International Journal of Research in Marketing 38 (2021) 32–49

Contents lists available at ScienceDirect

IJRM
International Journal of Research in Marketing

journal homepage: www.elsevier.com/locate/ijresmar

Full Length Article

The right metrics for marketing-mix decisions☆

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ARTICLE INFO

Article history:
First received on March 3, 2019 and was under review for 8 months
Available online 20 August 2020

Area Editor: Arvind Rangaswamy

Keywords:
Managerial decision-making
Metric effectiveness
Endogenous regression
Hierarchical Bayes
Rational expectations

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 1287 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.

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 et al., 2010), accountability (Rust et al., 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

☆ The authors thank the UCI Paul Merage School of Business Dean's Office for financial support and seminar participants at the AMA ART Forum, Hebrew University, HEC Paris, Technion – Israel Institute of Technology, Tulane University, and University of Alabama for their useful feedback. The authors dedicate this article to the late Tim Gilbride, their co-author and friend who is sincerely missed.

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https://doi.org/10.1016/j.ijresmar.2020.08.003
0167-8116/

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 et al., 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., Institute for the Study of Business Markets B-to-B Marketing Trends, 2008, 2010, 2012; Marketing Science Institute Research Priorities, 2000, 2002, 2004, 2006, 2008, 2010, 2012, 2014, 2016, 2018) 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 et al., 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 1287 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, industry, and marketing-mix decision setting. For example, using Ailawadi et al. (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

[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.

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.

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 Fig. 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

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

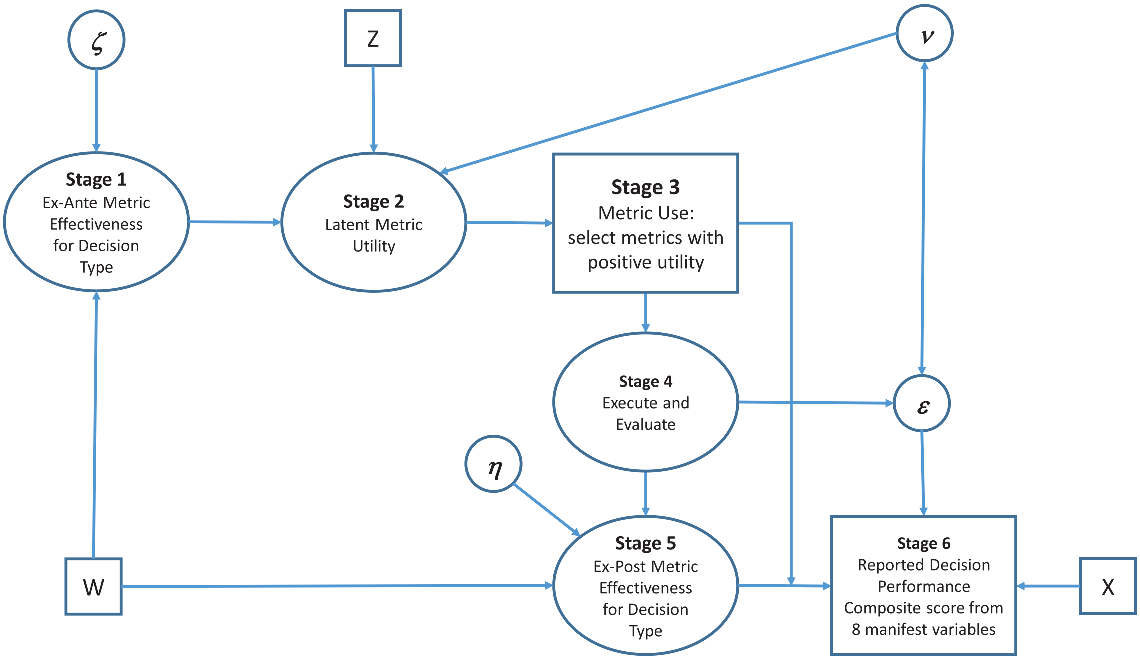

Fig. 1. Conceptual model for metric effectiveness and use and decision performance. Notes: 1. Rectangles are observed variables, and ovals are latent variables. 2. The reported decision performance is a composite score based on eight survey items. We represent these manifest variables with one rectangle 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.

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

Table 1
Manager, Firm, industry, and decision characteristics employed in models.

Model variables	Model for			Theory/justification (source(s))
	Performance (y) (Eq. (7))	Metric use (m) (Eq. (2))	Metric effectiveness (θ) (Eqs. (1) & (6))	
Individual metric use	x			Decision making theory (Abramson et al., 2005; Jaworski, 1988; Menon et al., 1999)
Recent business performance	x	z	w	State dependence/resource based theory (Wernerfelt, 1984)
Managerial characteristics • Top vs. mid-level manager • Marketing functional area • Managerial experience • Quantitative orientation • Metric-based compensation • Metric-based training		z	w	Decision maker's perspective/self-efficacy theory (Curren et al., 1992; Perkins & Rao, 1990)
Firm characteristics • 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)
Industry characteristics • Product life cycle • Industry concentration • Market growth • Market turbulence		z	w	Contingency theory (Donaldson, 2001)
Marketing-mix decision • Traditional advertising • Digital advertising • Direct to consumer • Social media • Price promotions • Pricing • New product development • Sales force • Distribution • PR/sponsorships			w	Value chain theory (Lehmann & 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 Fig. 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	$y_{id} = \sum_{k=1}^{K} m_{idk}\theta_{idk} + \boldsymbol{x}'_i\boldsymbol{\beta} + \varepsilon_{id}$	(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.
This table employs some notation on variables defined in Table 1.

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 Fig. 1. Slope endogeneity (Manchanda et al., 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 Fig. 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 Eq. (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:

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

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:

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

where ρ_k is a positive scale factor for ex-ante metric effectiveness, $\boldsymbol{z}_i$ is exogenous, decision context covariates (Table 1) with regression coefficients $\boldsymbol{\delta}_k$, which includes the intercept, and $\{\nu_{idk}\}$ is 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 et al., 2017). Then the scale factor ρ_k would be less than one and down-weight ex-ante metric effectiveness.

By substituting Eq. (1) into Eq. (2), we obtain the reduced form of the metric use utility:

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

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:

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

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 (Eq. (2)) result 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 Eq. (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, $\tilde{\theta}_{idk}$:

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

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 has 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 posit 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 assume that the ex-ante and ex-post expectations in Eqs. (1) and (5) are equal, so ex-post metric effectiveness becomes:

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

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:

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

where m_{idk} is the observed indicator of metric use (e.g., whether ROMI was or not used) from Eq. (4), θ_{idk} is the ex-post metric effectiveness in Eq. (6), $\boldsymbol{x}_i$ is 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 (Eq. (2)) and are independent of the ex-ante and ex-post effectiveness (Eqs. (1) and (6)). The full correlation matrix Σ and covariance matrix Ξ for the random shocks ε_{id} for latent metric utility and $\boldsymbol{\nu}_{id}$ for decision performance rating (Eqs. (2) and (7)) are:

$$\boldsymbol{\Sigma} = \begin{bmatrix} 1 & \boldsymbol{\Sigma}_{YU} \\ \boldsymbol{\Sigma}_{UY} & \boldsymbol{\Sigma}_U \end{bmatrix} \text{ and } \Xi = \begin{bmatrix} \sigma_Y^2 & \sigma_Y\boldsymbol{\Sigma}_{YU} \\ \sigma_Y\boldsymbol{\Sigma}_{UY} & \boldsymbol{\Sigma}_U \end{bmatrix} \tag{8}$$

where $\boldsymbol{\Sigma}_U$ is the K × K correlation matrix of the error terms for latent metric utility in Eq. (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, $\boldsymbol{\Sigma}_{YU} = \boldsymbol{\Sigma}_{UY}'$, and σ_Y is the error standard deviation for the performance Eq. (7). In our study, Σ and Ξ are 23 × 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 et al. (2012).

Slope endogeneity occurs because metric effectiveness determines both metric use (Eqs. (2) and (4)) and the performance rating (Eq. (7)). The presence of ex-ante metric effectiveness in Eq. (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 Eqs. (1) and (6), $\boldsymbol{z}$ in Eq. (2), and $\boldsymbol{x}$ in Eq. (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 Eq. (8), which use the prior of Barnard et al. (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 1287 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.

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

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 et al., 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 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).

Fig. 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.

Fig. 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, Fig. 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, Fig. 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.

Figs. 2 and 3 support 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

[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.

Table 3
Marketing-mix decisions and metrics.

Variable	Abbreviated name
Type of marketing-mix decision	
Direct to customer	D2C
Distribution	Distribution
Internet advertisement	Internet ad
New product development	NPD
Price promotion	Price promo
Pricing	Pricing
Public relations or sponsorships	PR
Sales force	Sales force
Social media	Social media
Traditional advertisement	Traditional ad
Financial metric	
Net profit	Net profit
Return on investment	ROI
Return on sales	ROS
Return on marketing investment	ROMI
Net present value	NPV
Economic value added	EVA
Marketing expenditures (% on brand building activities)	Expenditures
Stock prices/stock returns	Stock prices/returns[a]
Tobin's Q	Tobin's Q[a]
Target volume (units or sales)	Target volume
Customer segment profitability	Segment profit
Customer lifetime value (CLV)	CLV
Marketing metric	
Market share	Market share
Awareness	Awareness
Satisfaction	Satisfactions
Likeability	Likeability
Preference	Preference
Loyalty	Loyalty
Willingness to recommend	Recommend
Perceived product quality	Quality
Consideration set	Consideration
Total customers	Total customers
Share of customer wallet	Share of wallet
Share of voice	Share of voice

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

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 Fig. 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

Fig. 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 (Eqs. (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 Fig. 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

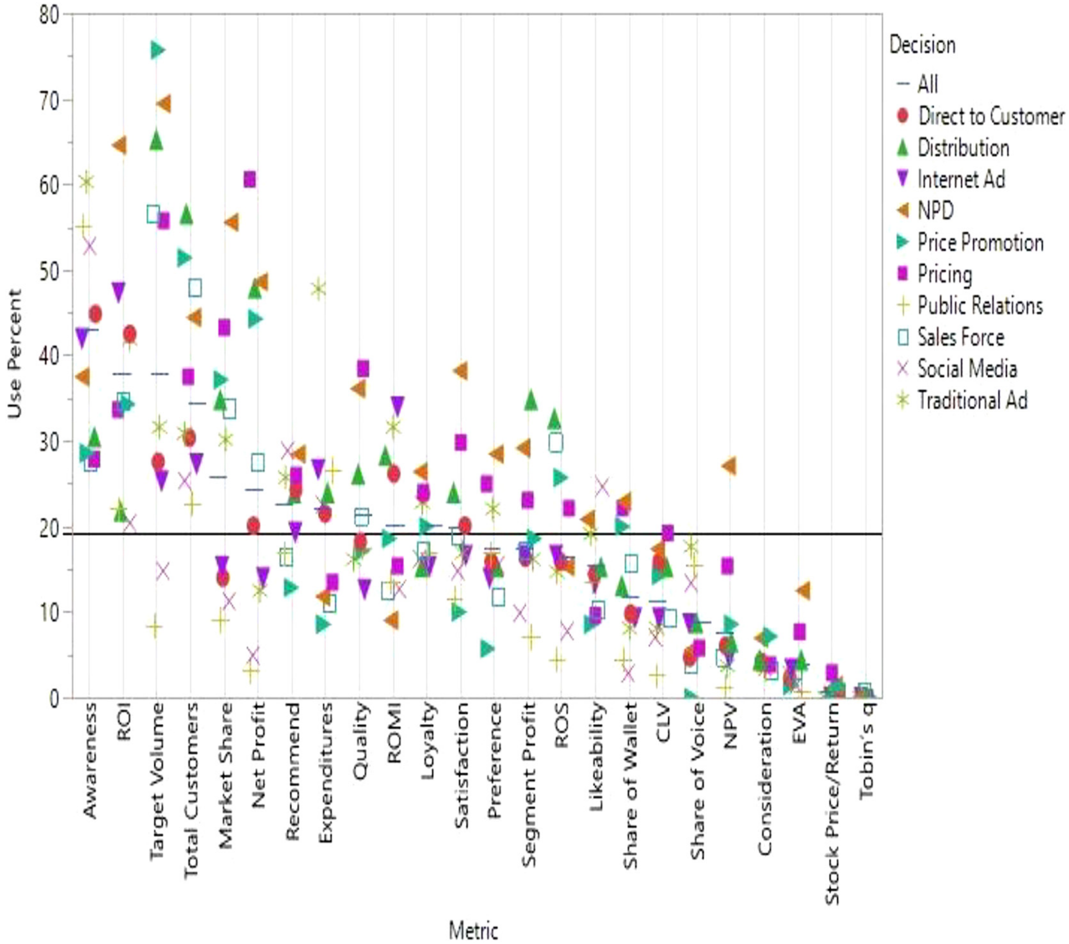

Fig. 2. Descriptive statistics of metric use by marketing-mix decision. "All" is the percent of time the metric was used for all decisions, and the metrics are ordered by "All." The percentages in this figure do not sum to 100 because each manager uses multiple metrics for each decision. The average 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.

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 (Eqs. (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.

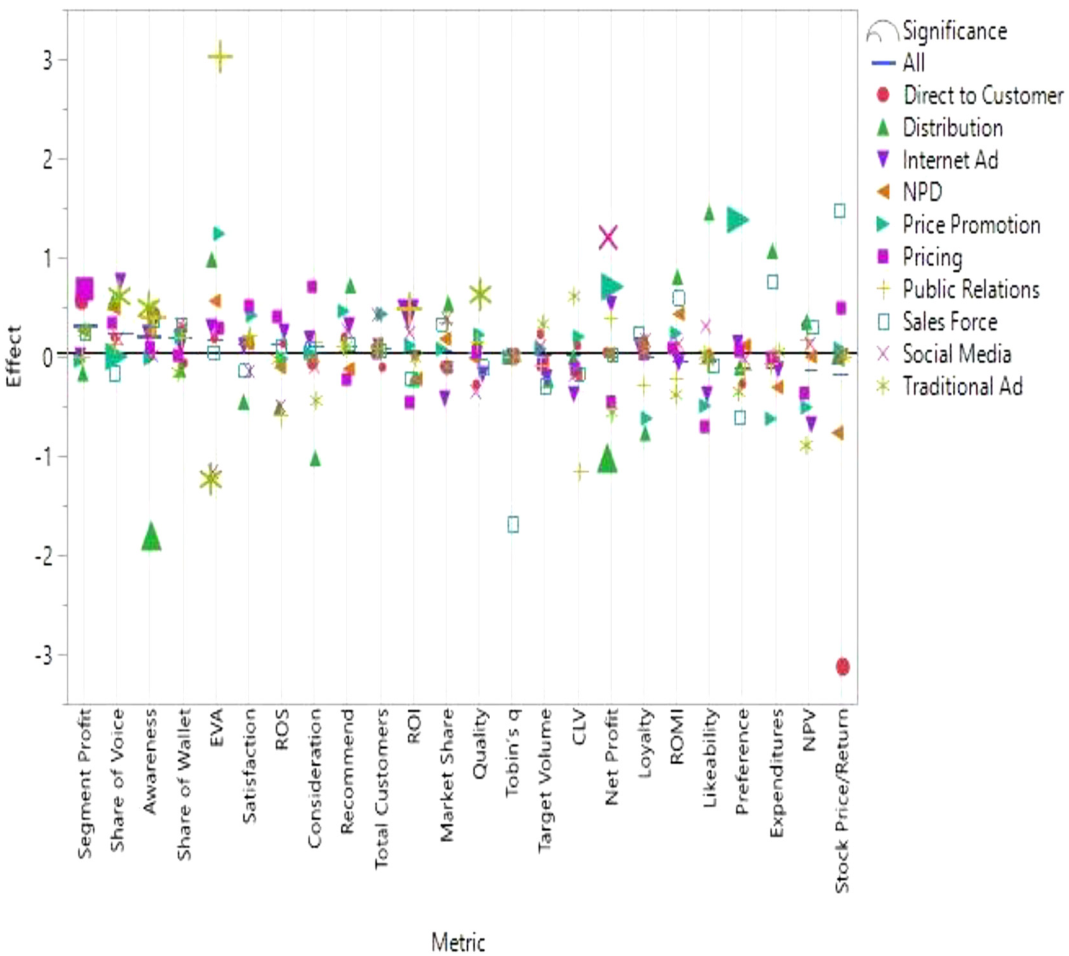

Fig. 3. Descriptive statistics of metric effectiveness by marketing-mix decision. Estimated OLS coefficients or effects from regressing the DV performance onto binary indicators (dummy variables) for metric use are shown. Each type of decision has a separate OLS regression. Symbol size is inversely proportion 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.

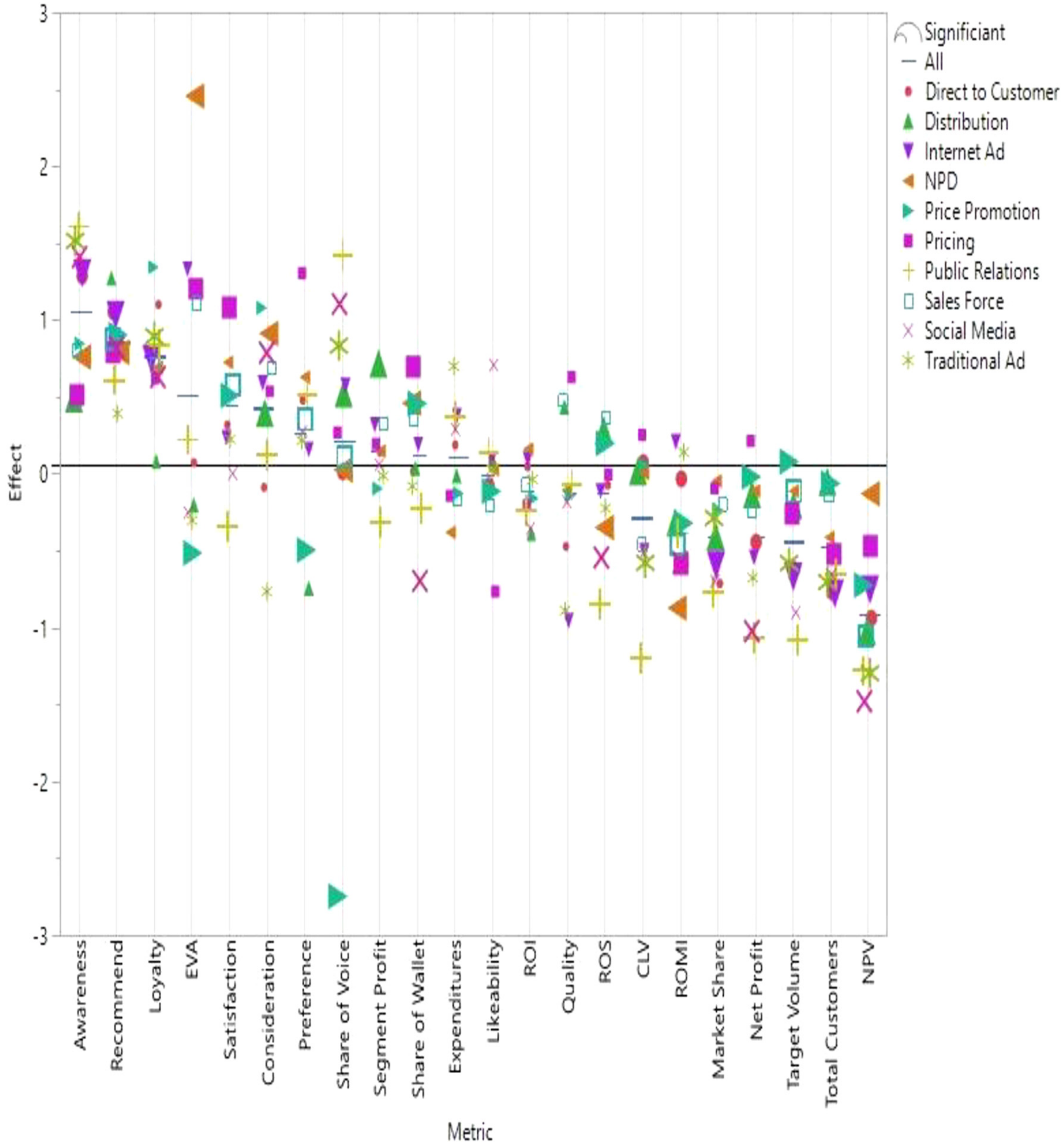

Fig. 4. Coefficients for expected metric effectiveness by decision. Notes: 1. Large symbols in indicate significant coefficients where the posterior distribution of the coefficient is above zero or below zero with probability 0.925, respectively. 2. “All” is the average of the coefficients of for a metrics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

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 Eq. (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.

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	Distribution	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)	1287 (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

5.4. Impact of ex-ante beliefs of effectiveness of metric use

In Table 5, we report the ρ_k multiplier scores from Eq. (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 determine 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 Eq. (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 Eq. (2) and the performance outcome in Eq. (7) are not zero. Eight of the 22 covariances between performance and metric utility are significantly negative. This negative correlation for these metrics implies that unobserved factors that contribute to metric use (positive random errors in metric utility, Eq. (2)) tend to reduce decision outcomes (negative random errors in performance, Eq. (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 Eq. (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 judgment 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 1287 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.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.ijresmar.2020.08.003.

References

Abramson, C., Currim, I. S., & Sarin, R. (2005). An experimental investigation of the impact of information on competitive decision making. *Management Science*, *51*(2), 195–207.

Ailawadi, K. L., Lehman, D. R., & Neslin, S. A. (2003). Revenue premium as an outcome measure of brand equity. *Journal of Marketing*, *67*(4), 1–17.

Ambler, T. (2003). *Marketing and the bottom line: The marketing metrics to pump up cash flow* (2nd ed.). London, England: FT Prentice Hall.

Bandura, A. (1982). Self-efficacy mechanism in human agency. *American Psychologist*, *37*(2), 122–147.

Barnard, J., McCulloch, R., & Meng, X. -L. (2000). Modeling covariance matrices in terms of standard deviations and correlations, with application to shrinkage. *Statistica Sinica*, *10*(4), 1281–1312.

Curren, M. T., Folkes, V. S., & Steckel, J. H. (1992). Explanations for successful and unsuccessful marketing decisions: The decision maker's perspective. *Journal of Marketing*, *56*(2), 18–31.

Donaldson, L. (2001). *The contingency theory of organizations.* Thousand Oaks, CA: Sage Publications.

Farris, P. W., Bendle, N. T., Pfeifer, P. E., & Reibstein, D. J. (2010). *Marketing metrics: The definitive guide to measuring marketing performance* (2nd ed.). Upper Saddle River, NJ: Wharton School Publishing.

Farris, P. W., Hanssens, D. M., Lenskold, J. D., & Reibstein, D. J. (2015). Marketing return on investment: Seeking clarity for concept and measurement. *Applied Marketing Analytics*, *1*(3), 267–282.

Fischer, M., & Himme, A. (2017). The financial brand value chain: How brand investments contribute to the financial health of firms. *International Journal of Research in Marketing*, *34*(1), 137–153.

Forrester (2017). AI: The next generation of marketing: Driving competitive advantage throughout the customer life cycle (a Forrester Consulting thought leadership paper commissioned by Adgorithms, Creators of Albert). Retrieved from https://albert.ai/wp-content/uploads/2017/02/AI-The-Next-Generation-Of-Marketing_Final.pdf.

Glazer, R., Steckel, J. H., & Winer, R. S. (1992). Locally rational decision making: The distracting effect of information on managerial performance. *Management Science*, *38*(2), 212–226.

Hanssens, D. M. (Ed.). (2015). *Empirical generalizations about marketing impact* (2nd ed.). Cambridge, MA: Marketing Science Institute.

Heckman, J. J. (1979). Sample selection bias as a specification error. *Econometrica*, *47*(1), 153–161.

Heckman, J. J., & Vytlacil, E. (1998). Instrumental variables methods for the correlated random coefficient model: Estimating the average rate of return to schooling when the return is correlated with schooling. *Journal of Human Resources*, *33*(4), 974–987.

HubSpot (2019). 2019 marketing statistics, trends & data — the ultimate list of digital marketing stats. Retrieved from https://www.hubspot.com/marketing-statistics.

Institute for the Study of Business Markets (2008). *B-to-B marketing trends.* University Park, PA: Institute for the Study of Business Markets.

Institute for the Study of Business Markets (2010). *B-to-B marketing trends 2010.* University Park, PA: Institute for the Study of Business Markets.

Institute for the Study of Business Markets (2012). *Insights into action: ISBM B-to-B marketing trends.* University Park, PA: Institute for the Study of Business Markets.

Jaworski, B. J. (1988). Toward a theory of marketing control: Environmental context, control types, and consequences. *Journal of Marketing*, *52*(3), 23–39.

Jaworski, B. J., & Kohli, A. K. (1993). Market orientation: Antecedents and consequences. *Journal of Marketing*, *57*(3), 53–70.

Katsikeas, C. S., Morgan, N. A., Leonidou, L. C., & Hult, G. T. M. (2016). Assessing performance outcomes in marketing. *Journal of Marketing*, *80*(2), 1–20.

Lehmann, D. R. (2004). Metrics for making marketing matter. *Journal of Marketing*, *68*(4), 73–75.

Lehmann, D. R., & Reibstein, D. J. (2006). *Marketing metrics and financial performance.* Cambridge, MA: Marketing Science Institute.

Lenk, P., & Orme, B. (2009). The value of informative priors in Bayesian inference with sparse data. *Journal of Marketing Research*, *46*(6), 832–845.

Lewis, M. (2004). *Moneyball: The art of winning an unfair game* (1st ed.). New York, NY: W. W. Norton & Company.

Li, M., & Tobias, J. L. (2011). Bayesian inference in a correlated random coefficients model: Modeling causal effect heterogeneity with an application to heterogeneous returns to schooling. *Journal of Econometrics*, *162*(2), 345–361.

Manchanda, P., Rossi, P. E., & Chintagunta, P. K. (2004). Response modeling with nonrandom marketing-mix variables. *Journal of Marketing Research*, *41*(4), 467–478.
Marketing Science Institute (2000). *2000–2002 research priorities: A guide to MSI research programs and procedures.* Cambridge, MA: Marketing Science Institute.
Marketing Science Institute (2002). *2002–2004 research priorities: A guide to MSI research programs and procedures.* Cambridge, MA: Marketing Science Institute.
Marketing Science Institute (2004). *2004–2006 research priorities: A guide to MSI research programs and procedures.* Cambridge, MA: Marketing Science Institute.
Marketing Science Institute (2006). *2006–2008 research priorities: A guide to MSI research programs and procedures.* Cambridge, MA: Marketing Science Institute.
Marketing Science Institute (2008). *2008–2010 research priorities: A guide to MSI research programs and procedures.* Cambridge, MA: Marketing Science Institute.
Marketing Science Institute (2010). *2010–2012 research priorities: A guide to MSI research programs and procedures.* Cambridge, MA: Marketing Science Institute.
Marketing Science Institute (2012). *2012–2014 research priorities: A guide to MSI research programs and procedures.* Cambridge, MA: Marketing Science Institute.
Marketing Science Institute (2014). *2014–2016 research priorities: A guide to MSI research programs and procedures.* Cambridge, MA: Marketing Science Institute.
Marketing Science Institute (2016). *2016–2018 research priorities: A guide to MSI research programs and procedures.* Cambridge, MA: Marketing Science Institute.
Marketing Science Institute (2018). *2018–2020 research priorities: A guide to MSI research programs and procedures.* Cambridge, MA: Marketing Science Institute.
Menon, A., Bharadwaj, S. G., Adidam, P. T., & Edison, S. W. (1999). Antecedents and consequences of marketing strategy making: A model and a test. *Journal of Marketing*, *63*(2), 18–40.
Mintz, O., & Currim, I. S. (2013). What drives managerial use of marketing and financial metrics and does metric use affect performance of marketing-mix activities? *Journal of Marketing*, *77*(2), 17–40.
Mintz, O., & Currim, I. S. (2015). When does metric use matter less? How firm and managerial characteristics moderate the relationship between metric use and marketing mix performance. *European Journal of Marketing*, *49*(11/12), 1809–1856.
Moorman, C., & Rust, R. T. (1999). The role of marketing. *Journal of Marketing*, *63*(4), 180–197.
Morgan, N. A., & Piercy, N. F. (1998). Interactions between marketing and quality at the SBU level: Influences and outcomes. *Journal of the Academy of Marketing Science*, *26*(3), 190–208.
O'Sullivan, D., & Abela, A. V. (2007). Marketing performance measurement ability and firm performance. *Journal of Marketing*, *71*(2), 79–93.
Perkins, W. S., & Rao, R. C. (1990). The role of experience in information use and decision making by marketing managers. *Journal of Marketing Research*, *27*(1), 1–10.
Pesaran, M. H., & Weale, M. (2006). Chapter 14: Survey expectations. In G. Elliott, C. Granger, & A. Timmermann (Eds.), *Handbook of economic forecasting. Vol. 1.* (pp. 715–776). Elsevier.
Rust, R. T., Ambler, T., Carpenter, G. S., Kumar, V., & Srivastava, R. K. (2004). Measuring marketing productivity: Current knowledge and future directions. *Journal of Marketing*, *68*(4), 76–89.
Sridhar, S., Naik, P. A., & Kelkar, A. (2017). Metrics unreliability and marketing overspending. *International Journal of Research in Marketing*, *34*(4), 761–779.
Talhouk, A., Doucet, A., & Murphy, K. (2012). Efficient Bayesian inference for multivariate probit models with sparse inverse correlation matrices. *Journal of Computational and Graphical Statistics*, *21*(3), 739–757.
Verhoef, P. C., & Leeflang, P. S. H. (2009). Understanding the marketing department's influence within the firm. *Journal of Marketing*, *73*(2), 14–37.
Wernerfelt, B. (1984). A resource-based view of the firm. *Strategic Management Journal*, *5*(2), 171–180.
Wind, J. Y. (2009). Rethinking marketing: Peter Drucker's challenge. *Journal of the Academy of Marketing Science*, *37*(1), 28–34.
Wooldridge, J. M. (2003). Further results on instrumental variables estimation of average treatment effects in the correlated random coefficient model. *Economics Letters*, *79*(2), 185–191.