilde{\mathbf{\Theta}}} \\ \mathbf{\Theta} &= \boldsymbol{W\Phi} + \mathbf{E}_{\mathbf{\Theta}}. \end{aligned}$$

For instance, the $\mathbf{\Theta}$ is a *M x K* matrix with rows being the transpose of $\boldsymbol{\theta}_{ij}$; the rows of $\boldsymbol{W}$ are the transpose of $\boldsymbol{w}_{ij}$; the columns of $\mathbf{\Phi}$ are $\boldsymbol{\varphi}_k$; and the rows of $\boldsymbol{E}_\Theta$ are the transpose of $\boldsymbol{\eta}_{ij}$, which are K vectors of error terms. Manager *i*'s latent metric utilities for decision *j* in Equation 2 is:

$$\boldsymbol{u}_{ij} = \mathbf{P}\widetilde{\boldsymbol{\theta}}_{ij} + \boldsymbol{\Delta}'\boldsymbol{z}_{ij} + \boldsymbol{\nu}_{ij} \text{ for } i = 1, \dots, N \text{ and } j = 1, \dots, n_i \qquad 9$$

where $\boldsymbol{u}_{ij}$ is a *K* vector of latent metric utilities; $\boldsymbol{P}$ is a K x K diagonal matrix with 0 on the off-diagonals and ρ_k for the (*k*,*k*) element; $\boldsymbol{\Delta} = [\boldsymbol{\delta}_1, \dots, \boldsymbol{\delta}_K]$; and $\boldsymbol{\nu}_{ij}$ is a *K* vector of normally distributed error terms. The entire data for the latent utilities can be written by stacking the transpose of Equation 9:

$$\boldsymbol{U} = \widetilde{\mathbf{\Theta}}\mathbf{P} + \boldsymbol{Z}\mathbf{\Delta} + \mathbf{E}_{\boldsymbol{U}}.$$

The Equation 7 for subject's i performance evaluation for decision j is

$$y_{ij} = \boldsymbol{m}'_{ij}\boldsymbol{\theta}_{ij} + \boldsymbol{x}'_{ij}\boldsymbol{\beta} + \varepsilon_{ij} \text{ for } i = 1, \dots, N \text{ and } j = 1, \dots, n_i.$$

Full Conditional Distributions for Performance Parameters

Because performance Y is correlated with the latent metric utility U, we need to condition Y on U when inferring the parameters for performance. Using the standard equations for conditional normal distributions and the correlation and covariance matrices in Equation 8, the variance of Y given U is:

$$\sigma_{Y|U}^2 = \sigma_Y^2(1 - \boldsymbol{\Sigma}_{YU}\boldsymbol{\Sigma}_U^{-1}\boldsymbol{\Sigma}_{UY}).$$

The conditional mean of y_{ij} given $\boldsymbol{u}_{ij}$ is:

$$E(y_{ij}|\boldsymbol{u}_{ij}) = \boldsymbol{m}_{ij}'\boldsymbol{\theta}_{ij} + \boldsymbol{x}_{ij}'\boldsymbol{\beta} + \sigma_Y\boldsymbol{\Sigma}_{YU}\boldsymbol{\Sigma}_U^{-1}\boldsymbol{r}_{Uij}$$

where the residual of the latent metric utility is:

$$\boldsymbol{r}_{Uij} = \boldsymbol{u}_{ij} - \mathbf{P}\widetilde{\boldsymbol{\theta}}_{ij} - \boldsymbol{\Delta}'\boldsymbol{z}_{ij}.$$

Full Conditional of $\boldsymbol{\beta}$

The prior distribution for $\boldsymbol{\beta}$ is:

$$\boldsymbol{\beta} \sim N(\boldsymbol{\mu}_{\beta 0}, \boldsymbol{V}_{\beta 0}).$$

The full conditional distribution is:

$$\begin{aligned}
\boldsymbol{\beta}|\text{Rest} &\sim N(\boldsymbol{\mu}_{\beta N}, \boldsymbol{V}_{\beta N}) \\
\boldsymbol{V}_{\beta N} &= \left(\boldsymbol{V}_{\beta 0}^{-1} + \sigma_{Y|U}^2 \sum_{i=1}^{N}\sum_{j=1}^{n_i} \boldsymbol{x}_{ij}\boldsymbol{x}_{ij}'\right)^{-1} \\
\boldsymbol{\mu}_{\beta N} &= \boldsymbol{V}_{\beta N}\left(\boldsymbol{V}_{\beta 0}^{-1}\boldsymbol{\mu}_{\beta 0} + \sigma_{Y|U}^2 \sum_{i=1}^{N}\sum_{j=1}^{n_i} \boldsymbol{x}_{ij}\left[y_{ij} - \boldsymbol{m}_{ij}'\boldsymbol{\theta}_{ij} - \sigma_Y\boldsymbol{\Sigma}_{YU}\boldsymbol{\Sigma}_U^{-1}\boldsymbol{r}_{Uij}\right]\right).
\end{aligned}$$

Full Conditional of Ex-post Metric Utility $\boldsymbol{\theta}_{ij}$

Ex-post metric utility follows population-level mode in Equation 6. Its full conditional distribution is:

$$\begin{aligned}
\boldsymbol{\theta}_{ij}|Rest &\sim N(\boldsymbol{\mu}_{\theta ij}, \boldsymbol{V}_{\theta ij}) \\
\boldsymbol{V}_{\theta ij} &= \left(\boldsymbol{\Lambda}^{-1} + \sigma_{Y|U}^{-2}\boldsymbol{m}_{ij}\boldsymbol{m}_{ij}'\right)^{-1} \\
\boldsymbol{\mu}_{\theta ij} &= \boldsymbol{V}_{\theta ij}\left(\boldsymbol{\Lambda}^{-1}\boldsymbol{\Phi}'\boldsymbol{w}_{ij} + \sigma_{Y|U}^{-2}\boldsymbol{m}_{ij}\left[y_{ij} - \boldsymbol{x}_{ij}'\boldsymbol{\beta} - \sigma_Y\boldsymbol{\Sigma}_{YU}\boldsymbol{\Sigma}_U^{-1}\boldsymbol{r}_{Uij}\right]\right)
\end{aligned}$$

Full Conditional Distributions for Metric Utility Parameters

We need to condition metric utility U on performance Y when generating the latent utilities and computing the full conditional distribution of the latent utility parameters because U and Y are correlated (Equation 8). The conditional variance (and correlation) of U given Y is:

$$\boldsymbol{\Sigma}_{U|Y} = \boldsymbol{\Sigma}_U - \boldsymbol{\Sigma}_{UY}\boldsymbol{\Sigma}_{YU}.$$

Define the residual for the performance equation:

$$r_{Yij} = y_{ij} - \boldsymbol{m}_{ij}^{'}\boldsymbol{\theta}_{ij} - \boldsymbol{x}_{ij}^{'}\boldsymbol{\beta},$$

and the M vector of residuals $\boldsymbol{r}_Y$, which stacks the individual residuals. The conditional mean of $\boldsymbol{u}_{ij}$ given y_{ij} is:

$$E\left(\boldsymbol{u}_{ij}|y_{ij}\right) = \mathbf{P}\widetilde{\boldsymbol{\theta}}_{ij} + \boldsymbol{\Delta}'\boldsymbol{z}_{ij} + \sigma_Y^{-1}\boldsymbol{\Sigma}_{UY}r_{Yij}.$$

Stacking these conditional means into a matrices gives:

$$E(\boldsymbol{U}|\boldsymbol{Y}) = \widetilde{\boldsymbol{\Theta}}\mathbf{P} + \boldsymbol{Z}\boldsymbol{\Delta} + \sigma_Y^{-1}\boldsymbol{r}_Y\boldsymbol{\Sigma}_{YU}$$

where the M vector r_Y stacks the residuals r_{yij}.

Full conditional of Δ

The prior distribution for $\boldsymbol{\Delta}$ is:

$$\text{vec}(\boldsymbol{\Delta}')\sim N(\boldsymbol{\mu}_{\Delta 0}, \boldsymbol{V}_{\Delta 0}).$$

The full conditional of $\boldsymbol{\Delta}$ is:

$$\begin{aligned}
\text{vec}(\boldsymbol{\Delta}')|\text{Rest} &\sim N(\boldsymbol{\mu}_{\Delta M}, \boldsymbol{V}_{\Delta M}) \\
\boldsymbol{V}_{\Delta M} &= \left[\boldsymbol{V}_{\Delta 0}^{-1} + \boldsymbol{Z}'\boldsymbol{Z}\otimes\boldsymbol{\Sigma}_{U|Y}^{-1}\right]^{-1} \\
\boldsymbol{\mu}_{\Delta M} &= \boldsymbol{V}_{\Delta M}\left\{\boldsymbol{V}_{\Delta 0}^{-1}\boldsymbol{\mu}_{\Delta 0} + \left(\boldsymbol{Z}'\otimes\boldsymbol{\Sigma}_{U|Y}^{-1}\right)\text{vec}\left[\left(\boldsymbol{U} - \widetilde{\boldsymbol{\Theta}}\mathbf{P} - \sigma_Y^{-1}\boldsymbol{r}_Y\boldsymbol{\Sigma}_{YU}\right)'\right]\right\}
\end{aligned}$$

where the Kronecker product is ⊗.

Full Conditional of ρ_k

Define $\boldsymbol{\rho} = (\rho_1,\ldots,\rho_K)'$ and $A_{ij} = \text{diag}(\widetilde{\boldsymbol{\theta}}_{ij})$, the bock diagonal matrix with zero off-diagonal elements and $\widetilde{\boldsymbol{\theta}}_{ij}$ on the diagonal. The prior distribution is a truncated normal distribution:

$$\boldsymbol{\rho} \sim N\left(\boldsymbol{\mu}_{\rho 0}, \boldsymbol{V}_{\rho 0}\right) \prod_{k=1}^{K} \chi[\rho_k > 0]$$

where χ is the indicator function. The full conditional distribution is:

$$\begin{aligned}
\boldsymbol{\rho}|\text{Rest} &\sim N\left(\boldsymbol{\mu}_{\rho M}, \boldsymbol{V}_{\rho M}\right) \prod_{k=1}^{K} \chi[\rho_k > 0] \\
\boldsymbol{V}_{\rho M} &= \left[\boldsymbol{V}_{\rho 0}^{-1} + \sum_{i=1}^{N} \sum_{j=1}^{n_i} \mathbf{A}_{ij}^{'} \boldsymbol{\Sigma}_{U|Y}^{-1} \mathbf{A}_{ij}\right]^{-1} \\
\boldsymbol{\mu}_{\rho M} &= \boldsymbol{V}_{\rho M} \left[\boldsymbol{V}_{\rho 0}^{-1} \boldsymbol{\mu}_{\rho 0} + \sum_{i=1}^{N} \sum_{j=1}^{n_i} \mathbf{A}_{ij}^{'} \boldsymbol{\Sigma}_{U|Y}^{-1} \left(\mathbf{u}_{ij} - \boldsymbol{\Delta}' \mathbf{z}_{ij} - \sigma_Y^{-1} r_{Yij} \boldsymbol{\Sigma}_{YU}\right)\right].
\end{aligned}$$

These coefficients are constrained to be positive. We sequentially generate each ρ_k from a truncated normal distribution by conditional on the other ρ's. We use the inverse CDF transform to generate truncated normal random variables.

Full Conditional of the Ex-Ante Error Terms ζ_{ik}

The ex-ante error terms act as random effects in the latent metric utility. Their "prior" distribution is:

$$\boldsymbol{\zeta}_i \sim N\left(\mathbf{0}, \boldsymbol{V}_{\zeta i}\right)$$

where $\boldsymbol{\zeta}_i = (\zeta_{i1}, \ldots, \zeta_{iK})$ does not depend on decision to identify the model.

Their full conditional distribution is:

$$\begin{aligned}
\boldsymbol{\zeta}_i|\text{Rest} &\sim N\left(\boldsymbol{\mu}_{\zeta i}, \boldsymbol{V}_{\zeta i}\right) \\
\boldsymbol{V}_{\zeta i} &= \left[V_{\zeta 0}^{-1} + n_i \mathbf{P} \boldsymbol{\Sigma}_{U|Y}^{-1} \mathbf{P}\right]^{-1} \\
\boldsymbol{\mu}_{\zeta i} &= \boldsymbol{V}_{\zeta i} \left[\sum_{j=1}^{n_i} \mathbf{P} \boldsymbol{\Sigma}_{U|Y}^{-1} \left(\boldsymbol{u}_{ij} - \mathbf{P} \boldsymbol{\Phi}' \boldsymbol{w}_{ij} - \boldsymbol{\Delta}' \boldsymbol{z}_{ij} - \sigma_Y^{-1} r_{Yij} \boldsymbol{\Sigma}_{YU}\right)\right].
\end{aligned}$$

Full Conditional of the Variance of the Ex-Ante Errors

The prior distributions of the variances are independent, inverse Gamma distributions:

$$\sigma^2_{\zeta k} \sim IG\left(\frac{r_{\zeta 0}}{2}, \frac{s_{\zeta 0}}{2}\right).$$

Their full conditional distributions are:

$$\begin{aligned} \sigma^2_{\zeta k}|\text{Rest} &\sim IG\left(\frac{r_{\zeta N}}{2}, \frac{s_{\zeta k}}{2}\right) \\ r_{\zeta M} &= r_{\zeta 0} + N \\ s_{\zeta k} &= s_{\zeta 0} + \sum_{i=1}^{N} \zeta^2_{ik}. \end{aligned}$$

Impute the Latent Metric Utility u_{ijk}

We sequentially generate u_{ijk} from truncated, conditional normal distributions with the condition that $u_{ijk} > 0$ if $m_{ijk} = 1$ and $u_{ijk} \leq 0$ if $m_{ijk} = 0$ (Albert & Chib, 1993). When generating the latent utility for metric k, the conditioning is on both the latent utilities for the other metrics and the performance equation. We use the CDF transform to generate truncated normal variates.

Full Conditional Distribution of the Covariance of Performance and Metric Utilities

The covariance matrix for the performance and metric utilities in Equation 8 presents a challenge because it does not have a standard form. First, we use the method of Talhouk et al. (2012) to generate the correlation matrix $\mathbf{\Sigma}$ for the vector (y_{ij} , $\boldsymbol{u}_{ij}$) when using the prior distribution from Barnard et al. (2000). Then we generate the conditional variance of y_{ij} given $\boldsymbol{u}_{ij}$ and solve for σ_Y (Lenk & Orme, 2009).

Full Conditional of the Correlations Σ

We use the prior distribution of in Barnard et al. (2000) for $\mathbf{\Sigma}$. The first step from (Talhouk et al., 2012) is to generate the "missing" variance parameters:

$$d_k^2 \sim IG\left(\frac{K+2}{2}, \frac{\Sigma^{kk}}{2}\right) \text{ for } k = 1, \ldots, K+1$$

where Σ^{kk} is the (k,k) element of $\boldsymbol{\Sigma}^{-1}$. Define the diagonal matrix $\mathbf{D} = \text{diag}(d_1, \ldots, d_{K+1})$ with zeros on the off-diagonals. Define the vector or standardized observations:

$$\boldsymbol{r}_{ij} = \begin{bmatrix} \sigma_Y^{-1}\boldsymbol{r}_{Yij} \\ \boldsymbol{r}_{Uij} \end{bmatrix}.$$

Next, generate an *K+1 x K+1* auxiliary covariance matrix $\boldsymbol{\Omega}$, which has an inverse Wishart prior distribution:

$$\boldsymbol{\Omega} \sim IW(f_{\Omega 0} = K, \boldsymbol{G}_{\Omega 0}^{-1} = \boldsymbol{I}_{K+1})$$

where $\boldsymbol{I}_{K+1}$ is the *K+1 x K+1* identity matrix. Its' full conditional distribution is:

$$\begin{array}{rcl} \boldsymbol{\Omega}|\text{Rest} & \sim & IW(f_{\Omega M}, \boldsymbol{G}_{\Omega M}^{-1}) \\ f_{\Omega M} & = & K + M \\ \boldsymbol{G}_{\Omega n}^{-1} & = & I_{K+1} + \sum_{i=1}^{N}\sum_{j=1}^{n_i} \boldsymbol{D}\boldsymbol{r}_{ij}\boldsymbol{r}_{ij}^{'}\boldsymbol{D}. \end{array}$$

The correct correlation matrix $\boldsymbol{\Sigma}$ is obtained by dividing the elements by their standard deviations:

$$\sigma_{ij} = \frac{\omega_{ij}}{\sqrt{\omega_{ii}\omega_{jj}}}.$$

Next, we generate the conditional variance of Y given U. It has an inverse Gamma prior distribution

$$\sigma_{Y|U}^2 \sim IG\left(\frac{r_{Y|U,0}}{2}, \frac{s_{Y|U,0}}{2}\right).$$

The posterior distribution is:

$$\begin{array}{rcl} \sigma_{Y|U}^2|\text{Rest} & \sim & IG\left(\frac{r_{Y|U,M}}{2}, \frac{s_{Y|U,M}}{2}\right) \\ r_{Y|U,M} & = & r_{Y|U,0} + M \\ s_{Y|U,M} & = & s_{Y|U,0} + \sum_{i=1}^{N}\sum_{j=1}^{n_i} r_{Y|U,ij}^2 \end{array}$$

where

$$r_{Y|U,ij} = r_{Yij} + \sigma_Y \boldsymbol{\Sigma}_{YU}\Sigma_{UU}^{-1}\boldsymbol{r}_{Uij}.$$

After generating the conditional variance, solve for the variance of Y.

$$\sigma_Y^2 = \sigma_{Y|U}^2(1 - \boldsymbol{\Sigma}_{YU}\boldsymbol{\Sigma}_U^{-1}\Sigma_{UY})^{-1}.$$

Full Conditional of Ex-post, Observed Heterogeneity Coefficients Φ

Two sources of information of **Φ** are Equations 3 and 6. Once again, we need to condition the metric utility on the performance since they are correlated. Define the *K* vector of conditional residuals:

$$\boldsymbol{b}_{ij} = \boldsymbol{u}_{ij} - \boldsymbol{\Delta}' \boldsymbol{w}_{ij} - \mathbf{P}\boldsymbol{\zeta}_i - \sigma_Y^{-1}\boldsymbol{\Sigma}_{UY} r_{ij}.$$

where $\boldsymbol{\zeta}_i$ is the *K* vector of random effects ($\boldsymbol{\zeta}_{i1}$, …, $\boldsymbol{\zeta}_{iK}$). Recall that for identification purposes, $\boldsymbol{\zeta}_{ik}$ only depends on subject *i* and metric *k* and not decision j. Define the *M x K* matrix **B** by stacking ***bij*** in its rows. The prior distribution of **Φ** is multivariate normal:

$$\mathrm{vec}(\boldsymbol{\Phi}') \sim N(\boldsymbol{\mu}_{\Phi 0}, \boldsymbol{V}_{\Phi 0}).$$

where vec(**Φ** ') is a vector that stacks the rows of **Φ**. Its full conditional distribution is:

$$\begin{aligned}
\mathrm{vec}(\boldsymbol{\Phi}')|\mathrm{Rest} &\sim N(\boldsymbol{\mu}_{\Phi M}, \boldsymbol{V}_{\Phi M}) \\
\boldsymbol{V}_{\Phi M} &= \left[\boldsymbol{V}_{\Phi 0}^{-1} + \boldsymbol{W}'\boldsymbol{W} \otimes \left(\mathbf{P}\Sigma_{U|Y}^{-1}\mathbf{P} + \boldsymbol{\Lambda}^{-1}\right)\right]^{-1} \\
\boldsymbol{\mu}_{\Phi M} &= \boldsymbol{V}_{\Phi M}\left[\boldsymbol{V}_{\Phi 0}^{-1}\boldsymbol{\mu}_{\Phi 0} + \left(\boldsymbol{W}' \otimes \mathbf{P}\Sigma_{U|Y}^{-1}\right)\mathrm{vec}(\mathbf{B}') + (\boldsymbol{W}' \otimes \boldsymbol{\Lambda}^{-1})\mathrm{vec}(\boldsymbol{\Theta}')\right].
\end{aligned}$$

Full conditional of the Ex-post, Unobserved Heterogeneity Variance Λ

The prior distribution of **Λ** is and inverted Wishart distribution:

$$\boldsymbol{\Lambda} \sim IW(f_{\Lambda 0}, \boldsymbol{G}_{\Lambda 0}^{-1}).$$

Its full conditional distribution is:

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

Web Appendix G. Identification of the Model

The reduced form model substitutes Equation 6 into Equation 7. Together with Equation 3, we obtain:

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

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 ρ^*_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 H. Details on Simulation Study

The purpose of this appendix is to demonstrate that the model is identified and that the MCMC algorithm can recover the unknown parameters. The simulation uses 500 "subjects" subjects and 5 observations per subject for a total of 2500 observations. There are 10 "metrics." There are six covariates or IVs: covariates one and two appear in the performance equation, covariates one to four appear in random metric utility, and all six covariates appear in the HB model for metric effectiveness. The IVs are randomly generated from a standard normal distribution. The true parameters are generated from various distributions, and are given in the following tables with their estimates. Given the covariance parameters, we generate the individual error terms for the random metric utility and performance equations. Given the parameters from the HB model for metric effectiveness and the IVs, we generate the subject-level ex-ante and ex-post metric effectiveness under the assumption of weak form rationality. Next, we generate the random metric utilities, and generate the metric use data according to the random utilities being larger than one. Finally, we combine metric use data with ex post metric effectiveness to generate the performance data.

We ran the MCMC algorithm for 100,000 iterations and use the last 50,000 iterations for estimation. Trace plots of the iterations indicate that the algorithm converges. We first examine the fit between the true and estimated values for metric effectiveness and metric utility since these are two of the most important features of the model. The fit between true ex-post metric effectiveness and its estimates (the posterior mean) has a correlation of 0.991 and a root mean square error (RMSE) of 0.406. The results are similar for ex-ante metric effectiveness because the two share the same means but ex-ante has a simpler error structure. The fit between the true latent metric utility and its MCMC estimate has a correlation of 0.967 and a RMSE of 1.328. The latent metric utility has an additional layer of random errors than metric effectiveness, which is the reason for the larger RMSE. Simulation Table 1 breaks the overall fit statistics into fit for each metric.

Simulation Table 1. Fit Statistics between True and Estimates of Ex-Post Metric Effectiveness and Latent Metric Utility.

	Metric Effectiveness		Metric Utility	
Metric	Correlation	RMSE	Correlation	RMSE
M01	0.995	0.291	0.962	1.246
M02	0.995	0.366	0.959	1.114
M03	0.989	0.475	0.955	0.986
M04	0.982	0.311	0.941	0.955
M05	0.991	0.439	0.953	1.511
M06	0.979	0.532	0.956	1.140
M07	0.988	0.361	0.949	1.113
M08	0.995	0.370	0.969	1.375
M09	0.995	0.425	0.973	1.461
M10	0.997	0.431	0.978	1.624

An overall measure is the RMSE of t-like ratios, (true parameter – posterior mean)/(posterior standard deviation):

$$\left[\frac{1}{\text{Number of Parameters}}\sum\left(\frac{\text{True Parameter} - \text{Posterior Mean}}{\text{Posterior Standard Deviation}}\right)^2\right]^{1/2}.$$

Overall, the MCMC algorithm recovers the true parameters. The above measure is 1.28, for the regression coefficients. The average, absolute values of the ratios is 1.014. 90% of the ratios were within ±2, and 95% were within ±2.5. If the posterior distributions had normal distributions, we would expect 95% and 99%, respectively, but the posterior distributions have longer tails than normal distributions. Though these statistics are not perfect at identifying good performance, if the model was not identified or the MCMC algorithm was not effective, we could reasonably expect much large ratios. The following table gives details about individual parameters.

The performance equation has a fixed effect β. Simulation Table 2 details the true values and their Bayes estimates. There are two, IVs in the performance equation: V01 and V02.

Simulation Table 2. True value and posterior mean and standard deviation for fixed effects β in the performance equation.

		Posterior	
Variable	True β	Mean	STD DEV
CNST	-1.3	-1.485	0.235
V01	0.5	0.306	0.129
V02	0.2	-0.110	0.251

The latent metric utility depends on ex-ante metric effectiveness. The coefficient that multiplies ex-ante metric effectiveness is ρ. Simulation Table 3 displays the true value and its Bayesian estimates.

Simulation Table 3. True value and posterior mean and standard deviation of ρ, the multiplier of ex ante metric effectiveness in latent metric utility.

		Posterior	
Variable	True ρ	Mean	STD DEV
M01	1.47	1.578	0.130
M02	1.14	1.103	0.068
M03	0.93	0.845	0.054
M04	1.24	1.216	0.110
M05	1.68	1.984	0.127
M06	1.28	1.608	0.105
M07	1.42	1.351	0.104
M08	1.62	1.423	0.123
M09	1.76	1.868	0.102
M10	1.57	1.656	0.160

The model for the latent metric utilities has regression coefficients for four IVs: V01 and V02, which also appear in the performance equation and V03 and V04. Each metric has a separate equation. Simulation Table 4 gives the true values and their estimates.

Simulation Table 4. True value and posterior mean and standard deviations for the regression coefficients δ in the latent metric utility.

		Posterior				Posterior	
Variable	True δ	Mean	STD DEV	Variable	True δ	Mean	STD DEV
CNST M01	0	-0.033	0.368	V02 M06	-1.5	-1.650	0.149
CNST M02	-1.1	-1.172	0.259	V02 M07	0	-0.415	0.172
CNST M03	0.8	0.640	0.172	V02 M08	-1.1	-0.968	0.193
CNST M04	0.9	0.963	0.170	V02 M09	0	0.778	0.314
CNST M05	0.7	0.071	0.419	V02 M10	-0.6	-0.605	0.170
CNST M06	1.3	1.364	0.259	V03 M01	0	0.193	0.203
CNST M07	1.3	1.159	0.209	V03 M02	-0.9	-0.692	0.160
CNST M08	-1.1	-0.807	0.246	V03 M03	0	0.069	0.115
CNST M09	-1.4	-0.989	0.292	V03 M04	0	-0.031	0.125
CNST M10	0	-0.254	0.239	V03 M05	1.3	1.823	0.240
V01 M01	0.8	0.774	0.212	V03 M06	1.2	1.575	0.200
V01 M02	0	-0.157	0.116	V03 M07	-1.1	-1.177	0.135
V01 M03	-1.9	-1.754	0.125	V03 M08	-0.6	-1.091	0.288
V01 M04	0	0.128	0.153	V03 M09	-1.3	-1.178	0.161
V01 M05	0	-0.429	0.198	V03 M10	1.2	1.285	0.228
V01 M06	-0.7	-0.714	0.144	V04 M01	-0.9	-0.955	0.145
V01 M07	0.9	0.590	0.142	V04 M02	0	0.030	0.139
V01 M08	0.9	0.772	0.259	V04 M03	-1.2	-1.303	0.098
V01 M09	1.4	1.426	0.206	V04 M04	1.3	1.085	0.123
V01 M10	0	-0.121	0.263	V04 M05	0.7	0.978	0.196
V02 M01	0	0.089	0.197	V04 M06	0	-0.480	0.156
V02 M02	1.1	1.088	0.157	V04 M07	1	0.917	0.114
V02 M03	0	-0.215	0.086	V04 M08	-0.9	-0.468	0.128
V02 M04	0	-0.041	0.101	V04 M09	-0.7	-0.482	0.140
V02 M05	0	-0.261	0.251	V04 M10	0	0.126	0.179

Ex-ante and ex-post metric effectiveness has the same population means, which are function of six IVs: V01, V02, V03, and V04, which appear in the equation for latent metric utility, and V05 and V06, which only appear in the equation for metric effectiveness. Simulation Table 5 gives the true and estimated values of the regression coefficients.

Simulation Table 5. True and posterior mean and standard deviation of the regression coefficients φ for the ex-ante and ex-post means of metric effectiveness.

		Posterior				Posterior	
Variable	True φ	Mean	STD DEV	Variable	True φ	Mean	STD DEV
CNST M01	0	-0.055	0.198	V03 M06	0	-0.174	0.112
CNST M02	0.96	1.139	0.197	V03 M07	0	0.034	0.083
CNST M03	0	0.051	0.182	V03 M08	-2.01	-1.884	0.152
CNST M04	0	0.088	0.131	V03 M09	0	-0.096	0.102
CNST M05	2.4	2.612	0.224	V03 M10	1.91	2.105	0.165
CNST M06	1.1	0.941	0.171	V04 M01	1.18	1.196	0.093
CNST M07	-0.61	-0.622	0.148	V04 M02	0	-0.010	0.114
CNST M08	0	-0.125	0.131	V04 M03	0	-0.009	0.097
CNST M09	1.37	1.158	0.148	V04 M04	0	0.160	0.090
CNST M10	-0.86	-0.840	0.154	V04 M05	0	-0.101	0.085
V01 M01	0	0.059	0.117	V04 M06	0	0.229	0.092
V01 M02	-1.05	-0.895	0.121	V04 M07	-0.58	-0.563	0.062
V01 M03	0.82	0.681	0.112	V04 M08	1.36	1.216	0.100
V01 M04	0	-0.090	0.116	V04 M09	0	-0.149	0.068
V01 M05	0.59	0.785	0.083	V04 M10	0	-0.089	0.094
V01 M06	0	0.005	0.072	V05 M01	-1.43	-1.376	0.057
V01 M07	-1.17	-1.099	0.090	V05 M02	1.48	1.538	0.075
V01 M08	-1.92	-1.954	0.090	V05 M03	0.54	0.613	0.054
V01 M09	-0.85	-0.839	0.107	V05 M04	-1.19	-1.222	0.086
V01 M10	0	0.044	0.146	V05 M05	-1.63	-1.535	0.077
V02 M01	1.05	1.044	0.103	V05 M06	1.89	1.616	0.083
V02 M02	0.99	1.011	0.142	V05 M07	-0.5	-0.479	0.039
V02 M03	-0.68	-0.549	0.087	V05 M08	0.67	0.755	0.085
V02 M04	0	0.062	0.077	V05 M09	0.9	0.815	0.064
V02 M05	0.62	0.704	0.113	V05 M10	2.82	3.084	0.172
V02 M06	0	0.028	0.076	V06 M01	-0.72	-0.715	0.038
V02 M07	-1.42	-1.258	0.100	V06 M02	0	0.021	0.040
V02 M08	0	-0.038	0.126	V06 M03	-2.06	-2.296	0.089
V02 M09	-3.05	-3.212	0.170	V06 M04	-0.92	-0.987	0.072
V02 M10	0	-0.061	0.090	V06 M05	-1.22	-1.165	0.064
V03 M01	-1.72	-1.833	0.114	V06 M06	-0.96	-0.787	0.052
V03 M02	2.58	2.543	0.130	V06 M07	1.15	1.273	0.067
V03 M03	1.47	1.657	0.107	V06 M08	-0.98	-1.038	0.103
V03 M04	0	0.006	0.100	V06 M09	0	-0.024	0.033
V03 M05	-1.64	-1.739	0.091	V06 M10	0	0.047	0.050

The standard deviations of the error terms for the ex-ante and ex-post metric effectiveness are in Simulation Table 6.

Simulation Table 6. True value and posterior mean and standard deviation of the ex-ante SD(ζ) and ex-post random SD(η) error standard deviations.

	Ex-Ante			Ex-Post		
	True	Posterior		True	Posterior	
Variable	SD(ζ)	Mean	STD DEV	SD(η)	Mean	STD DEV
M01	1	1.010	0.062	0.249	0.224	0.102
M02	1	1.010	0.088	0.258	0.224	0.080
M03	1	1.272	0.094	0.316	0.243	0.101
M04	1	1.143	0.102	0.218	0.230	0.102
M05	1	0.944	0.074	0.258	0.256	0.115
M06	1	0.823	0.065	0.267	0.294	0.148
M07	1	1.117	0.082	0.285	0.364	0.127
M08	1	1.099	0.144	0.249	0.248	0.096
M09	1	0.875	0.087	0.258	0.301	0.104
M10	1	1.241	0.097	0.249	0.305	0.131

The error terms for the performance equation and the latent metric utilities are correlated. The latent metric utilities have multivariate probit models that fix the error variance to one. However, they are correlated with each other and the performance equation. Simulation Table 7 presents the true values and their Bayes estimates.

Simulation Table 7. True values and posterior mean of the covariance for the error terms in the performance equation Y and the latent metric utilities. The true values are in the lower diagonal, and the posterior means are in the upper diagonal.

Σ	Y	M01	M02	M03	M04	M05	M06	M07	M08	M09	M10
Y	4 / 3.979	1.028	0.938	0.969	0.888	0.814	0.890	1.100	1.138	1.017	0.680
M01	1	1.000	0.768	0.648	0.430	0.445	0.246	0.111	-0.023	-0.152	-0.305
M02	1	0.700	1.000	0.808	0.668	0.486	0.114	0.210	0.027	-0.031	-0.083
M03	1	0.490	0.700	1.000	0.818	0.682	0.357	0.416	0.288	0.072	-0.005
M04	1	0.343	0.490	0.700	1.000	0.718	0.441	0.567	0.434	0.243	0.191
M05	1	0.240	0.343	0.490	0.700	1.000	0.694	0.506	0.487	0.011	-0.075
M06	1	0.168	0.240	0.343	0.490	0.700	1.000	0.605	0.662	0.196	-0.030
M07	1	0.118	0.168	0.240	0.343	0.490	0.700	1.000	0.809	0.645	0.494
M08	1	0.082	0.118	0.168	0.240	0.343	0.490	0.700	1.000	0.628	0.496
M09	1	0.058	0.082	0.118	0.168	0.240	0.343	0.490	0.700	1.000	0.750
M10	1	0.040	0.058	0.082	0.118	0.168	0.240	0.343	0.490	0.700	1.000

Web Appendix I. Survey Data Quality

To assess the quality of our survey data, first, we compute reliability for our measures based on Cronbach coefficient alphas scores (all > .7 except for three of our covariates [market turbulence is .63, market growth is .66, managerial experience is .68]). Second, analyses of the data shows no indication of multicollinearity based on variance inflation factor scores well below 6 (Hair, Anderson, Tatham, & Black, 1998) and over 99% of pairwise correlation coefficients are less than .40 (e.g., Leeflang, Wittink, Wedel, & Naert, 2000). Third, 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, MacKenzie, Lee, & Podsakoff, 2003). Fourth, 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. Fifth, in 26% (333 of 1,287) of the decisions, managers reported employing three or fewer 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 number of metrics. Sixth, the average marketing-mix performance score had a mean of 4.9 and 75% of the decisions were rated less than 5.8 out of 7.0, which provides evidence against ego self-preservation, demand effects, or a reluctance by managers to report marketing-mix decisions with poorer performance.

Web Appendix J. Details on Model Comparisons

A valid concern is the necessity of our proposed model, which controls for endogeneity and heterogeneity. Fit statistics are unreliable indicators for endogeneity because models that ignore endogeneity will have better fit statistics. For example, ordinary least squares (OLS) regression minimized squared error loss by definition, while two-stage least squares (2SLS) that corrects for endogeneity does not minimize OLS but provides unbiased estimates. In our analysis, the non-zero correlations between the error terms of the performance equation and the error terms of the latent use utilities indicate selection bias, while the error variances for the hierarchical model of ex-ante and ex-post metric effectiveness indicates variation across managers in their beliefs about metric effectiveness. These estimates indicate the need for the full model. However, we display various reduced-form models for completeness.

To illustrate the impact of ignoring selection effects and heterogeneity, Web Appendix Table 7 reports the average metric effectiveness for our full model with reduced versions of the model that ignore endogeneity or heterogeneity. The coefficients for the full model, which is hierarchical and has intercept and slope endogeneity correction, is in column one, which is repeated from Table 4. However, note that unlike in Table 5 in the manuscript, the results are by metric, not metric-by-decision. Thus, the first column in Web Appendix Table 7 represents results by just regressing decision outcome on the binary indicators for which metric was used. As previously noted, awareness, willingness-to-recommend, and loyalty have significant, positive effects when averaged over all decision, while NPV, market share, and total customers have significant negative effects. The third model (Reduced Model 2) removes intercept endogeneity but accounts for heterogeneity by setting the covariance Σ_{YU} between performance and use to zero. The fourth model (Reduced Model 3) removes both intercept and slope endogeneity. However, we note that ignoring such endogenous selection effects tends to result in biased coefficients that underestimate the effect. The fifth and sixth models (Reduced Models 4 and 5) are homogeneous models.

Overall, across the different models, we find that the results vary considerably with and without correction for selection effects. If endogeneity were not present, we would not see changes in the parameter estimates. Further, the results demonstrate that failing to appropriately account for both heterogeneity and endogeneity leads to materially different conclusions about metric effectiveness. Consequently, if we did not model observed and unobserved heterogeneity, we would draw very different conclusions about metric effectiveness. Hence, the full model that allows for selection effects and heterogeneity is preferred to reduced models that ignore some or all of these important features.

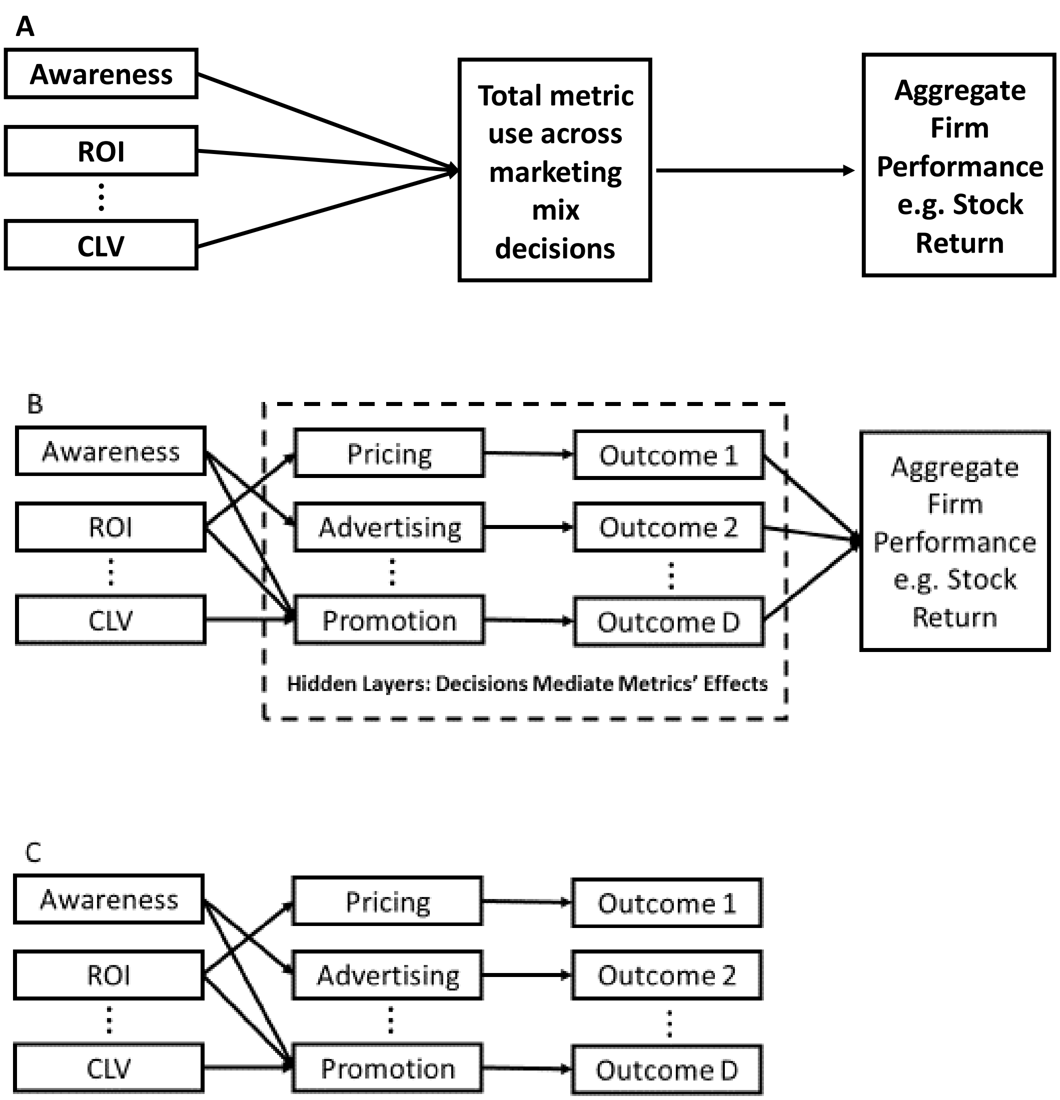
In addition, the estimated error covariances between the performance equation and the latent utility for metric use, $\sigma_y \Sigma_{YU}$ from Equation (4), indicate that metric use is endogenous in the full model. This vector captures the covariance between the performance equation (1) and the use 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.

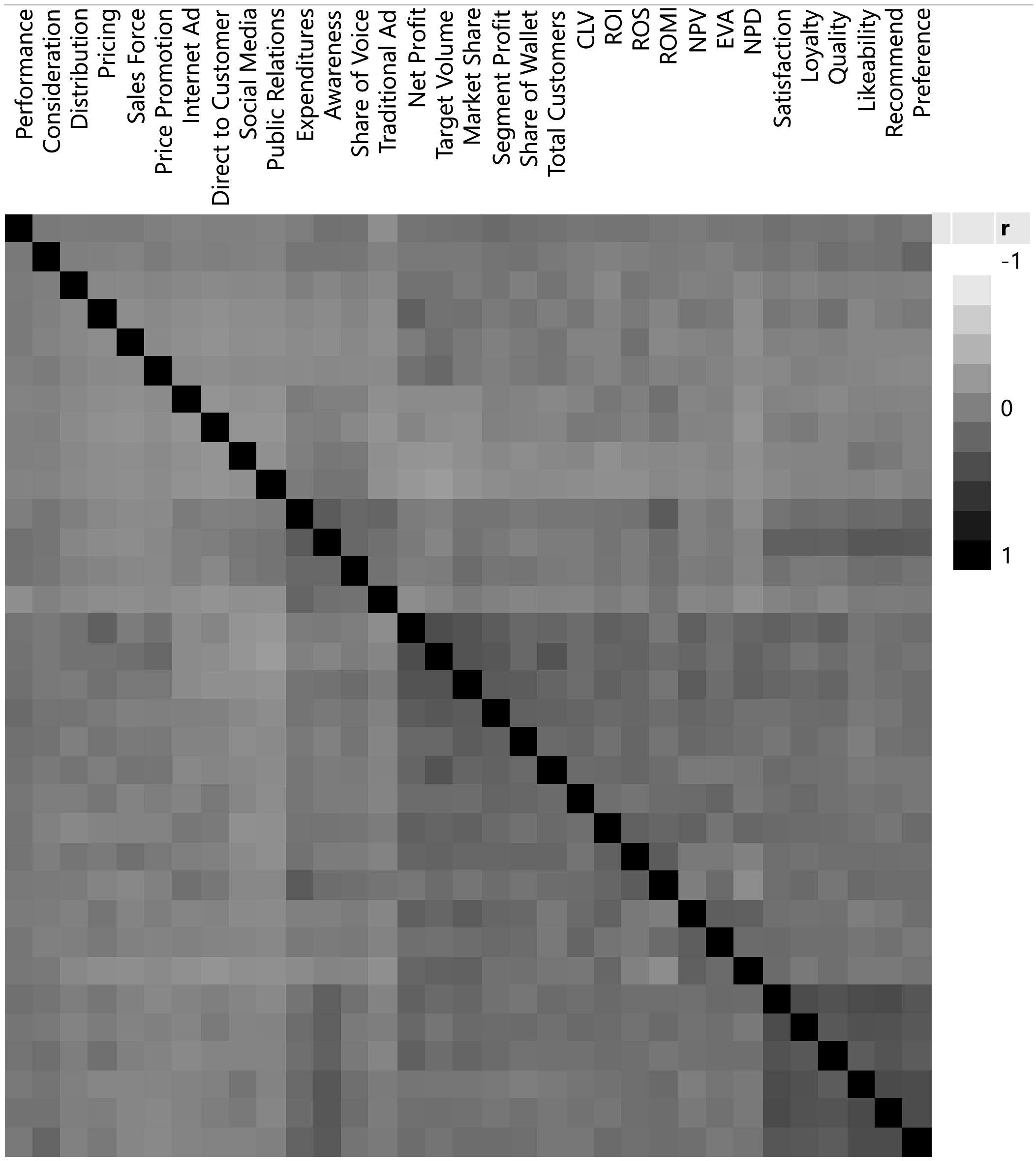
B. Individual marketing-mix decisions and their outcomes mediate the effects of metrics on aggregate firm performance.

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



Web Appendix Figure 2. **Map that Clusters the Empirical Correlations**

Point bi-serial correlations between Performance and the binary indicators, and Pearson correlations among the binary indicators.



Web Appendix 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
Le Bon and Merunka (2006)	Aggregate	No	No	No	No	No	Examines the factors which influence sales managers' contribution to market intelligence and information
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
Sridhar et al. (2017)	Aggregate	No	No	No	No	No	Examines how unreliability of metrics can affect the forecasted consequences of marketing efforts
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 & Fischer, 2016; van Doorn, Leeflang, & Tijs, 2013). Aggregate = examines total amount of metric or information use; Individual = examines individual metric use

Web Appendix Table 2. Definition of Constructs and Operational Measures

Construct Basis	Definition and Operational Measures	α	Mean	St. Dev.
Metric Effectiveness	**Definition**: a <u>latent variable</u> that measures the association between a manager using a certain metric in a specific marketing-mix decision and that decision's performance outcome **Measure**: This is the regression coefficient from regressing individual metric use (IV) onto marketing-mix decision performance (DV)	N/A	N/A	N/A
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	--- --- --- --- --- --- --- --- --- ---
Metric Use (Ambler, 2003; Ambler, Kokkinaki, & Puntoni, 2004; Barwise & Farley, 2004; Du, Kamakura, & Mela, 2007; Farris et al., 2010; Hoffman & Fodor, 2010; Lehmann & Reibstein, 2006; Pauwels et al., 2009; Srinivasan, Vanhuele, & Pauwels, 2010)	**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.* **Measures:** Please indicate if you used any of the following MARKETING or FINANCIAL metrics when making your marketing-mix decision: See Table 4 for the list of metrics.	N/A	---	---
Marketing-mix Decision Performance (Jaworski & Kohli, 1993; Moorman & Rust, 1999; Verhoef & Leeflang, 2009)	**Definition:** *The performance of a marketing-mix decisiony 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
Recent Business Performance (Jaworski & 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
Managerial Level (Finkelstein, Hambrick, & Cannella, 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,	N/A	0.58	---

	Director of Sales, Brand Manager, Marketing Manager, Product Manager, Sales Manager, Other (Please list)			
Managerial 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 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 Orientation	**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
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 • Marketing Metrics • Financial Metrics	0.94	4.45	1.68
Market Orientation (Deshpandé & Farley, 1998; Kohli & Jaworski, 1990; Verhoef & 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, Slater, & Hult, 2005; Slater & 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. ☐ *Analyzers:* These firms are seldom first-in with new products or services or first to enter emerging market segments. However, by monitoring market activity,	N/A	0.29 0.24 0.12	--- --- ---

	they can be early followers with a better targeting strategy, increased customer benefits, or lower costs. *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. *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 & 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
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 & 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	---
B2B vs. B2C (Verhoef & 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 & 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 & 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, Homburg, & Robertson, 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, Burke, & Glick, 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.* **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	0.63	4.29	1.07

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

Web Appendix Table 3. Correlation among Performance and Metric Use

	Performance	Net Profit	ROI	ROS	ROMI	NPV
Net Profit	0.097	1.000	0.250	0.214	0.070	0.257
ROI	0.091	0.250	1.000	0.242	0.197	0.231
ROS	0.102	0.214	0.242	1.000	0.281	0.060
ROMI	0.055	0.070	0.197	0.281	1.000	0.022
NPV	0.036	0.257	0.231	0.060	0.022	1.000
EVA	0.078	0.129	0.100	0.062	0.159	0.259
Expenditures	0.022	0.027	0.098	0.104	0.294	-0.007
Target Volume	0.104	0.400	0.216	0.226	0.154	0.202
Segment Profit	0.172	0.278	0.165	0.193	0.147	0.198
CLV	0.072	0.154	0.127	0.096	0.154	0.162
Market Share	0.121	0.349	0.239	0.194	0.082	0.275
Awareness	0.117	0.041	0.088	0.027	0.146	-0.003
Satisfaction	0.118	0.240	0.169	0.132	0.140	0.125
Likeability	0.061	0.082	0.109	0.133	0.176	0.022
Preference	0.057	0.147	0.161	0.119	0.144	0.127
Recommend	0.106	0.124	0.074	0.128	0.143	0.053
Loyalty	0.085	0.187	0.149	0.109	0.166	0.109
Quality	0.101	0.247	0.144	0.140	0.078	0.113
Consideration	0.050	0.053	-0.012	0.011	0.040	0.027
Total Customers	0.106	0.211	0.176	0.199	0.147	0.060
Share of Wallet	0.121	0.188	0.114	0.198	0.096	0.182
Share of Voice	0.104	0.022	0.086	0.024	0.131	0.024

Web Appendix Table 3 Continued

	EVA	Expenditures	Target Volume	Segment Profit	CLV	Market Share
Net Profit	0.129	0.027	0.400	0.278	0.154	0.349
ROI	0.100	0.098	0.216	0.165	0.127	0.239
ROS	0.062	0.104	0.226	0.193	0.096	0.194
ROMI	0.159	0.294	0.154	0.147	0.154	0.082
NPV	0.259	-0.007	0.202	0.198	0.162	0.275
EVA	1.000	0.047	0.117	0.173	0.206	0.147
Expenditures	0.047	1.000	-0.001	0.090	0.078	0.093
Target Volume	0.117	-0.001	1.000	0.318	0.153	0.346
Segment Profit	0.173	0.090	0.318	1.000	0.215	0.285
CLV	0.206	0.078	0.153	0.215	1.000	0.144
Market Share	0.147	0.093	0.346	0.285	0.144	1.000
Awareness	0.037	0.291	-0.040	0.053	0.024	0.106
Satisfaction	0.171	0.101	0.170	0.113	0.138	0.199
Likeability	0.081	0.175	0.074	0.059	0.083	0.075
Preference	0.055	0.220	0.091	0.144	0.065	0.146
Recommend	0.112	0.161	0.128	0.074	0.103	0.115
Loyalty	0.129	0.145	0.082	0.152	0.178	0.166
Quality	0.131	0.141	0.144	0.161	0.117	0.206
Consideration	-0.002	0.084	0.053	0.098	0.022	0.053
Total Customers	0.048	0.075	0.346	0.231	0.160	0.207
Share of Wallet	0.150	0.052	0.184	0.243	0.193	0.275
Share of Voice	0.051	0.184	0.024	0.082	0.027	0.155

Web Appendix Table 3 Continued

	Awareness	Satisfaction	Likeability	Preference	Recommend	Loyalty
Net Profit	0.041	0.240	0.082	0.147	0.124	0.187
ROI	0.088	0.169	0.109	0.161	0.074	0.149
ROS	0.027	0.132	0.133	0.119	0.128	0.109
ROMI	0.146	0.140	0.176	0.144	0.143	0.166
NPV	-0.003	0.125	0.022	0.127	0.053	0.109
EVA	0.037	0.171	0.081	0.055	0.112	0.129
Expenditures	0.291	0.101	0.175	0.220	0.161	0.145
Target Volume	-0.040	0.170	0.074	0.091	0.128	0.082
Segment Profit	0.053	0.113	0.059	0.144	0.074	0.152
CLV	0.024	0.138	0.083	0.065	0.103	0.178
Market Share	0.106	0.199	0.075	0.146	0.115	0.166
Awareness	1.000	0.244	0.319	0.301	0.321	0.255
Satisfaction	0.244	1.000	0.414	0.335	0.419	0.415
Likeability	0.319	0.414	1.000	0.407	0.420	0.368
Preference	0.301	0.335	0.407	1.000	0.403	0.312
Recommend	0.321	0.419	0.420	0.403	1.000	0.361
Loyalty	0.255	0.415	0.368	0.312	0.361	1.000
Quality	0.237	0.359	0.280	0.278	0.338	0.309
Consideration	0.085	0.089	0.093	0.219	0.109	0.059
Total Customers	0.026	0.162	0.046	0.068	0.070	0.123
Share of Wallet	-0.013	0.074	0.009	0.140	0.111	0.162
Share of Voice	0.186	0.112	0.133	0.095	0.147	0.042

Web Appendix Table 3 Continued

	Quality	Consideration	Total Customers	Share of Wallet	Share of Voice
Net Profit	0.247	0.053	0.211	0.188	0.022
ROI	0.144	-0.012	0.176	0.114	0.086
ROS	0.140	0.011	0.199	0.198	0.024
ROMI	0.078	0.040	0.147	0.096	0.131
NPV	0.113	0.027	0.060	0.182	0.024
EVA	0.131	-0.002	0.048	0.150	0.051
Expenditures	0.141	0.084	0.075	0.052	0.184
Target Volume	0.144	0.053	0.346	0.184	0.024
Segment Profit	0.161	0.098	0.231	0.243	0.082
CLV	0.117	0.022	0.160	0.193	0.027
Market Share	0.206	0.053	0.207	0.275	0.155
Awareness	0.237	0.085	0.026	-0.013	0.186
Satisfaction	0.359	0.089	0.162	0.074	0.112
Likeability	0.280	0.093	0.046	0.009	0.133
Preference	0.278	0.219	0.068	0.140	0.095
Recommend	0.338	0.109	0.070	0.111	0.147
Loyalty	0.309	0.059	0.123	0.162	0.042
Quality	1.000	0.137	0.111	0.107	0.059
Consideration	0.137	1.000	0.052	0.103	0.072
Total Customers	0.111	0.052	1.000	0.177	0.046
Share of Wallet	0.107	0.103	0.177	1.000	0.098
Share of Voice	0.059	0.072	0.046	0.098	1.000

Web Appendix Table 4. 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 4 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 5. 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 5 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 6: Error Covariances for Performance and Metric Utility

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

	Performance	Net Profit	ROI	ROS	ROMI	NPV	EVA	Marketing Expenditures	Target Volume	Segment Profitability	CLV	Market Share
Performance	***2.133***	-0.083	0.021	-0.057	-0.295	-0.125	-0.287	***-0.454***	0.192	-0.049	-0.106	-0.170
Net Profit	-0.083	***1.000***	***0.543***	***0.331***	***0.461***	***0.571***	***0.690***	***0.373***	***0.577***	***0.587***	***0.313***	***0.364***
ROI	0.021	***0.543***	***1.000***	***0.516***	***0.621***	***0.682***	***0.668***	0.211	***0.374***	***0.253***	***0.292***	***0.368***
ROS	-0.057	***0.331***	***0.516***	***1.000***	***0.539***	0.253	0.357	***0.357***	***0.326***	0.164	-0.116	***0.319***
ROMI	-0.295	***0.461***	***0.621***	***0.539***	***1.000***	***0.500***	***0.646***	***0.598***	***0.379***	***0.298***	0.231	0.243
NPV	-0.125	***0.571***	***0.682***	0.253	***0.500***	***1.000***	***0.700***	***0.403***	***0.338***	***0.518***	***0.618***	***0.380***
EVA	-0.287	***0.690***	***0.668***	0.357	***0.646***	***0.700***	***1.000***	0.414	***0.497***	***0.479***	***0.418***	***0.360***
Marketing Expenditures	***-0.454***	***0.373***	0.211	***0.357***	***0.598***	***0.403***	0.414	***1.000***	0.129	***0.426***	***0.428***	***0.381***
Target Volume	0.192	***0.577***	***0.374***	***0.326***	***0.379***	***0.338***	***0.497***	0.129	***1.000***	***0.601***	0.206	***0.473***
Segment Profitability	-0.049	***0.587***	***0.253***	0.164	***0.298***	***0.518***	***0.479***	***0.426***	***0.601***	***1.000***	***0.582***	***0.595***
CLV	-0.106	***0.313***	***0.292***	-0.116	0.231	***0.618***	***0.418***	***0.428***	0.206	***0.582***	***1.000***	***0.403***
Market Share	-0.170	***0.364***	***0.368***	***0.319***	0.243	***0.380***	***0.360***	***0.381***	***0.473***	***0.595***	***0.403***	***1.000***
Awareness	***-0.993***	***0.362***	***0.270***	0.174	***0.473***	0.334	***0.438***	***0.506***	0.173	***0.245***	0.131	***0.415***
Satisfaction	***-0.820***	***0.470***	***0.403***	***0.299***	***0.587***	0.298	***0.575***	***0.429***	***0.345***	***0.294***	0.260	***0.341***
Likeability	***-0.884***	***0.440***	***0.407***	***0.372***	***0.597***	0.399	***0.616***	***0.421***	***0.336***	***0.320***	0.248	***0.268***
Preference	***-0.788***	***0.495***	***0.432***	***0.424***	***0.605***	***0.579***	***0.561***	***0.651***	***0.299***	***0.522***	***0.400***	***0.415***
Recommend	***-0.880***	***0.444***	0.193	***0.350***	***0.424***	***0.352***	***0.517***	***0.558***	***0.419***	***0.471***	***0.301***	***0.423***
Loyalty	***-0.730***	***0.476***	***0.336***	0.237	***0.600***	***0.334***	***0.580***	***0.589***	***0.252***	***0.494***	***0.375***	***0.353***
Quality	***-0.652***	***0.514***	***0.419***	***0.456***	***0.434***	***0.360***	***0.499***	***0.589***	0.219	***0.391***	***0.326***	***0.593***
Consideration	-0.304	0.099	0.036	0.000	0.174	0.388	0.142	***0.592***	-0.004	0.375	***0.562***	0.369
Total Customers	0.183	***0.316***	***0.248***	0.033	***0.348***	0.149	***0.316***	***0.309***	***0.422***	***0.302***	***0.365***	***0.367***
Share of Wallet	-0.219	***0.396***	***0.317***	0.018	0.295	***0.690***	***0.540***	***0.522***	0.216	***0.572***	***0.793***	***0.359***
Share of Voice	-0.267	0.326	0.336	-0.143	0.245	***0.581***	***0.492***	0.258	***0.333***	***0.347***	0.583	***0.417***

Web Appendix Table 6 Continued.

	Awareness	Satisfaction	Likeability	Preference	Recommend	Loyalty	Quality	Consideration	Total Customers	Share of Wallet	Share of Voice
Performance	***-0.993***	***-0.820***	***-0.884***	***-0.788***	***-0.880***	***-0.730***	***-0.652***	-0.304	0.183	-0.219	-0.267
Net Profit	***0.362***	***0.470***	***0.440***	***0.495***	***0.444***	***0.476***	***0.514***	0.099	***0.316***	***0.396***	0.326
ROI	***0.270***	***0.403***	***0.407***	***0.432***	0.193	***0.336***	***0.419***	0.036	***0.248***	***0.317***	0.336
ROS	0.174	***0.299***	***0.372***	***0.424***	***0.350***	0.237	***0.456***	0.000	0.033	0.018	-0.143
ROMI	***0.473***	***0.587***	***0.597***	***0.605***	***0.424***	***0.600***	***0.434***	0.174	***0.348***	0.295	0.245
NPV	0.334	0.298	0.399	***0.579***	***0.352***	***0.334***	***0.360***	0.388	0.149	***0.690***	***0.581***
EVA	***0.438***	***0.575***	***0.616***	***0.561***	***0.517***	***0.580***	***0.499***	0.142	***0.316***	***0.540***	***0.492***
Marketing Expenditures	***0.506***	***0.429***	***0.421***	***0.651***	***0.558***	***0.589***	***0.589***	***0.592***	***0.309***	***0.522***	0.258
Target Volume	0.173	***0.345***	***0.336***	***0.299***	***0.419***	***0.252***	0.219	-0.004	***0.422***	0.216	***0.333***
Segment Profitability	***0.245***	***0.294***	***0.320***	***0.522***	***0.471***	***0.494***	***0.391***	0.375	***0.302***	***0.572***	***0.347***
CLV	0.131	0.260	0.248	***0.400***	***0.301***	***0.375***	***0.326***	***0.562***	***0.365***	***0.793***	0.583
Market Share	***0.415***	***0.341***	***0.268***	***0.415***	***0.423***	***0.353***	***0.593***	0.369	***0.367***	***0.359***	***0.417***
Awareness	***1.000***	***0.599***	***0.636***	***0.647***	***0.609***	***0.570***	***0.540***	0.272	0.085	0.225	***0.407***
Satisfaction	***0.599***	***1.000***	***0.791***	***0.657***	***0.683***	***0.766***	***0.672***	0.139	***0.392***	0.253	***0.316***
Likeability	***0.636***	***0.791***	***1.000***	***0.713***	***0.728***	***0.704***	***0.563***	0.138	0.094	0.274	0.315
Preference	***0.647***	***0.657***	***0.713***	***1.000***	***0.737***	***0.651***	***0.641***	0.488	0.144	***0.510***	***0.347***
Recommend	***0.609***	***0.683***	***0.728***	***0.737***	***1.000***	***0.633***	***0.678***	0.370	0.160	***0.468***	***0.351***
Loyalty	***0.570***	***0.766***	***0.704***	***0.651***	***0.633***	***1.000***	***0.621***	0.202	***0.345***	***0.417***	0.205
Quality	***0.540***	***0.672***	***0.563***	***0.641***	***0.678***	***0.621***	***1.000***	0.381	***0.332***	***0.390***	0.246
Consideration	0.272	0.139	0.138	0.488	0.370	0.202	0.381	***1.000***	0.183	0.580	0.402
Total Customers	0.085	***0.392***	0.094	0.144	0.160	***0.345***	***0.332***	0.183	***1.000***	***0.275***	***0.309***
Share of Wallet	0.225	0.253	0.274	***0.510***	***0.468***	***0.417***	***0.390***	0.580	***0.275***	***1.000***	***0.570***
Share of Voice	***0.407***	***0.316***	0.315	***0.347***	***0.351***	0.205	0.246	0.402	***0.309***	***0.570***	***1.000***

Web Appendix Table 7. Model Comparison of Posterior Means for Metric Effectiveness when Averaged across Decisions

Model/Components	**Full**	**Reduced 1**	**Reduced 2**	**Reduced 3**	**Reduced 4**	**Reduced 5**
Hierarchical	Yes	Yes	Yes	Yes	No	No
Intercept Endogeneity	Yes	Yes	No	No	Yes	No
Slope Endogeneity	Yes	No	Yes	No	Yes	No
Metrics						
Net Profit	-0.40	0.19	-0.07	0.20	0.07	0.00
ROI	-0.11	0.15	0.05	0.30	0.71	0.04
ROS	-0.13	0.11	0.27	-0.12	0.35	0.09
ROMI	-0.32	-0.10	-0.20	-0.17	-0.09	0.02
NPV	***-0.91***	-0.18	-0.35	0.44	-0.31	-0.21
EVA	0.51	0.43	0.31	-0.29	-0.24	0.05
Expenditures	0.11	0.24	0.14	***0.40***	***-0.69***	***-0.17***
Target Volume	***-0.45***	-0.18	-0.21	-0.04	***0.81***	0.09
Segment Profit	0.15	0.17	0.19	-0.28	***0.51***	***0.28***
CLV	-0.28	-0.04	-0.27	0.02	0.01	0.10
Market Share	***-0.40***	-0.09	-0.15	-0.08	-0.31	0.00
Awareness	***1.05***	-0.07	-0.09	-0.02	***-0.71***	***0.13***
Satisfaction	0.44	0.30	-0.23	0.24	-0.31	0.10
Likeability	-0.01	***-0.48***	***-0.71***	***-0.39***	-0.28	-0.03
Preference	0.27	-0.22	-0.03	-0.04	-0.37	-0.08
Recommend	***0.86***	***0.34***	0.35	0.32	-0.41	0.07
Loyalty	***0.77***	0.03	0.25	-0.09	-0.13	0.01
Quality	-0.13	-0.13	-0.19	-0.09	0.14	0.06
Consideration	0.43	0.90	***-0.80***	-0.42	0.09	0.08
Total Customers	***-0.47***	0.15	-0.09	0.03	***0.76***	0.05
Share of Wallet	0.12	0.38	-0.25	0.12	-0.09	0.18
Share of Voice	0.21	***-0.99***	-0.04	***0.77***	-0.41	***0.27***

Bolded, italicized numbers indicate significant coefficient where 97.5% of the posterior distribution is either above or below zero.

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