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Abstract

Establishing generalized preferences for marketing performance metrics is critical for practice. However, little to no empirical work has investigated the type of performance metric that matters most to which stakeholder (i.e., marketing executives, non-marketing executives, and investors) and under which conditions (i.e., performance and uncertainty levels of metric outcomes). This research proposes a framework that incorporates three competing mechanisms on drivers of managers' marketing performance assessments. We investigate managerial relative preferences for five metric types that underlie marketing performance outcomes, and how such preferences vary based on the type of stakeholder and the uncertainty of the metric while controlling for managerial, firm, and marketing characteristics. We test our framework using a choice-based conjoint experiment involving 431 participants with near-equal representation of marketing executives, non-marketing executives, and investors. Our findings indicate that bottom-line metrics have the greatest impact on marketing performance assessments and top-line metrics have the least impact, while avoiding "certain" bottom-line losses is the greatest driver of performance assessments. An additional survey involving 130 marketing academics reveals stark differences (and some similarities) between academics' and practitioners' preferences for marketing metrics. The proposed framework and empirical results enable us to provide theory and practice-based guidance for marketing performance metric selections.

Keywords: metrics; marketing performance; marketing strategy; marketing-finance interface; conjoint analysis;

"*There can be few (if any) issues more central to the well-being of the marketing discipline than establishing the performance value of marketing*"
--- Katsikeas, Morgan, Leonidou, and Hult (*Journal of Marketing* 2016, p. 17)

A common source of managerial confusion that limits marketing's relevance to the firm exists based on what is considered as better marketing performance and what drives marketing performance assessments (e.g., Hanssens and Pauwels 2016; Moorman and Lehmann 2004; Srivastava, Shervani, and Fahey 1998). Conceptually, marketing performance is a multi-item construct comprised of several types of performance: customer mindsets (e.g., awareness, satisfaction), marketing assets (e.g., customer lifetime value [CLV], brand or customer equity), top-line impact (e.g., sales and market share), bottom-line profits (e.g., net profit, return on investment [ROI]), and capital market outcomes (e.g., market value, stock market returns) (Rust et al. 2004). However, it is not always clear how performance metrics are weighted by various stakeholders (e.g., marketing and non-marketing executives, investors) when assessing marketing campaigns. For example, consider which marketing campaign resulted in better performance for a S&P 500 listed firm?

(a) 3% increase in awareness, 1% increase in average CLV, 3% increase in sales, 1% increase in ROI, and 3% increase in market value; or,
(b) 1% increase in awareness, 3% increase in average CLV, 3% increase in sales, 3% increase in ROI, and 1% increase in market value.

To answer this question, managers and investors must make trade-offs between the metrics most important to themselves, their firm, and their marketing or investment goals; making it difficult for such stakeholders to determine whether (a) or (b) indicates better performance.

In addition, perfect correlation among marketing performance metrics does not always occur; not all metric types increase or decrease by the same extent nor result in the same positive or negative direction (Hanssens and Pauwels 2016). Indeed, Katsikeas et al. (2016) reported the average correlation between performance metrics employed in marketing academic empirical studies is only about 0.25. Variance or uncertainty also exists in performance metric outcomes (Morgan et al. 2022) due to difficulties in attribution, firm measurement capabilities, time horizons, and measurement errors (Sridhar, Naik, and Kelkar 2017). Thus, firms can rarely assess a performance metric result with complete certainty. Further, marketing campaigns have different specific goals, such as targeting for growth or profit maximization, and firms have different strategic orientations, such as focusing on costs or differentiation (Mintz and Currim 2013) that can result in idiosyncratic performance metric weightings. Marketing performance is also assessed by non-marketers and investors in addition to marketers (Srivastava, Shervani, and Fahey 1998), and these stakeholders may possess different importance metric weights than marketers (Lehmann and Reibstein 2006).

Consequently, it is no surprise practitioner-focused reports indicate managers are often unsure how to best assess their marketing performance (e.g., Gibbs 2022). However, it is a surprise that scholars have noted less academic understanding exists of what drives marketing assessments and how managers evaluate marketing performance metrics relative to each other when assessing marketing performance (e.g., Hanssens and Pauwels 2016). Thus, the Marketing Science Institute (MSI) has designated a better understanding of marketing performance metrics as a research priority in each of its biennial reports for over the last twenty-five years (MSI Research Priorities 1998-2024).

Several scholars have attempted to provide some resolve. Lehmann and Reibstein (2006), Morgan et al. (2022), Rust et al. (2004), and Srivastava, Shervani, and Fahey (1998), among others, provide theoretical frameworks for how marketing efforts *should* be assessed from a normative perspective. Empirical research on marketing metrics has examined which performance metrics managers' report to the board (Barwise and Farley 2004), use to evaluate marketing performance outcomes (e.g., Ambler 2003; Bendle et al. 2021), and employ when making marketing decisions (Mintz et al. 2021a; Mintz and Currim 2013). The empirical marketing performance assessment literature has focused on how performance measurement systems (e.g., Frösén et al. 2016; Menon et al. 1999) and individual metric use (Mintz et al. 2021b) relate with overall firm performance.[1] In addition, Katsikeas et al. (2016) conducted a comprehensive review of the marketing performance metrics used as dependent variables in academic research papers and found academics most frequently employ bottom-line and top-line metrics. Yet, a knowledge gap remains due to little research that empirically examines how managers assess marketing campaign performance outcomes (see Table 1, following references).

Our research aims to overcome this gap by developing a theoretical framework that details, and then integrates, how three underlying competing mechanisms force managers to make trade-offs in their marketing performance assessments:

(i) Performance metrics' normative value, or importance, to the firm (e.g., Lehmann and Reibstein 2006; Srivastava, Shervani, and Fahey 1998);
(ii) Performance metrics' direct responsiveness, or attributability, to the results of marketing efforts (e.g., Liberman, Trope, and Stephan 2007; Pauwels, Erguncu, and Yildirim 2013);
(iii) Performance metrics' interpretability, or understandability, to stakeholders in and out of the organization (e.g., Argote, McEvily, and Reagans 2003; Stewart 2009).

We build on a review of the marketing, managerial accounting, information systems, psychology, and statistics literatures (e.g., Henri 2006; Rust et al. 2004; Wang and Strong 1996) to consider how the type of stakeholder making the assessment impacts the weightings of the three competing mechanisms, while also controlling for the marketing decision, firm strategy, and managerial respondent. Our work further considers the aggregated outcome of the three competing frameworks when stakeholders assess performance metrics that vary with high or low uncertainty and are indicative of favorable or unfavorable performance outcomes.

We conduct a choice-based conjoint (CBC) analysis experiment of 145 marketing executives, 143 non-marketing executives, and 143 investors to overcome the empirical challenge of respondents possessing heterogenous and endogenous constraints that restrict a common availability, accuracy, and attributability of marketing performance metrics across firms. The experiment forced respondents to select the best performing campaign for a hypothetical S&P 500 firm based on the results of five experimentally altered level of performance and uncertainty metric outcomes (i.e., customer mindsets, marketing assets, top-line impact, bottom-line profits, and capital market metrics). Further, the experiment altered each hypothetical firm's marketing campaign goal and firm strategy and held the industry constant to provide respondents context for their decisions.

We find, in line with our expectations, marketing executives, non-marketing executives, and investors assessments of marketing performance are predominantly driven by the outcomes of bottom-line metrics, particularly by avoiding "certain" losses to bottom-line performance. In addition, each stakeholder group considers both the positive and negative level of performance, as well as the uncertainty of such performance when assessing marketing performance, which indicates the criticality of including the uncertainty and non-positively preforming results when academics and managers assess marketing performance. However, counter to our expectations, top-line metrics are the least impactful metrics on marketing assessments for the aggregate sample, whilst marketing executives and non-marketing executives are aligned in their relative valuations of the metrics. In addition, we find investors and marketing executives overall valuations of customer performance outcomes are similar, but the focus of those customer outcomes significantly differs as investors value marketing asset over customer mindset outcomes while marketing executives value customer mindset over marketing asset outcomes.

To help guide marketing academic performance metric selections and examine potential disconnects between practitioners and academics marketing performance assessments, we conducted a follow-up study of 130 US-based marketing academics. We find marketing academics and marketing executives possess similar performance assessments in terms of the relative value of each metric. However, academics possess significantly less acceptance of greater uncertainty in successful metric outcomes (i.e., those above expectations) than marketing executives. We also find academics differ from investors performance assessments in terms of the importance of mindset, marketing asset, and capital market metrics. Further, we find academics' performance assessments are least impacted by the results of capital market metrics, indicating a disconnect from the marketing-finance literature's encouragement for academics to employ capital market marketing outcomes as dependent variables in studies.

Taken together, our efforts assist marketing researchers and practitioners to better establish what is considered as better marketing performance, what drives marketing performance assessments, how metric outcome uncertainty impacts performance, and how such assessments differ across each stakeholder. Further, our research helps provide clarity on the relative importance of each performance metric when compared against each other. Finally, our framework and results enable the development of detailed recommendations to assist managers and academics selections of marketing performance evaluation metrics.

Conceptual Framework

Background

Marketing performance refers to the outcomes of a firm's marketing efforts (Moorman and Day 2016). To provide some theoretical clarity on the marketing performance concept and drivers of managerial assessments of marketing performance, we build on research from data quality, information systems, managerial accounting, and statistics (e.g., Henri 2006; Lipe and Salterio 2000). Those literatures reviewed various components of performance metrics and identified a metric's relevancy, interpretability, accessibility, and accuracy as the most important factors underlying its quality (Pipino, Lee, and Wang 2002; Wang and Strong 1996).

Rust et al. (2004) linked marketing efforts to performance outcomes by positing a value-chain of marketing productivity metrics. The value-chain, with each metric posited to affect the subsequent metric, begins with (i) customer mindset metrics (e.g., awareness, satisfaction, which is followed by (ii) marketing asset metrics (e.g., CLV, brand equity), (iii) top-line metrics (e.g., sales, market share), and (iv) bottom-line metrics (e.g., ROI, net profits), and concludes with (v) bottom-line metrics (e.g., stock returns, market value). Customer mindset metrics are considered as the left-side of the chain while bottom-line are consider as the right-side of the chain. Each of the five value-chain performance metric types vary in their perceived normative value to firm (e.g., relevancy), understandability to others inside and outside the firm (e.g., interpretability), attributability to specific marketing decisions (e.g., accessibility), and uncertainty in their provided results (e.g., accuracy) (Katsikeas et al. 2016). We summarize metric type differences in Table 2 and provide further details about metrics' advantages and disadvantages in Web Appendix A.

Managers assessing marketing performance typically must make trade-offs between metrics that may be strong in one of the factors (e.g., interpretability), but weak on another factor (e.g., accessibility) (Morgan et al. 2022). We next detail how understanding the trade-offs managers make between the metrics' relevancy, interpretability, accessibility, and accuracy provides a framework for understanding which metrics are valued relatively more (less) than others and how those valuations differ across stakeholders.

Three Competing Mechanisms that Drive Marketing Performance Assessments

The first proposed mechanism impacting marketing performance assessments is based on value chain theory (e.g., Rust et al. 2004) and focuses on performance metrics' normative value to the firm. Value chain theory posits that publicly listed firms' marketing efforts need to demonstrate their ultimate impact on capital market performance (Lehmann and Reibstein 2006). For example, Hanssens, Rust, and Srivastava (2009, p. 115) state in a *Journal of Marketing* editorial introducing a special issue on marketing drivers of firm value: "The ultimate goal of any marketing expenditure should be to increase the value of the firm."

Value chain theory also generally acknowledges the importance for marketing results to impact non-financial outcomes (e.g., Lehmann and Reibstein 2006), and, more specifically, to impact the outcomes of customer mindsets, marketing assets, and product-market top-line metrics (e.g., Srivastava, Shervani, and Fahey 1998). However, those non-financial outcomes are predominantly seen as enablers of marketing campaigns to reach an ultimate goal of affecting capital market outcomes (Rust et al. 2004). Thus, in terms of marketing performance metrics, *value chain theory posits that managers should consider performance metrics located further to the right on the value chain, such as capital market metrics, to be normatively more* *relevant or important to the firm than metrics located further left on the value chain, such as customer mindset metrics (see Figure 1, Panel A, following references).*

A second proposed underlying mechanism of marketing performance assessments builds on construal level theory (e.g., Liberman, Trope, and Stephan 2007), and focuses on metrics' accessibility and attributability. Construal level theory describes the importance of the psychological distance between a decision and its outcome. Distant events with intervening variables generate abstract construals focusing on broad generalizations, while immediate events that relate with direct decision outcomes elicit concrete construals focusing on the specifics of its potential outcomes (Milkman, Akinola, and Chugh 2012). Performance metrics further to the right of the value chain are typically distant outcomes from a direct marketing effort (Morgan et al. 2022). For example, Hanssens, Rust, and Srivastava (2009, p. 115) state in their aforementioned editorial: "But the road from marketing expenditure to stock price is usually circuitous. This is because marketing's path to financial impact is through revenues, and the road to revenues runs through the customer. Typically, a long chain of effects is involved to account for the impact of a marketing expenditure (Rust et al. 2004), and the effects of marketing investments play out over time." Consequently, the distance (i.e., long chain of effects) from direct marketing outcomes to performance metrics located farther to the right side of the value chain generates a greater level of abstraction, and hence, skepticism about those metrics' attribution and accessibility (Katsikeas et al. 2016).

In contrast, performance metrics located on the left of the value chain framework, such as customer mindset metrics, are more a function of the results of a specific marketing campaign, and less a function of other firm actions (Pauwels, Erguncu, and Yildirim 2013). Hence, managers generally feel directly responsible for the casualty of the results of metrics on the left side of the value chain emanating from marketing efforts (Hanssens et al. 2014). Therefore, *construal level theory posits that managers should consider results of performance metrics located further to the left of the value chain, such as customer mindset metrics, as more* *accessible and attributable due to their closer distance from the decision than metrics located further right on the value chain, such as capital market metrics (see Figure 1, Panel B, following references).*

A third proposed underlying mechanism driving marketing performance assessments builds on knowledge management theory (e.g., Tanriverdi 2005) and focuses on metrics' interpretability, or understandability. Knowledge management theory, which scholars regularly employ when examining managers' performance measurement system use (e.g., Argote, McEvily, and Reagans 2003; Henri 2006), suggests that metric information is considered more valuable when it is easily understood and transferable by relevant stakeholders both across and within organizational functions (van Veen-Dirks 2010). Knowledge management theory also posits that performance metrics with unique functional or unit-specific measures are not easily codified nor well understood across the organization, so those metrics are often disregarded for decision and performance evaluations (Lipe and Salterio 2000).

For marketing performance assessments, customer mindset and marketing asset metrics contain marketing-unique terms that may not translate across the firm, limiting their interpretability (Katsikeas et al. 2016). Further, capital market metrics are generally understood at a broad level, but managers often find those results difficult to understand and relate to marketing campaigns (Mintz and Currim 2013). Knowledge management theory also posits that metrics need to be considered as "hard," unambiguous, and as difficult as possible to argue against in order to evaluate managerial and firm behavior (e.g., van Veen-Dirks 2010). Accounting-based bottom-line performance is typically the language of the firm (Lehmann 2004), with measures such as ROI and profits widely employed and understood measures by stakeholders across the firm (Stewart 2009). Further, bottom-line accounting performance metrics are often operationalized into singular or simpler dimensions to provide a common language of measures across the firm (Wind 2008), which make those performance measures typically easy to comprehend, communicate, and justify (Farris et al. 2015). In contrast, top-line performance metrics, such as sales, do not consider the costs of conducting marketing, potentially limiting their relevance (Farris et al. 2015), and top-line metrics, such as market share, have been criticized for its lack of clarity and how it relates to financial performance (Edeling and Himme 2018). Thus, *knowledge management theory posits that managers should consider bottom-line performance metrics as more interpretable than performance metrics on the right or left side of the value chain (see Figure 1, Panel C, following references).*

Next, we note several moderators and controls of marketing performance evaluations to develop a more comprehensive framework and, subsequently, we posit hypotheses for the performance metrics most impactful to marketing performance assessments.

Moderators of Drivers of Marketing Performance Evaluation

Marketing executives, non-marketing executives, and investors possess different objectives for successful marketing campaign outcomes (Lehmann and Reibstein 2006). Thus, for each of the three stakeholder types, the prominence of the three mechanisms driving marketing performance assessments is likely to differ. Performance metrics also rarely provide managers results of marketing outcomes with complete certainty (Sridhar, Naik, and Kelkar 2017). This forces managers to evaluate metrics also based on the extent of uncertainty in those outcomes (Bendle et al. 2021). The marketing campaign goal (growth vs. profits), firm strategy (low-cost vs. differentiated), and a number of additional managerial characteristics (e.g., risk orientation, work experience, quantitative background, compensation, gender, and age) (Mintz and Currim 2013; Morgan et al. 2022) all can also impact the prominence of the three mechanisms driving marketing assessments.

Consequently, Figure 1, Panel D summarizes our proposed generalized framework of drivers of marketing performance evaluation. The framework integrates three competing mechanisms driving marketing performance assessments together (i.e., value chain, psychological distance, and knowledge management) and considers three main trade-offs managers must make when assessing marketing performance (i.e., outcomes considered most normatively relevant to the firm, outcomes considered closer in distance to marketing decisions, and outcomes most understood and translatable across the organization). The framework also considers how stakeholder type skews the prominence, or moderates, the three-mechanism effect and accounts for metric outcome uncertainty and several manager, firm, and marketing controls. Further, the framework considers how metric outcome uncertainty impacts stakeholders marketing performance assessments differently.

Hypotheses

Relative Metric Impact on Performance Evaluations

Value chain theory (the first theoretical mechanism) assumes a left to right increase in marketing performance metric importance (e.g., customer mindsets < marketing assets < top-line < bottom-line < capital market) based on metrics' normative value to the firm. Construal level psychological distance (the second theoretical mechanism) assumes a right to left increase in performance metric importance (e.g., customer mindsets > marketing assets > top-line > bottom-line > capital market) based on metrics' accessibility and attributability. Hence, value chain theory and psychological distance-based accounts of performance assessments should counter-act each other for the general case of marketing performance assessments.

In contrast, knowledge management theory (the third theoretical mechanism) posits bottom-line results as the most valued metric due to their easier interpretability and understanding across and outside the organization. Farris et al. (2015), Stewart (2009), and Wind (2008), among others, describe the managerial importance for using bottom-line metrics such as ROI and net profits to assess the financial returns of marketing efforts using well-understood, standardized, and regularly employed accounting-based measures (Katsikeas et al. 2016). Consequently, considering the three competing theoretical mechanisms, we expect:

H1: Bottom-line performance metrics will have a greater impact on marketing performance evaluations than customer mindset, marketing asset, top-line, and capital market metrics.

The stakeholder assessing the performance, i.e., whether it is a marketing executive, non-marketing executive, or investor, is likely to place different weights on the three theoretical performance assessment mechanisms (Lehmann and Reibstein 2006). Marketing executives are responsible for designing, implementing, and analyzing firm marketing campaigns (Morgan et al. 2022), making the responsiveness of metrics terms more important than for the general case. Metrics on the left side of the value chain, such as customer mindset metrics, are more directly responsive, accessible, and attributable to marketing campaigns than metrics on the right side of the value chain, such as capital market metrics (Pauwels, Erguncu, and Yildirim 2013). Thus, for marketing executives, the distance from the decision and its outcomes (the second theoretical mechanism) is likely to become a more prominent driver than in the general case. This will skew the performance metric valuation curve to the left.

In contrast, investors are far removed from marketing decisions and, thus, possess fewer concerns than marketers about managerial control of the outcomes (Srivastava, Shervani, and Fahey 1998). Further, investors fiduciary responsibility is to monitor the firm's financial performance through performance metrics on the right side of the value chain, such as market value or stock market returns, making those metrics more salient to their marketing assessments (Hanssens and Pauwels 2016). Consequently, for investors, value chain theory (the first theoretical mechanism), which focuses on marketing performance normative importance to the firm, is likely to become a more prominent driver than in the general case. This will skew the performance metric valuation curve to the right.

Non-marketing executives help devise marketing strategies (Lehmann and Reibstein 2006), communicate performance outcomes with key stakeholders in and out of the organization (Srivastava, Shervani, and Fahey 1998), and possess fiduciary responsibilities to maximize firm long-term financial performance (Edeling, Srinivasan, and Hanssens 2021). Hence, non-marketing executives are expected to possess a more equal weighting of the three mechanisms of marketing performance assessments than marketing executives or investors, resulting in a performance metric valuation curve similar to the general case noted in H1. Thus:

H2: Marketing executives marketing performance assessments are more impacted by customer mindset metric results than (a) non-marketing executives or (b) investors marketing performance assessments.

H3: Non-marketing executives marketing performance assessments are more impacted by bottom-line metric results than (a) marketing executives or (b) investors marketing performance assessments.

H4: Investors marketing performance assessments are more impacted by capital market metric results than (a) marketing or (b) non-marketing executives marketing performance assessments.

Evaluations of Uncertainty in Performance Metric Outcomes

Metrics with certain outcomes are generally considered to possess a superior quality than metrics with uncertain outcomes since they provide greater accuracy, less variance, and less risk of unknown outcomes (e.g., Shugan and Mitra 2009). However, this does not consider managers' potential for risk seeking behavior. In seminal research, Thaler and Johnson (1990) employ prospect theory to describe why decision makers become increasingly risk seeking by trying to "break-even" with higher gambles if performance below expectations were previously attained or build on their winnings by gambling with "house money" through higher risk and reward choices if performance above expectations were previously attained.

For marketing performance assessments with below expectation outcomes, the convex shape of prospect theory's loss function suggests decision makers become more risk-seeking when evaluating negative outcomes (Thaler and Johnson 1990). The below expectation outcome lowers decision makers' perceived risk of attaining greater losses since the negative outcome is already anchored (Cheng and Cryder 2018). In addition, greater accuracy and less variance in below expectation performance outcomes indicates greater certainty to attain losses, whereas lesser accuracy and greater variance in the outcomes indicates a likelihood of attaining less or no loss. Thus, marketing performance evaluators should prefer to avoid "certain losses" for each below expectation metric and instead value lesser over greater certainty in metric outcomes.

Similarly, less certainty for marketing performance with above expectation outcomes enables managers to believe their firms may have attained superior results than if metrics had greater certainty. This produces a "house-money" effect: evaluators become risk seeking when presented with positive outcomes since they have already achieved "winnings," and those winnings mitigate the effect of loss aversion in line with the concave shape of prospect theory's gain function (Jindal and Aribarg 2021). Hence, marketing evaluators are likely to prefer lesser over greater certainty for each above expectation performance metric outcome because it represents a greater chance to attain higher performance, even if less certainty also indicates a likelihood the campaign performed worse (Thaler and Johnson 1990). Thus:

H5: Stakeholders will be more likely to prefer (avoid) performance metrics with less (vs. more) certain outcomes, given the outcomes are known to result in performance that is above expectations.

H6: Stakeholders will be more likely to avoid (prefer) performance metrics with more (vs. less) certain outcomes, given the outcomes are known to result in performance that is below expectations.

When combining the previous moderators, it is expected that stakeholder type will affect how metric outcome uncertainty impacts marketing performance evaluations. The greater (lesser) the performance metrics value to stakeholders, the more (less) attention stakeholders are likely to place on the metric's uncertainty, since those performance outcomes are more (less) directly related to the stakeholder's ultimate goal (e.g., Novemsky and Dhar 2005). Hence, marketing executives are more (less) likely than investors to consider the importance of the uncertainty of metrics at the left (right) of the value chain such as customer mindset (capital market) metrics. Thus:

H7: Marketing executives will be more likely to avoid (prefer) performance metrics with more (vs. less) certain outcomes for customer-mindset metrics than (a) non-marketing executives or (b) investors.

H8: Non-marketing executives will be more likely to avoid (prefer) performance metrics with more (vs. less) certain outcomes for bottom-line metrics than (a) marketing executives or (b) investors.

H9: Investors will be more likely to avoid (prefer) performance metrics with more (vs. less) certain outcomes for capital market metrics than (a) marketing or (b) non-marketing executives.

Controlling for Characteristics of Marketing Effort, Firm, and Respondent

Prior research (e.g., Lehmann and Reibstein 2006; Mintz and Currim 2013; Morgan et al. 2022) indicates that the relative relevance of marketing performance metrics may vary based on characteristics of the marketing effort (i.e., growth or profit focused campaign), firm strategy (i.e., low-cost or differentiated strategy), and manager (i.e., risk orientation, work experience, quantitative background, compensation, gender, and age). Our integrated framework can adjust for those variations by skewing the graph in Figure 1, Panel D for each characteristic, in line with how the graph skews for the stakeholder assessing the performance.

Web Appendix Figure 1, Panel A (B) demonstrates how the framework skews more towards performance metrics at the end (beginning) of the value chain for marketing campaigns that have a maximizing profit (growth) focus and for firms with a low-cost (differentiated) firm strategy, since those campaigns and strategy focus generally attempt to attain financial (non-financial) outcomes (Mintz and Currim 2013). Further, uncertainty in metric outcomes is more likely to impact metrics at the end (beginning) of the value chain for marketing campaigns attempting to maximize profit (growth) and for firms with a low-cost (differentiated) firm strategy due to greater relevancy to those firms. However, rather than hypothesizing each marketing, firm, and respondent effect on marketing evaluations, we note their importance here and include them as control variables in our empirical test.

Empirical Test

Research Method

To empirically test our hypotheses, we need to isolate each metric's impact on marketing performance assessments. However, managers are typically constrained in their marketing assessments due to firm resources, data availability, and lengthy time-frames, among additional factors (Hanssens and Pauwels 2016). This precludes the use of secondary data or primary survey data since each may suffer from potential endogenous and heterogeneity biases emanating from unobserved marketing assessment constraints. Further, unless such data is focused on a single firm, all respondents would be unable to assess marketing performance results on a similar scale, and this would bias empirical comparisons (Morgan et al. 2022).

Therefore, we employed a choice-based conjoint (CBC) experiment that permitted an elicitation of relative preferences for marketing performance metrics across a common and experimentally controlled set of variables and outcomes. Our CBC experiment asked marketing executives, non-marketing executives, and investors which of two marketing performance outcomes performed better based on the five metrics' level of performance and uncertainty for a hypothetical S&P 500 firm, while holding the firm, marketing campaign, and industry constant. The outcome of the CBC analysis provides each metric's preference weights, enabling a quantification of the marginal impact that variation in a metric's performance and uncertainty has on performance assessments.

Choice Task and Experimental Design. Figure 2 provides an example of our choice task. Each choice option was described by the five metrics in the value chain (e.g., Lehmann and Reibstein 2006; Rust et al. 2004): (i) customer mindsets, (ii) marketing assets, (iii) top-line, (iv) bottom-line, and (v) capital market. Each metric's outcome was experimentally varied based on whether (a) its performance was above or below expectations and (b) its uncertainty was high or low. This levels-based variable approach avoids biases associated with the use of absolute or relative numbers that may indicate different levels of metric success for different respondents (e.g., Avagyan et al. 2022).

The choice tasks were constructed using an orthogonal main effects approach, simultaneously varying performance (above or below expectations) and uncertainty (high or low) in outcomes for each of the five metrics, and giving rise to a 4^5 fractional factorial design. The four-level design allowed the estimation of interactions between performance and uncertainty for each metric, as well as the respective main effects of performance and uncertainty. The second-choice option was determined by a fold-over of the first-choice option.

The resulting design consisted of 16 total choice sets. The metric presentation order (left to right; right to left) varied using a between-subjects design, but we found metric order to not significantly affect our results, so we only present the aggregated results. Pre-tests conducted on 100 undergraduate students, 60 managers at an industry conference, and 25 academics in two research workshops involving multiple universities provided inputs for the CBC questionnaire, feedback on how to best display performance and uncertainty in outcomes (e.g., arrows, lines, or bars, length and width of arrows, extent of overlap with above/below performance expectation), and tests of internal and external validity prior to obtaining our practitioner sample.

The CBC task asked respondents: "*In your expert opinion*, which of the following marketing campaigns would you rank as having the "better" performance for a large S&P 500 firm/business unit that focuses on its cost (or differentiation) advantage and growth (or profits)?" The two differentiating factors in the conjoint task description, the firm's strategic orientation, specified as cost- or differentiation-based (McAlister et al. 2016), and the firm's integrated marketing campaign, specified as either a growth or profit-focused (Lehmann and Reibstein 2006), provided context to the S&P 500 firm's marketing campaign. Each of the 2 x 2 strategic orientation and integrated marketing campaign combinations appeared four times across the 16 choice sets for any individual, so orthogonality was ensured at the aggregate level for performance level (above or below expectations) and uncertainty outcomes (low or high).

We provided respondents a list of definitions for variables in the CBC and an example of the choice task prior to partaking in the experiment (see Web Appendix B, pg. WA5). Further, every choice task provided respondents the definition of the firm's strategic orientation and marketing campaign goal to ensure decision context awareness.

Covariates. Table 3 provides covariate measures and their literature sources. The key covariate in our study is stakeholder type, which we classify in line with Lehmann and Reibstein (2006) as marketing executives (e.g., S/VP or C-level marketer), non-marketing executives (e.g., CEO, COO, CFO), and professional investors (e.g., analyst, investor, broker). Additional covariates included risk orientation, work experience, quantitative background, short versus long term compensation, gender, and age, which are considered based on the prior literature on metrics and performance evaluations (e.g., Currim, Lim, and Kim 2012; Lehmann and Reibstein 2006; Mintz and Currim 2013; Zhang, Highhouse, and Nye 2019).

Data

431 managers completed our CBC experiment: 145 marketing executives, 143 non-marketing executives, and 143 professional investors. The managers were recruited and paid for their services through *Precision Sample*, a managerial panel service. *Precision Sample* invited their panelists to participate in the CBC that fulfilled the definitions of marketing executives, non-marketing executives, and investors previously noted. Further, *Precision Sample* employed a 20-step validation process that includes a credit activity, address, and job title verifications to ensure its respondents' qualifications.[2]

Respondent data quality was checked via the use of attention checks, consistency over repeated questions, analysis for patterned responses, and minimum completion times (Mintz and Currim 2013). Further, multiple response scales (nominal, constant sum, Likert scales) were employed to lessen concerns about common method variance (Podsakoff et al. 2003). Respondents were only paid for fully-completed quality submissions (i.e., must pass the data quality checks). *Precision Sample* also employs a two-strike removal rule that prohibits panelists not passing quality checks from participating in any future paid panel, thereby motivating respondents to provide truthful answers (Mintz et al. 2021a).

We obtained an experienced sample to enable an investigation of executives' marketing performance assessments. The median respondent had six to ten years of experience working in their current position (see Table 3, following references). Roughly three-quarters (73%) of the sample has worked in their current position for over five years, with 30% of marketing executives, 45% of non-marketing executives, and 39% of investors working in their current role for more than 10 years (see Web Appendix Table 1, pg. WA9). Around two-thirds (68%) of non-marketing and marketing-executives work in firms with more than 100 full-time employees. Marketing executives had a mean risk orientation of 5.0 out of 7.0 (based on a seven-measure construct using a 7-point Likert scale; seven = more risk-seeking), a compensation scheme that is a mix of short-term bonuses and long-term equity (4.9 out of 7.0; seven = long-term equity based), and a mixture of qualitative and quantitative backgrounds (4.6 out of 7.0; seven = primarily quantitative). Each of the seven-point Likert scaled measures had standard deviations over one for each stakeholder. Thus, we obtained a diverse, acceptable mix of respondents and responses.

Statistical Model

We estimate the following conditional logit model to test our conceptual framework:

$$U_{MO_i} = \beta_0 + \sum_{m=1}^{5}[\beta_{Xm}X_{mi} + \beta_{Vm}X_{mi} + \beta_{XVm}(X_{mi} * V_{mi})] + \sum_{m=1}^{5}\big[\beta_{X\_NONm}(X_{mi} * Z_{NON}) + \beta_{V\_NONm}(V_{mi} * Z_{NON}) + \beta_{XV\_NONm}(X_{mi} * V_{mi} * Z_{NON})\big] + \sum_{m=1}^{5}\big[\beta_{X\_INVm}(X_{mi} * Z_{INV}) + \beta_{V\_INVm}(V_{mi} * Z_{INV}) + \beta_{XV\_INVm}(X_{mi} * V_{mi} * Z_{INV})\big] + \sum_{C=1}^{8}\sum_{m=1}^{5}\big[\beta_{X\_Cm}(X_{mi} * Z_C) + \beta_{V\_Cm}(V_{mi} * Z_C) + \beta_{XV\_Cm}(X_{mi} * V_{mi} * Z_C)\big] + \varepsilon$$

where U_{MOi} is the utility associated with the overall evaluation of marketing outcome i in terms of its marketing performance. The latent utility is unobserved with error (ε); instead, we estimate the model based on observing discrete choice outcomes between competing marketing outcomes. The chosen option (i.e., Y_{MOi}=1) is assumed to be observed following a respondents' judgement of utility maximization, indicating a given marketing outcome has a greater marketing performance than a competing marketing outcome option (i.e., when $U_{MOi} > U_{MOj}$), or zero otherwise (i.e., Y_{MOi}=1).

Each marketing performance outcome MO_i is described by five metric types (customer mindsets, marketing assets, top-line, bottom-line, and capital markets). Each metric type m affects performance MO_i by: (i) X_{mi}, its performance (above/below expectations), (ii) V_{mi}, its uncertainty (high/low), and (iii) $X_{mi}*V_{mi}$, the interaction between performance and uncertainty. Stakeholder type influences each metric type's effect on marketing performance assessments by interacting each of the 15 metric parameters (five X_{mi}, five V_{mi}, and five X_{mi}*V_{mi}) with two effects-coded variables, one for non-marketing executives (Z_{NON}) and one for investors (Z_{INV}). We specify marketing executives as the base-level and calculate the negative sum of coefficient estimates for the non-marketing and investor stakeholder to determine the variation of effects for each of the 15 marketing executive parameters.

Controls (specified by variables in Z_C*)* include two conjoint context variables, type of firm strategy (cost vs. differentiated) and integrated marketing campaign goal (growth vs. profits), and six subject-level variables, the respondent's risk orientation, work experience, quantitative background, compensation, gender, and age. We introduce these variables as interaction terms similarly to our stakeholder specification to examine whether variation in performance utility is significantly different on a metric dimension (e.g., performance or uncertainty) for a given metric for a given control variable. To minimize concerns about overfitting due to the interaction terms in the model, we estimated models with and without the control variables and obtained similar hypotheses results (see Web Appendix Table 2, pg. WA10).

The CBC controls for endogeneity by employing a controlled hypothetical experiment that provides respondents the context, performance, and uncertainty of the metric outcomes. Further, the CBC provides respondents a common set of metric types and those metrics availability and attributability to minimize endogenous concerns about what metrics managers have access to and can link with marketing campaign outcomes at a given time. We account for respondent observed heterogeneity through the inclusion of the noted controls and through testing models with additional controls, such as the respondent's education, firm customer focus (B2B vs. B2C), industry lifecycle stage, and market concentration, which did not impact the hypotheses results or provide significant results. Finally, as an additional method to account for unobserved heterogeneity, we estimate a mixed logit model with similar specifications to the conditional logit model, but include random parameters that allow for individual-level heterogeneity in the coefficients (e.g., Avagyan et al. 2022). We find the hypotheses tests of the mixed logit model to be similar in signs and significance levels as the conditional logit model (df = 100; p=.25 in a comparison test). Hence, for reasons of brevity, we proceed by only discussing results of the conditional logit and the reduced number of control variables.

Results

Model-Free Analysis

Figure 3 provides participants' self-reported 1-7 scaled ratings on their (i) use, (ii) importance, (iii) reliability, (iv) interpretability, and (v) compensation based on each metric.[3] Bottom-line metrics have the maximum ratings on all five dimensions across the entire sample (Panel A). Marketing and non-marketing executives' metric ratings are similar to the aggregated sample (Panel B), with the exception of non-marketing executives rating customer metrics as the most important metric and rating capital metrics as the lowest on all dimensions (Panel C). Investors differ from other stakeholders by rating top-line metrics the most used, important, reliable, and interpretable (Panel D). Taken together, the model-free evidence shows bottom-line metrics are rated highly by the entire sample, but differences in metric ratings exist by stakeholder. However, the model-free findings are based on self-reported questions that do not force respondents to make trade-offs on performance assessments or control for managerial or firm characteristics. Thus, we next provide the statistical model results.

Model-Based Analysis of Hypotheses

Table 4, Panel A provides the parameter estimates of the conditional logit model. To test H1-4, which examine the relative importance of a given metric on marketing performance evaluations, we assess the combined outcomes of metric performance (above or below expectations) and metric uncertainty (high or low) simultaneously. We first calculate each metric's marginal probability for each of the four possible outcomes (two performance outcomes x two levels of uncertainty). Then, we determine the relative importance of a metric by its range in marginal probabilities, which are normalized with respect to the sum of the range in marginal probabilities across all five metrics. This provides metric importance values that range between 0 and 100%, with higher numbers indicating a greater impact on performance assessments (Ben-Akiva and Lerman 1985). Finally, we conduct significant tests by calculating the standard errors of relative importance for each metric based on sampling 1,000 draws from a multivariate normal distribution of mean marginal probabilities and subsequent mean relative importance measures using the mean and variance covariance matrix of parameter estimates (Louviere, Hensher, and Swait 2000).

Table 4, Panel B provides the five metrics computed relative importance for the aggregated sample and for each stakeholder group. H1 posited that bottom-line metrics have the greatest impact on practitioners' marketing performance assessments. Across the sample, we find support for H1: bottom-line metrics (27.45%) have the greatest importance to marketing performance assessments, followed by capital markets (19.33%), marketing assets (17.92%), customer mindsets (17.80%), and top-line (17.50%) metrics. Further, bottom-line metrics impact on performance assessments is significantly greater than each of the four other metrics (each comparison is $p<.001$).

H2-H4 posited differences in the impact of metric types based on the stakeholder type. For each of our stakeholders, bottom-line metrics are significantly more impactful to marketing performance assessments than the other four metrics (each comparison is $p<.05$), similar to the aggregated sample. However, customer mindset metrics have a significantly greater impact on marketing executives' assessments than investors' assessments (20.95% vs. 13.26%; $p<.05$), providing support for H2b, while marketing asset metrics have a significantly greater impact on investors' assessments than marketing executives' assessments (21.49% vs. 16.51%; $p<.05$). In addition, customer mindset and marketing asset metrics impact performance assessments significantly differently for investors than for non-marketing executives (customer mindsets: 13.26% vs. 18.34%; $p<.05$; marketing assets: 21.49% vs. 17.06%; $p<.05$). Thus, we find the two customer performance metrics (mindsets and marketing assets) have a nearly similar total impact on marketing executives (37.46%) and investors (34.75%) performance assessments (p=.484), and non-marketing executives (35.4%) and investors (34.75%) performance assessments (p=.777). Yet, differences exist between investors and marketing executives, and investors and non-marketing executives, on which type of customer performance metric (mindsets or marketing assets) has the greater impact on marketing performance assessments.

In contrast, we do not find significant differences between marketing executives and non-marketing executives metric importances. Further, we do not find significant differences between the three stakeholders on the impact of bottom-line or capital market metrics. Hence, we do not find support for H2a, H3, or H4. Yet, these counter to expectation results demonstrate an important alignment between how marketing and non-marketing executives assess marketing performance and how different stakeholders value top-line, bottom-line, and capital markets.

Next, we consider the role of metric uncertainty on performance assessments. Figure 4, Panel A presents the aggregate estimated mean marginal probabilities for the four possible outcomes (two performance x two certainty levels) for each metric from the conditional logit model. Stakeholders are more likely to select above expectation marketing performance outcomes with higher uncertainty for each metric (p<.05) except for bottom-line, and not select below expectations marketing performance outcomes for each metric with higher certainty (each p<.05). Further, the condition with the largest difference from the base-choice probability (indicated by the dotted line in Figure 4) is bottom-line below expectation performance with higher certainty (i.e., less uncertainty), indicating stakeholders' selections of marketing performance outcomes are most impacted by avoiding certain bottom-line losses.

To formally test H5 and H6, which posit that stakeholders choose outcomes that have less over more certainty for above (H5) and below (H6) performance outcomes, we separately compute managers' marginal utility for metrics that have high versus low uncertainty based on whether the metric outcome occurs with above or below expectations (see Table 5, following references). The aggregated sample's estimated marginal utilities for performance above expectation outcomes are significantly higher for top-line ($p<.05$) and capital market ($p<.01$) metrics that have higher rather than lower uncertainty; providing partial support for H5. Further, the aggregate sample's marginal utilities for performance below expectation outcomes are significantly higher for all five performance metric types that have higher rather than lower uncertainty (each $p<.01$). Thus, we find support for H6 across the sample; stakeholders avoid incurring "certain" losses implied by high certainty for performance metrics below expectations.

H7-H9 posited that metric uncertainty will affect the preferences of performance metrics that are relatively more important to each stakeholder. To test H7-9, we directly compare stakeholders' above expectations and performance below expectations marginal utilities for each metric (see Table 5, following references). For the performance below expectations condition, uncertainty affects (i) marketing executives' value of customer mindset metrics more than investors (0.264 vs. 0.020; $p<.05$) and non-marketing executives (0.264 vs. 0.138; $p<.05$), and (ii) non-marketing executives' value of bottom-line metrics significantly more than marketing executives (0.738 vs. 0.458; $p<.05$) and investors (0.738 vs. 0.297; $p<.05$), but (iii) not investors value of capital market metrics more than non-marketing and marketing executives (both p=n.s.). However, for the performance above expectations condition, we find no support for any of our three expectations. Thus, we find partial support for H7-H9 where uncertainty appears to affect stakeholders' preferences of metrics that are relatively more important to them than other stakeholders for below but not above performance expectation outcomes. Indeed, for above performance expectations, non-marketing executives least value differences in uncertainty in bottom-line metrics and investors least value differences in uncertainty in capital market metrics. Hence, stakeholders appear indifferent to metric uncertainty for those valued metrics when assessing performance above expectations, but not for those valued metrics when assessing performance below metrics.

Web Appendix Table 2 provides the results of the control variables effects on marketing performance assessments. Overall, we do not find many significant control variable coefficients. Notable exceptions include practitioners exhibiting greater preferences for capital market metrics when presented with firms with a cost-focused rather than a differentiation-focused strategic orientation ($p<.05$), risk-oriented practitioners exhibiting lesser preferences for customer mindset ($p<.01$), marketing assets ($p<.01$), and bottom-line metrics ($p<.001$), and long-term compensated practitioners exhibiting lesser preferences for top-line and capital market metrics (both $p<.05$).

Robustness Tests of Alternative Model Specifications

We estimated three alternative model specifications to provide robustness tests for unique aspects of our data collection and analyses. First, since each stakeholder type may systematically differ in their responses to the CBC, we estimated a scale heterogeneity model that specifies the variance of the random component of the model to vary across non-marketing managers and investors relative to marketing executives (e.g., Swait and Louviere 1993). We find the results of this scale heterogeneity model to not significantly differ from our scale homogeneity base-model when conducting a likelihood-ratio (LR) test of the competing models (Burke and Reitzig 2007). Second, as noted in the model section, we estimated a mixed logit model to include random parameters to allow for individual-level heterogeneity in the coefficients (e.g., Avagyan et al. 2022). We find similar results in terms of coefficient mean estimates and significance levels as our original model results (see Web Appendix Table 4, pg. WA13). Third, we conducted a series of LR-tests to test our hypotheses in an alternative approach to the relative importance comparisons discussed throughout the model and empirical analysis. The LR-tests compared the changes in log-likelihood attributable to the variation in choice explained with (i.e., unrestricted model) and without (i.e., restricted model with $\beta_{Xm}=\beta_{Vm}=\beta_{XVm}=0$) a particular metric, *m*, in the model. We find results of the chi-square-based hypotheses tests, as well as comparison of AIC and BIC scores for each model, to be consistent with our original results.

Academic Sample Analysis

To inform marketing academic practice, we now assess the current state of academic performance outcome assessments and compare academics' and practitioners' assessments. We collected the CBC responses of 130 marketing academics working at the top 100 University of Texas - Dallas ranked US business schools.[4] The marketing academics' CBC experiment was similar to the practitioners' experiment, apart from including academic-related (e.g., academic title, research focus) rather than managerial-related questions. The academic sample comprises of a representative mix of job levels and specialties: over half were full professors (52%), over half (52%) indicated consumer behavior described their research very or extremely well, and about a third of indicated modelling (35%) or strategy (30%) described their research very or extremely well (see Web Appendix Table 5, WA14).

The marketing academics differ from marketing practitioners in self-reported metric ratings by ranking top-line performance as the most reliable and interpretable metrics, and capital marketing performance as the least important and least used metrics (see Figure 5 Panel A, following references).[5] Katsikeas et al. (2016) find academics employ top-line metrics the second most as performance variables in their studies. Thus, academics appear to highly rate the top-line metrics that are often employed in their research, even if those metrics do not necessarily align with practitioners' ratings.

The model-based analysis finds marketing academics significantly prefer bottom-line performance metrics over the four other metric types (each comparison $p<.001$), similar to the aggregated practitioner sample (see Figure 5, Panel B, following references). Yet, unlike practitioners, academics possess the least preferences for capital market metrics, second-least for marketing assets, third-least for top-line, and fourth-least for customer mindset metrics. When statistically comparing marketing academics relative metric importances with each stakeholder, marketing academics significantly value customer mindset metrics more than investors ($p<.05$), but marketing assets and capital market less than investors (both $p<.05$). In addition, marketing academics significantly value capital market metrics less than non-marketing executives ($p<.05$). However, marketing academics possess similar relative metric importances as marketing executives (each comparison was $p>.05$).

Marketing academics also exhibit similar preferences to practitioners by preferring high over low uncertainty for all metrics with below expectation performance. Yet, academics differ from practitioners by possessing greater preferences for lower rather than higher uncertainty for all above expectation performance metrics except for top-line (each $p<.01$; see Figure 5, Panels A and B, following references).

Consequently, marketing academics appear to undervalue capital market metrics compared to investors and non-marketing executives, despite the marketing-finance literature's efforts to encourage academics to use and link marketing efforts to capital market performance. In contrast, marketing academics and marketing executives relative valuations of metrics were not significantly different, indicating less disconnect between marketing academia and marketing practitioners than feared in the literature (Lilien 2011; Reibstein, Day, and Wind 2009). However, academics were less risk-seeking than marketing executives when evaluating above performance expectations by favoring more certain metrics, but both academics and marketing executives avoid metrics with certain losses for performance below expectations.

Discussion

Marketing performance metric selection influences how firms identify marketing campaign outcomes (Bendle et al. 2021). Over the years, multiple frameworks have been recommended for how academics and practitioners should assess marketing performance outcomes (e.g., Morgan et al. 2022; Stewart 2009). However, to our knowledge, little to no research has empirically examined how marketing performance is evaluated by managers and academics. Hence, practitioners (e.g., Gibbs 2022; JICMAIL and Data & Marketing Association 2022) and academics (e.g., Hanssens and Pauwels 2016; Katsikeas et al. 2016) have repeatedly voiced concerns about how marketing performance is assessed and what types of performance metrics are more important to those assessments (e.g., MSI Research Priorities 1998-2024).

Our research proposed a theoretical framework that explains how three mechanisms are traded-off when different managerial stakeholders (marketing executives, non-marketing executives, and investors) assess marketing performance, while also considering the role of metric uncertainty. We test our framework on a sample of 441 practitioners and 130 academics that provides benchmarks on relative metric importance for different stakeholders. We now synthesize the framework and results to assist academic and practitioner dependent variable selections for their marketing performance assessments.

Theoretical Implications

We propose a three-mechanism competing trade-off framework on how managers make performance assessments, integrating metric relevancy from value chain theory from the marketing literature (Rust et al. 2004), metric accessibility and attributability from construal level theory from the psychology and marketing literatures (Liberman, Trope, and Stephan 2007), and metric interpretability from knowledge management theory from the information systems, managerial accounting, and statistics literatures (Tanriverdi 2005). Further, our framework posits that each of the three mechanisms effect on performance assessments will differ by stakeholder and that metric performance uncertainty will have a greater impact on metrics that stakeholders consider most important to them.

The framework provides theoretical guidance for academics' performance metric dependent variables selections. For example, academics interested in dependent variables associated with outcomes directly related to specific marketing manager decisions, such as customer mindset metrics, can employ the three-mechanism framework to detail why managers ability to elicit concrete construals based on the direct responsiveness of a marketing campaign is the primary driver for their dependent variable selection. However, those academics need to discuss limits with their metric selection, such as how those metrics provide less normative value to the firm and are less interpretable to stakeholders inside and outside the firm.

Consequently, an important by-product of our framework and results is its ability to provide academics an overview of which marketing performance metrics to select as dependent variables for their research and to bring attention to important debates needing to be settled within marketing academia. Hence, we provide the following guidance:

1) *Include the reasoning for the selection of marketing performance metrics*: Our research establishes the relative importance for each of the five metric types when compared against each other so academics know which metric types are more impactful to performance assessments and for which stakeholder. Yet, ideally, academic studies should employ multiple performance metric types to overcome the disadvantages of the metrics (e.g., Morgan et al. 2022). Each metric type varies in its normative value to the firm, accessibility, and interpretability, and we find all five metric types were important to performance assessments. Thus, it is critical for academics to employ multiple performance metric types and explain the choice of why they are employing those metrics over relying only a single metric type for their studies.

2) *Consider negative and not just positive performance:* As a field, we typically focus on marketing's positive performance outcomes. However, our research demonstrates that negative performance has a greater asymmetrical effect on marketing campaign assessments than positive performance metrics, with avoidance of negative, certain bottom-line performance metric losses having the greatest impact on performance assessments. This overall finding is in line with prospect theory's proposition that losses loom larger than gains. Hence, if researchers find that marketing campaigns result in some metrics attaining positive performance and other metrics attaining negative performance, they need to provide the implications on how the negative metrics are likely to outweigh the positive metrics in campaign assessments.

3) *Employ metrics as dependent variables that better align with practitioners:* We find that practitioners value top-line metrics less than all other metrics. Yet, Katsikeas et al. (2016) find top-line metrics are the second most employed performance metrics used in academic research. Hence, if, we as a field believe top-line metrics to be valuable to practitioners, then we need to do a better job translating their importance to practice. Otherwise, the disconnect between academics' and practitioners' valuations of top-line metrics would indicate that we as academics need to rely on top-line metrics less as sole dependent variables in our studies.

4) *Consider how uncertainty in outcomes has a different impact on practitioner evaluations than on academic evaluations:* We find marketing academics performance assessments are mostly aligned with marketing executives' performance assessments. This is great news!

However, one key difference between marketing academics and marketing executives is academics are more risk-averse and prefer greater certainty in above performance expectation metric outcomes than marketing executives preferred in those outcomes. Thus, it is important for marketing academics to realize marketing executives possess differing preferences for uncertainty than themselves and consider how uncertainty in positively performing metrics can be considered as valuable to practitioners.

5) *Settle debates with other marketing academics*: The marketing-finance literature and value chain theory posit that capital market performance is the most normatively important metric for public firms' marketing campaigns. However, we find academics value capital market metrics the least of all the performance metrics. Thus, if capital market performance should indeed be the most normatively important metric to the firm, academics need to provide greater clarity to other academics to resolve questions about capital market metrics.

Managerial Implications

A primary motivation to conduct our research was the lack of clarity about which metrics matter most when stakeholders assess marketing performance and how types of stakeholders consider which metrics matter most differently; a similar motivation for the developments of the Marketing Accounting Standards Board and the Marketing Meets Wall Street Conference. Thus, we provide practitioners the following recommendations derived from our framework and results to assist their marketing performance assessments:

1) *Use our research to "speak the same marketing performance language" as other important stakeholders:* Our integrated theoretical framework describes three primary mechanisms that underlie marketing performance evaluations, e.g., normative value to the firm, accessibility and attributability, and interpretability of results. Further, our empirical analysis finds that bottom-line metrics are the most valued marketing performance metrics and top-line metrics are the least valued. Taken together, the theory and practice approach assist managers' understanding of drivers of marketing performance assessments and provides benchmarks on the metrics that matter most and least to different stakeholders.

2) *Include at least include one bottom-line performance metric for marketing assessments:* Our theory and results provide robust support on the importance of bottom-line metrics over other metric types. We understand practitioners' difficulties in always attaining clear and accurate bottom-line metrics (e.g., Farris et al. 2015). Further, our discussion of metrics' advantages and disadvantages also details the importance for practitioners to employ more than just bottom-line metrics for their assessments. However, we urge practitioners to exhibit upmost effort to employ bottom-line metrics as at least one marketing performance variable, as we find bottom-line metrics with even high uncertainty are also main drivers of managerial marketing performance assessments.

3) *Consider that investors also value customer-focused metrics:* Investors combined value of customer mindset and marketing asset metrics are insignificantly different than marketing executives combined value of the two metrics. However, the main difference is that investors possess greater preferences for marketing asset metrics and lesser preferences for customer mindset metrics than marketing executives. This indicates investors do in fact perceive customer-based outcomes as important as marketers, just investors value those outcomes linked to financial values that marketing asset metrics such as CLV, brand equity, and customer equity provide. Hence, we are very supportive of efforts such as Keller (1993) and McCarthy and Fader (2018), among the many others, which provide managers and investors a path to better understand how to combine customer outcomes directly with marketing asset based financial valuations.

4) *Recognize that marketing executives' preferences for marketing performance metrics are aligned with non-marketing executives:* Our analysis finds similarities between marketing and non-marketing executives. This is a positive but unexpected result since much has been written about the disconnect between marketers and the rest of the organization (e.g., Lilien 2011; Reibstein, Day, and Wind 2009). Of course, this result could be a function of our sample. Yet, the rapid development and applications of big data since those initial concerns were expressed may have enhanced marketers perceptions of the importance of metrics at the end of the value chain and non-marketers understanding of metrics at the beginning of the value chain (e.g., Mintz et al. 2021b).

5) *Account for uncertainty in metric outcomes.* Traditionally, greater uncertainty and variance in metric outcomes should make those metrics less preferred (Shugan and Mitra 2009). However, we find managers avoid "certainty" in their negatively performing metrics, with avoidance of more certain negatively performing bottom-line metrics the most impactful driver of marketing assessments. Thus, managers need to measure and understand how uncertainty in metrics impacts marketing assessments, with greater uncertainty often being preferred since it enables a greater chance of success (and failure).

Limitations and Future Research

The limitations of this research should inspire future research. Our empirical approach relies on managers from one panel provider assessing marketing performance for a hypothetical S&P 500 firm in a controlled experiment. Field experiments would enhance the external validity of our findings, but must be considered against their own limitations to reliably isolate and assess relative metric importance. In addition, our experiment employs graphical results of absolute-levels of performance, whereas follow-up research could be employed using alternative descriptors of performance outcomes, such as text involving numbers or percentages (e.g., Hutchinson, Alba, and Eisenstein 2010). In addition, there are opportunities to conduct further research involving growth focused metrics (e.g., Spiller, Reinholtz, and Maglio 2020), which may also activate alternative cognitive processes. Future research should develop additional boundary conditions not accounted for in this research. For example, future research should assess interactions between manager, firm, and a broader range of industry characteristics to establish further and more complex conditions when certain mechanisms have greater influence on marketing performance assessments. Finally, future research should attempt to extend our framework to additional types of managers, such as on mid- and entry-level marketers, and to test on additional samples.

Conclusion

Establishing what drives assessments of marketing performance and documenting the marketing metrics that matter most is critical for managerial practice (Hanssens and Pauwels 2016; Katsikeas et al. 2016). However, less is empirically known on how managers and academics assess marketing performance. Our results and proposed recommendations for academics and practitioners provide actionable insights designed to improve research and practice. Further, we compare and contrast how marketing academics and practitioners value marketing performance metrics, and note several important discrepancies that need to be addressed to bridge the divide between what we research and what is valued in practice (Lilien 2011; Reibstein, Day, and Wind 2009). We hope future research expands on our work to provide further clarity on the metrics that matter most for marketing performance assessments.

References

Ambler, Tim (2003), *Marketing and the Bottom Line: The Marketing Metrics to Pump Up Cash Flow*, London: FT Prentice Hall.

Argote, Linda, Bill McEvily, and Ray Reagans (2003), "Managing Knowledge in Organizations: An Integrative Framework and Review of Emerging Themes," *Management Science*, 49 (4), 571–82.

Avagyan, Vardan, Nuno Camacho, Wim A. Van der Stede, and Stefan Stremersch (2022), "Financial projections in innovation selection: The role of scenario presentation, expertise, and risk," *International Journal of Research in Marketing*, 39 (3), 907–26.

Barwise, Patrick and John U. Farley (2004), "Marketing Metrics: Status of Six Metrics in Five Countries," *European Management Journal*, 22 (3), 257–62.

Ben-Akiva, Moshe and Steven R. Lerman (1985), *Discrete Choice Analysis: Theory and Application to Travel Demand*, Cambridge, Mass: The MIT Press.

Bendle, Neil T., Paul W. Farris, Phillip E. Pfeifer, and David J. Reibstein (2021), *Marketing Metrics: The Definitive Guide to Measuring Marketing Performance*, Pearson FT Press.

--- and Xin (Shane) Wang (2017), "Marketing accounts," *International Journal of Research in Marketing*, 34 (3), 604–21.

Burke, Paul F. and Markus Reitzig (2007), "Analyzing the Degree and Kind of (In)Consistency in Patent Offices' Decision Making," *Research Policy*, 36 (9), 1404–30.

Cheng, Andong and Cynthia Cryder (2018), "Double Mental Discounting: When a Single Price Promotion Feels Twice as Nice," *Journal of Marketing Research*, 55 (2), 226–38.

Currim, Imran S., Jooseop Lim, and Joung W. Kim (2012), "You Get What You Pay For: The Effect of Top Executives' Compensation on Advertising and R&D Spending Decisions and Stock Market Return," *Journal of Marketing*, 76 (5), 33–48.

Edeling, Alexander and Alexander Himme (2018), "When Does Market Share Matter? New Empirical Generalizations from a Meta-Analysis of the Market Share–Performance Relationship," *Journal of Marketing*, 82 (3), 1–24.

---, Shuba Srinivasan, and Dominique M. Hanssens (2021), "The marketing–finance interface: A new integrative review of metrics, methods, and findings and an agenda for future research," *International Journal of Research in Marketing*, 38 (4), 857–76.

Farris, Paul W., Dominique M. Hanssens, James D. Lenskold, and David J. Reibstein (2015), "Marketing Return on Investment: Seeking Clarity for Concept and Measurement," *Applied Marketing Analytics*, 1 (3), 267–82.

Frösén, Johanna, Jukka Luoma, Matti Jaakkola, Henrikki Tikkanen, and Jaakko Aspara (2016), "What Counts Versus What Can Be Counted: The Complex Interplay of Market Orientation and Marketing Performance Measurement," *Journal of Marketing*, 80 (3), 60–78.

Gibbs, Ian (2022), "Marketing effectiveness double jeopardy," *WARC*, (accessed May 16, 2022).

Hanssens, Dominique M. and Koen H. Pauwels (2016), "Demonstrating the Value of Marketing," *Journal of Marketing*, 80 (6), 173–90.

---, ---, Shuba Srinivasan, Marc Vanhuele, and Gokhan Yildirim (2014), "Consumer Attitude Metrics for Guiding Marketing Mix Decisions," *Marketing Science*, 33 (4), 534–50.

---, Roland T Rust, and Rajendra K Srivastava (2009), "Marketing Strategy and Wall Street: Nailing Down Marketing's Impact," *Journal of Marketing*, 73 (6), 115–18.

Henri, Jean-François (2006), "Management Control Systems and Strategy: A Resource-Based Perspective," *Accounting, Organizations and Society*, 31 (6), 529–58.

Homburg, Christian, Martin Artz, and Jan Wieseke (2012), "Marketing Performance Measurement Systems: Does Comprehensiveness Really Improve Performance?" *Journal of Marketing*, 76 (3), 56–77.

Hutchinson, J. Wesley, Joseph W. Alba, and Eric M. Eisenstein (2010), "Heuristics and Biases in Data-Based Decision Making: Effects of Experience, Training, and Graphical Data Displays," *Journal of Marketing Research*, 47 (4), 627–42.
JICMAIL and Data & Marketing Association (2022), "Mind the Measurement Gap."
Jindal, Pranav and Anocha Aribarg (2021), "The Importance of Price Beliefs in Consumer Search," *Journal of Marketing Research,* 58 (2), 321–42.
Katsikeas, Constantine S., Neil A. Morgan, Leonidas C. Leonidou, and G. Tomas M. Hult (2016), "Assessing Performance Outcomes in Marketing," *Journal of Marketing,* 80 (2), 1–20.
Keller, Kevin Lane (1993), "Conceptualizing, Measuring, and Managing Customer-Based Brand Equity," *Journal of Marketing,* 57 (1), 1–22.
Lehmann, Donald R. (2004), "Metrics for Making Marketing Matter," *Journal of Marketing*, 68 (4), 73–75.
--- and David J. Reibstein (2006), *Marketing Metrics and Financial Performance,* Relevant Knowledge Series, Cambridge, Massachusetts: Marketing Science Institute.
Liberman, Nira, Yaacov Trope, and Elena Stephan (2007), "Psychological Distance," in *Social Psychology: Handbook of Basic Principles,* A. W. Kruglanski and E. T. Higgins, eds., Guilford Press, 350–81.
Lilien, Gary L. (2011), "Bridging the Academic-Practitioner Divide in Marketing Decision Models," *Journal of Marketing,* 75 (4), 196–210.
Lipe, Marlys Gascho and Steven E. Salterio (2000), "The Balanced Scorecard: Judgmental Effects of Common and Unique Performance Measures," *Accounting Review,* 75 (3), 283–98.
Louviere, Jordan J., David A. Hensher, and Joffre D. Swait (2000), *Stated Choice Methods: Analysis and Applications,* Cambridge: Cambridge University Press.
Marketing Science Institute (1998, 2000, 2002, 2004, 2006, 2008, 2010, 2012, 2014, 2016, 2018, 2020, 2022), *Research Priorities: A Guide to MSI Research Programs and Procedures*, Marketing Science Institute, Cambridge, Massachusetts.
McAlister, Leigh M., Raji Srinivsan, Niket Jindal, and Albert A. Cannella (2016), "Advertising Effectiveness: The Moderating Effect of Firm Strategy," *Journal of Marketing Research*, 53 (2), 207–24.
McCarthy, Daniel M. and Peter S. Fader (2018), "Customer-Based Corporate Valuation for Publicly Traded Noncontractual Firms," *Journal of Marketing Research*, 55 (5), 617–35.
Menon, Anil, Sundar G. Bharadwaj, Phani Tej Adidam, and Steven W. Edison (1999), "Antecedents and Consequences of Marketing Strategy Making: A Model and a Test," *Journal of Marketing*, 63 (2), 18–40.
Milkman, Katherine L., Modupe Akinola, and Dolly Chugh (2012), "Temporal Distance and Discrimination: An Audit Study in Academia," *Psychological Science*, 23 (7), 710–17.
Mintz, Ofer and Imran S. Currim (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.
---, ---, Jan-Benedict E. M. Steenkamp, and Martijn de Jong (2021a), "Managerial metric use in marketing decisions across 16 countries: A cultural perspective," *Journal of International Business Studies,* 52 (8), 1474–1500.
---, Timothy J. Gilbride, Peter Lenk, and Imran S. Currim (2021b), "The right metrics for marketing-mix decisions," *International Journal of Research in Marketing*, 38 (1), 32–49.
Moorman, Christine and George S. Day (2016), "Organizing for Marketing Excellence," *Journal of Marketing*, 80 (6), 6–35.
--- and Donald R. Lehmann (Eds.) (2004), *Assessing Marketing Strategy Performance*, Cambridge, Mass: Marketing Science Institute.

Morgan, Neil A., Satish Jayachandran, John Hulland, Binay Kumar, Costas Katsikeas, and Agnes Somosi (2022), "Marketing performance assessment and accountability: Process and outcomes," *International Journal of Research in Marketing*, 39 (2), 462-481.
Novemsky, Nathan and Ravi Dhar (2005), "Goal Fulfillment and Goal Targets in Sequential Choice," *Journal of Consumer Research*, 32 (3), 396–404.
Pauwels, Koen, Selin Erguncu, and Gokhan Yildirim (2013), "Winning hearts, minds and sales: How marketing communication enters the purchase process in emerging and mature markets," *International Journal of Research in Marketing*, Special Issue on Marketing in Emerging Markets, 30 (1), 57–68.
Pipino, Leo L., Yang W. Lee, and Richard Y. Wang (2002), "Data Quality Assessment," *Communications of the ACM*, 45 (4), 211–218.
Podsakoff, Philip M., Scott B. MacKenzie, Jeong-Yeon Lee, and Nathan P. Podsakoff (2003), "Common Method Biases in Behavioral Research: A Critical Review of the Literature and Recommended Remedies," *Journal of Applied Psychology*, 88 (5), 879–904.
Reibstein, David J., George S. Day, and Yoram Wind (2009), "Guest Editorial: Is Marketing Academia Losing Its Way?" *Journal of Marketing*, 73 (4), 1–3.
Rust, Roland T., Tim Ambler, Gregory S. Carpenter, V. Kumar, and Rajendra K. Srivastava (2004), "Measuring Marketing Productivity: Current Knowledge and Future Directions," *Journal of Marketing*, 68 (4), 76–89.
Shugan, Steven M. and Debanjan Mitra (2009), "Metrics—When and Why Nonaveraging Statistics Work," *Management Science*, 55 (1), 4–15.
Spiller, Stephen A., Nicholas Reinholtz, and Sam J. Maglio (2020), "Judgments Based on Stocks and Flows: Different Presentations of the Same Data Can Lead to Opposing Inferences," *Management Science*, 66 (5), 2213–31.
Sridhar, Shrihari, Prasad A. Naik, and Ajay Kelkar (2017), "Metrics unreliability and marketing overspending," *International Journal of Research in Marketing*, 34 (4), 761–79.
Srivastava, Rajenda K., Tasadduq A. Shervani, and Liam Fahey (1998), "Market-Based Assets and Shareholder Value: A Framework for Analysis," *Journal of Marketing*, 62 (1), 2–18.
Stewart, David W. (2009), "Marketing Accountability: Linking Marketing Actions to Financial Results," *Journal of Business Research*, 62 (6), 636–43.
Swait, Joffre and Jordan Louviere (1993), "The Role of the Scale Parameter in the Estimation and Comparison of Multinomial Logit Models," *Journal of Marketing Research*, 30 (3), 305–14.
Tanriverdi, Hüseyin (2005), "Information Technology Relatedness, Knowledge Management Capability, and Performance of Multibusiness Firms," *MIS Quarterly*, 29 (2), 311–34.
Thaler, Richard H. and Eric J. Johnson (1990), "Gambling with the House Money and Trying to Break Even: The Effects of Prior Outcomes on Risky Choice," *Management Science*, 36 (6), 643–60.
van Veen-Dirks, Paula (2010), "Different Uses of Performance Measures: The Evaluation versus Reward of Production Managers," *Accounting, Organizations and Society*, 35 (2), 141–64.
Wang, Richard Y. and Diane M. Strong (1996), "Beyond Accuracy: What Data Quality Means to Data Consumers," *Journal of Management Information Systems*, 12 (4), 5–33.
Wind, Yoram (2008), "A Plan to Invent the Marketing We Need Today," *MIT Sloan Management Review*, 49 (4), 21–28.
Zhang, Don C., Scott Highhouse, and Christopher D. Nye (2019), "Development and validation of the General Risk Propensity Scale (GRiPS)," *Journal of Behavioral Decision Making*, 32 (2), 152–67.

Footnotes

[1] Katsikeas et al. (2016) reported that around 40% of academic studies only employ a single measure of marketing performance and another 40% of studies treat marketing performance as latent variable but do not report the correlations between the performance measures. For instance, Mintz et al. (2021b) examined the link between the metrics managers employ when making marketing-mix decisions with subjective assessments of performance. However, Mintz et al. (2021b) considered marketing performance as a multi-item, equally weighted construct based on a mixture of performance metrics without investigating managers' preference weights for such performance.

[2] As an additional quality check, we also forced respondents to self-identify their job titles at the onset of the conjoint survey and excluded all respondents that did not match the qualifications for our target stakeholders.

[3] Web Appendix Table 3 provides averages, standard deviations, and statistical comparisons between the measures.

[4] We emailed all 1,428 full-time faculty with email addresses listed on faculty websites that work at the top 100 ranked US business schools, using the 2010-2020 University of Texas – Dallas rankings.

[5] Web Appendix Table 3 provides comparisons between marketing academics and executives self-reported metric performance ratings. Academics rated mindset and marketing asset metrics as significantly more important ($p<.01$) and used more than marketing executives but also rated those two metrics as less reliable than the executives ($p<.001$). On the other hand, academics rated top-line ($p < .001$) and bottom-line ($p < .01$) metrics significantly lower than marketing executives for all dimensions except metric importance, and capital metrics significantly less used and reliable (both $p<.05$).

Figure 1. Three-Mechanism Marketing Performance Assessment Conceptual Framework

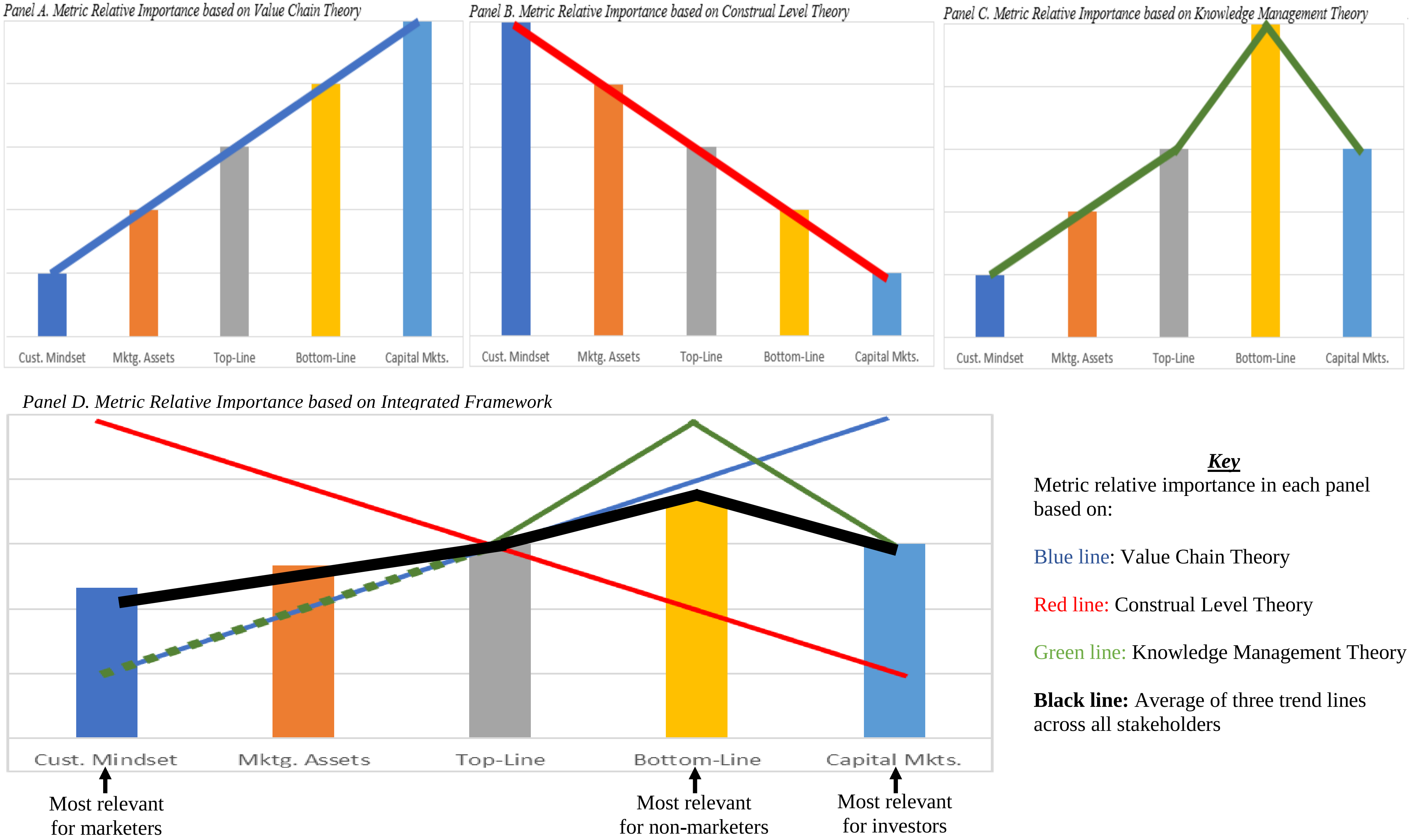


Figure 2. Choice-based Conjoint Example

Instructions:
For the following set of questions: consider a large S&P 500 firm that focuses on its cost (differentiated) advantage in an industry very similar to yours with respect to its level of growth, turbulence, and life cycle. Recently, the Chief Marketing Officer (CMO) of that firm implemented two large different integrated marketing campaigns focusing on profits (growth). Each of these integrated marketing campaigns were implemented through all 4 main marketing "P's", such as promotions, pricing, products, and placements (i.e., distribution). The success of these integrated marketing campaigns were measured in terms of 5 different types of metrics. In the following, we will provide you whether the performance was above or below your *initial* expectations for each of these 5 types of performance.

Choice Experiment:
In your expert opinion, which of the following marketing campaigns would you rank as having the "best" performance for this large S&P 500 firm that focuses on its **cost (differentiated) advantage** and has implemented two large different integrated marketing campaigns focusing on **profits (growth)**?

Which of the following two options has performed ***best***?

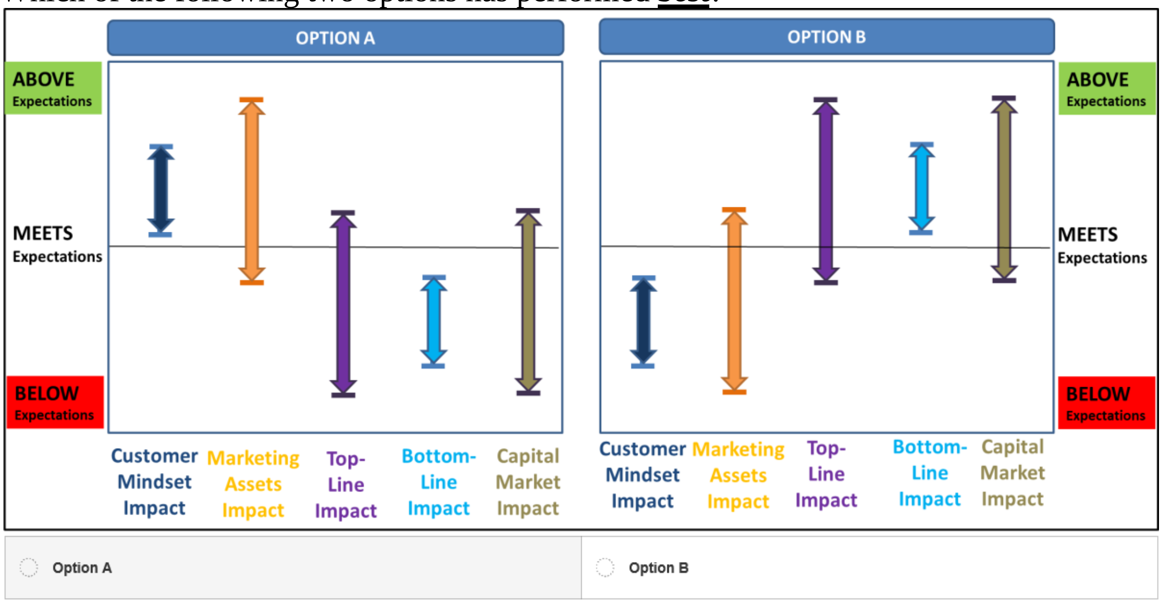
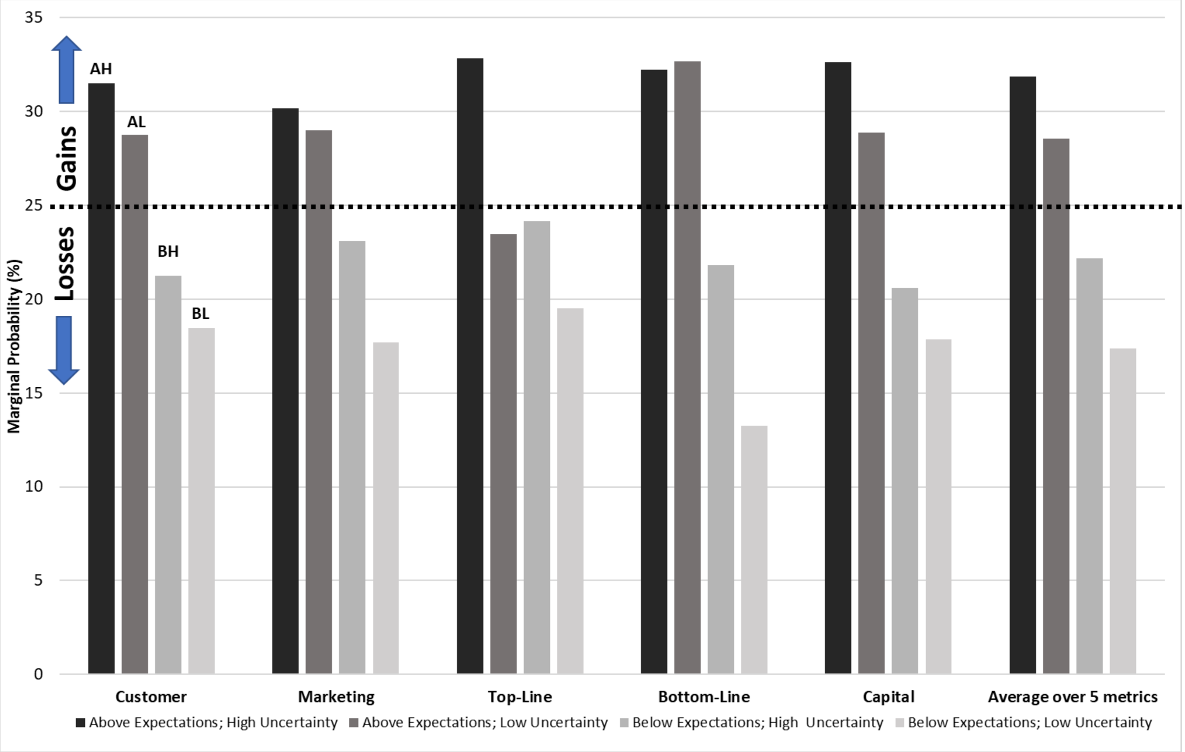


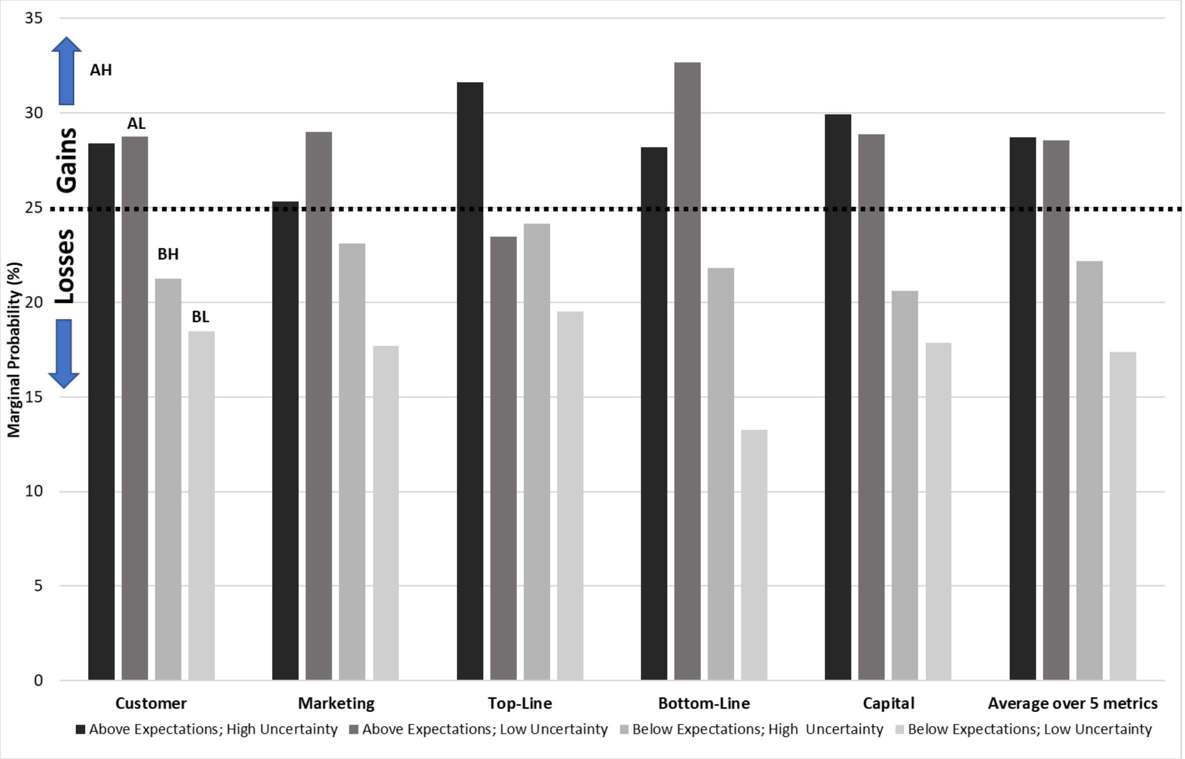
Figure 3. Model-Free Self-Reported Ratings on 1-7 Scale (7 = greater rating)

Figure 4. Choice Probabilities Across Four Outcomes Per Metric

Panel A. Aggregate Managerial Sample



Panel B. Academic Sample

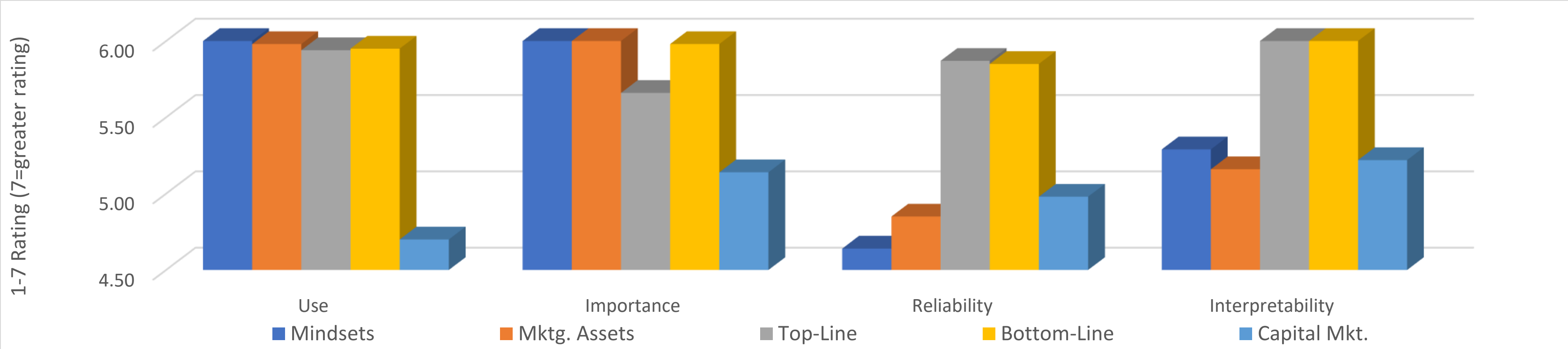


AH=Above expectations, High uncertainty; AL = Above expectations, Low uncertainty;
BH = Below expectations, High uncertainty; BL = Below expectations, Low uncertainty.

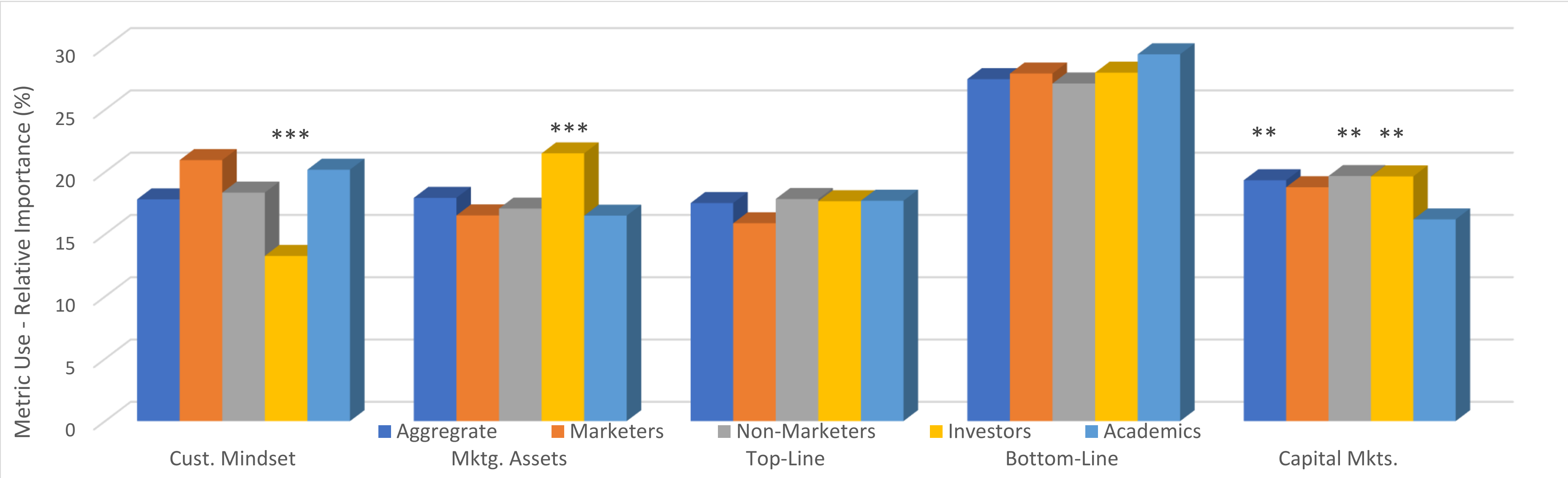
Dotted line represents equal choice probabilities across four outcomes.

Figure 5. Marketing Academic Results

Panel A. Academic Self-Reported Ratings on Performance Metrics



Panel B. Academic Performance Metrics Relative Importance Compared to Practitioners



*/**/*** indicate a significant difference between academics and stakeholder type (p<.05/.01/.001).

Table 1: Related Recent Literature on Performance Metrics

Authors	Metric Focus	Study Design	Unit of Analysis	Individual or Total Metrics	How Performance is Determined	Compares Various Stakeholders	Considers Metric Uncertainty	Compares to Practitioners w/Academics
Bendle and Wang (2017)	Conceptual: Posits how marketing performance can be reported internally throughout firms	Th	Overall Firm	---	**NA**	×	×	×
Bendle et al. (2021)	Conceptual: Posits which marketing metrics managers should employ and surveys managers to see which metrics are employed	Th, Surv	Overall Firm	I	**NA**	×	×	×
Frösén et al. (2016)	Empirical: Links marketing performance measurement system use to firm performance, while considering effect of market orientation and firm size	Surv	Overall Firm	T	Bottom-line (Profit Margin)	×	×	×
Hanssens and Pauwels (2016)	Conceptual: Reviews how academics have demonstrated marketing's value to the firm	Rev	Overall Firm	---	**NA**	×	×	×
Homburg et al. (2012)	Empirical: Links marketing performance measurement system use to firm performance, while considering effect of the firm's marketing and its market	Surv	Overall Firm	T	SelfRpt, Arch ROS	×	×	×
Katsikeas et al. (2016)	Conceptual: Examines what performance metrics marketing academics used in empirical research studies	Acad Use	Overall Firm	I	Acad Use	×	×	×
Mintz and Currim (2013)	Empirical: Describes what drives managers to use metrics when making their marketing decisions and how metric use associates with performance	Surv	One MMD	T	SelfRpt Composite Average of 8 Items	M, NM	×	×
Mintz et al. (2021a)	Empirical: Investigates how national and organizational culture drives managers to use metrics when making their marketing decisions	Surv	One MMD	I	SelfRpt Composite Average of 8 Items	M, NM	×	×
Mintz et al. (2021b)	Empirical: Examines how use of a metric when managers make marketing decisions relates with an equally weighted multi-item performance construct	Surv	One MMD	T	SelfRpt Composite Average of 8 Items	M, NM	×	×
Moorman and Day (2016)	Conceptual: Reviews how academics have linked marketing efforts with firm performance	Rev	Overall Firm	---	**NA**	×	×	×
Morgan et al. (2021)	Empirical: Examines which metrics academics have used as performance dependent variables	Th	Overall Firm	I	Posited categories	×	×	×
Sridhar et al. (2017)	Empirical: Demonstrates how not accounting for metric uncertainty affects marketing decisions	Panel	Sales Data	T	Top-line (Sales)	×	✓	×
This Paper	***Empirical: Propose a three-mechanism framework of drivers of marketing performance assessments and examine relative metric importance weights for practitioners' and academics' marketing performance assessments***	***Exp CBC***	***IMC Perf Outcome***	***I***	***5 Metric Types to Decide Better Perf***	M, NM, Inv	✓	✓

Key: Study Design: Acad Use=academic use, Rev=review, Surv=survey, Th=theoretical, Exp CBC=experimental choice-based conjoint; Unit of Analysis: MMD=marketing-mix decision, IMC =integrated marketing campaign; How Performance is Determined: SelfRpt=self-reported, Arch=archival; Compares Various Stakeholders: M=marketers, NM=non-marketers, Inv=investors;

This review focuses on metric use and performance assessment related studies published between 2010-2022 as books or in the *Journal of Marketing, Journal of Marketing Research, Marketing Science, Journal of International Business Studies,* and *International Journal of Research in Marketing.* The review does not include studies that focus on linking a metric outcome with another metric outcome (e.g., customer satisfaction [or another metric] effect on net profits or stock market returns) as those studies do not examine marketing performance assessments.

Table 2. Summary of Performance Metrics

Performance Metric	Examples	Advantages	Disadvantages
Customer Mindset	• Awareness • Satisfaction	• Easier to measure since causally close to marketing actions • Commonly used to set marketing-specific goals and assess marketing performance in practice	• Differences across firms in how observed behaviors are defined and calibrated • Unique terms to marketing (vs. other disciplines) that are not always directly aligned with financial outcomes
Marketing Assets	• Brand equity • Customer Lifetime Value	• Provide financial measures for customer-mindsets and behaviors • Commonly used to provide forward-looking assessments of the firm based on its customers	• Harder to calculate compared to customer mindsets and unique terms to marketing (vs. other disciplines) • More firm related than based on consequences of individual marketing efforts
Top-line	• Market Share • Sales	• Commonly used by most organizations • Related to customer actions with data typically widely available	• Firm level, so subject to factors unrelated to marketing • Not always well-defined (firms vary in market definitions) and does not consider financial costs
Bottom-line	• Net Profit • Return on Investment	• Well-defined and standardized measures • Commonly understood and used across the firm to provide direct indicator of performance success	• Firm level, so subject to factors unrelated to marketing • Not forward-looking and sometimes far removed from the marketing decision maker
Capital Market	• Stock Return • Tobin's Q	• Forward looking measures with widely available data (for public firms) • Ultimate metric of firm value and finance theory suggests investors may be more goal agnostic	• Corporate level, so subject to the most factors unrelated to marketing • Far removed from marketing decisions with the majority of decisions not impacting this performance

Table is based on Katsikeas et al. (2016). For a more detailed overview of the advantages and disadvantages of each performance metric, we refer the reader to Web Appendix A and Katsikeas et al. (2016).

Table 3. Sample Descriptive Statistics

Variable	Source	Measure(s)	Aggregated Sample		Marketing Executives			Non-Marketing Executives			Investors		
			Mean	*S.D.*	*Mean*	*S.D.*	*Sig.*	*Mean*	*S.D.*	*Sig.*	*Mean*	*S.D.*	*Sig.*
Risk Orientation	Zhang, Highhouse, and Nye (2019)	Indicate the extent you agree or disagree with the following statements (1-7 scale; 1 = strongly disagree and 7 = strongly agree): 1. Taking risks makes life more fun 2. My friends would say that I'm a risk taker 3. I enjoy taking risks in most aspects of my life 4. Taking risks is an important part of my life 5. I am a believer of taking chances 6. I am attracted, rather than scared, by risk 7. I commonly make risky decisions	5.04	1.27	5.23	1.08	n	4.59	1.51		5.30	1.06	n
Work Experience	Mintz and Currim (2013)	How long have you worked in your current function? (less than a year; 1 to 5 years; 6 to 10 years; 11 to 20 years; more than 20 years)^	8.98	6.5	8.06	4.87		11.09	8.48	m,i	7.81	4.97	
Quantitative Orientation	Mintz and Currim (2013)	Rate your overall quantitative vs. qualitative background? (1-7 scale; 1 = entirely qualitative and 7 = entirely quantitative)	4.67	1.42	4.63	1.42		4.61	1.25		4.76	1.56	
Compensation	Currim, Lim, and Kim (2012)	How much of your compensation last year was based on short versus long-term measures? (1-7 scale; 1 = short-term cash bonus or commission only and 7 = long-term equity only)	4.87	1.49	4.89	1.36		4.63	1.56		5.08	1.50	n
Gender		Male (vs. non-male)	69.4	---	73.1	---	n	53.1	---		81.8	---	m,n
Age		What is your age? (19 or less; 20-29; 30-39; 40-49; 50-59; 60-64; $\geq$65)^	41.30	11.03	38.77	9.84		45.38	13.40	m,i	39.78	7.96	
N (% of sample)			431		145 (34%)			143 (33%)			143 (33%)		

S.D. = standard deviation; Sig. = p<.05; m/n/i indicates mean is significantly higher for given stakeholder relative to marketers/non-marketers/investors (p<.05). Marketing executives = S/VP or C-level marketer; non-marketing executives = CEO, COO, CFO, or equivalent; investor = analyst, investor, broker, or equivalent (all based on Lehmann and Reibstein 2006). ^ Mid-point of each outcome used to calculate means and standard deviations for age and work experience.

Table 4A. Conditional Logit Model Estimates

Variable	Aggregate			Marketing Manager			Non-Marketing Manager			Investor		
	Est.	S.E.	Sig.	Est.	S.E.	Sig.[1,2]	Est.	S.E.	Sig.[1,2]	Est.	S.E.	Sig.[1,2]
Performance												
Cust. Mindset	0.304	0.026	***	0.308	0.028	***	0.432	0.029	***a	0.173	0.027	***b
Mktg. Assets	0.287	0.025	***	0.227	0.028	***	0.370	0.028	***a	0.263	0.027	***
Top-Line	0.218	0.026	***	0.175	0.029	***	0.297	0.030	***a	0.183	0.028	***
Bottom-Line	0.424	0.024	***	0.393	0.027	***b	0.530	0.027	***a	0.349	0.026	***b
Capital Mkts.	0.329	0.026	***	0.276	0.028	***	0.439	0.029	***a	0.272	0.027	***b
Uncertainty												
Cust. Mindset	0.058	0.014	***	0.088	0.024	***	0.069	0.026	***	0.017	0.025	b
Mktg. Assets	0.077	0.014	***	0.081	0.024	***	0.080	0.026	***	0.070	0.025	***
Top-Line	0.137	0.014	***	0.124	0.024	***	0.190	0.026	***a	0.097	0.025	***
Bottom-Line	0.121	0.014	***	0.137	0.024	***	0.159	0.026	***	0.066	0.025	**b
Capital Mkts.	0.066	0.020	**	0.082	0.034	***	0.099	0.036	***	0.018	0.035	
Performance x Uncertainty												
Cust. Mindset	-0.012	0.020		-0.044	0.034		0.000	0.036		0.007	0.035	
Mktg. Assets	-0.057	0.020	**	-0.043	0.034		-0.082	0.036	**	-0.045	0.035	
Top-Line	0.030	0.020		0.071	0.033	**	0.062	0.035	*	-0.042	0.034	b
Bottom-Line	-0.128	0.021	***	-0.092	0.036	***	-0.210	0.038	***b	-0.082	0.037	***
Capital Mkts.	-0.005	0.014		0.019	0.024		-0.016	0.026		-0.017	0.025	

[1] */**/*** = p < .05/.01/.001; [2] a/b denotes significantly higher/lower estimate (p<.05) for stakeholder than aggregate.

Table 4B. Relative Importance of Metrics

Metric	Aggregate			Marketers			Non-Marketers			Investors		
	Est. (%)	S.E.	Sig.[1]	Est. (%)	S.E.	Sig.[1,2]	Est. (%)	S.E.	Sig.[1,2]	Est. (%)	S.E.	Sig.[1]
Cust. Mindset	17.80	1.30	***	20.95	2.75	*a	18.34	1.56	***a	13.26	2.48	***
Mktg. Assets	17.92	1.22	***	16.51	2.70	***b	17.06	1.57	***b	21.49	2.56	*
Top-Line	17.50	1.27	***	15.88	2.77	***	17.83	1.66	***	17.65	2.54	***
Bottom-Line	**27.45**	1.31	*base*	**27.90**	2.83	*base*	**27.10**	1.69	*base*	**27.97**	2.72	*base*
Capital Mkts.	19.33	1.44	***	18.77	3.01	**	19.67	1.77	***	19.64	2.53	**

Description for how relative importance is computed is on pgs. 21-22. Most important metric per stakeholder is bolded;
[1] */**/*** metric significantly less important relative to bottom-line (i.e., *base*) (p<.05/.01/.001);
[2] a/b denotes metric is significantly above/below level of importance for stakeholder relative to investors (p<.05);
No significant differences in metric importance found between marketers and non-marketers for any metric (p<.05).

Table 5. Marginal Utility of High Over Low Uncertain Outcomes

Panel A. Results from Metrics Above Performance Expectations

	Aggregate (H5)			Marketers (H7)			Non-Marketers (H8)			Investors (H9)		
Metric	**Est.**	**S.E.**	**Sig.**	**Est.**	**S.E.**	**Sig.**[1,2]	**Est.**	**S.E.**	**Sig.**[1,2]	**Est.**	**S.E.**	**Sig.**[1,2,3]
Cust. Mindset	0.092	0.052		0.089	0.070		0.138	0.070	*	0.049	0.078	*
Mktg. Assets	0.041	0.046		0.077	0.064		-0.005	0.064		0.049	0.068	
Top-Line	0.335	0.053	**	0.391	0.070	**	0.503	0.070	**ai	0.110	0.080	**b
Bottom-Line	-0.014	0.046		0.091	0.064	i	-0.101	0.064		-0.032	0.067	
Capital Mkts.	0.123	0.048	*	0.202	0.066	**	0.166	0.066	*	0.002	0.072	*b

Panel B. Results from Metrics Below Performance Expectations

	Aggregate (H6)			Marketers (H7)			Non-Marketers (H8)			Investors (H9)		
Metric	**Est.**	**S.E.**	**Sig.**	**Est.**	**S.E.**	**Sig.**[1,2]	**Est.**	**S.E.**	**Sig.**[1,2]	**Est.**	**S.E.**	**Sig.**[1,2,3]
Cust. Mindset	0.141	0.052	**	0.264	0.070	**ai	0.138	0.070	*	0.020	0.078	*
Mktg. Assets	0.267	0.046	**	0.248	0.064	**	0.323	0.064	**	0.231	0.068	**
Top-Line	0.213	0.053	**	0.106	0.070		0.256	0.070	**	0.278	0.080	**
Bottom-Line	0.498	0.046	**	0.458	0.064	**	0.738	0.064	**ai	0.297	0.067	**
Capital Mkts.	0.142	0.048	**	0.124	0.066		0.231	0.066	**i	0.072	0.072	**

*/**/*** preference for greater metric uncertainty significantly different to greater metric certainty at .05/.01/.001 level.
a/b denotes preference for greater metric uncertainty significantly higher/lower for stakeholder relative to aggregate (p<.05).
m/n/i denotes preference for greater metric uncertainty significantly higher for stakeholder relative to marketer/non-marketer/investor (p<.05).

Web Appendices for “Executives, Investors, and Academics Assessments of Marketing Performance: Trade-offs between Metric Type, Uncertainty, and Performance”

Table of Contents

Web Appendix A. Advantages and Disadvantages of Metric Types

To establish a better understanding of what drives greater relative managerial preferences for one type of performance metric over another, we provide an overview of the advantages and disadvantages of each the five performance metric types, i.e., customer mindset, marketing asset, top-line, bottom-line, and capital market.

Customer mindset metrics, such as awareness and satisfaction, typically capture top of the purchase funnel results about the customers' minds and hearts (Katsikeas et al. 2016), and are typically assessed via primary survey collections and analytical techniques from observed data (Hult et al. 2017). These metrics are employed to provide current and predictive long-term indicators about the firm's underlying health beyond what financial indicators can provide (Himme and Fischer 2014). Thus, without knowledge on such customer mindsets, firms struggle to understand their customers and their marketing efforts will not succeed (Fornell, Morgeson, and Hult 2016). In addition, mindset metrics are causally the closest, provide managers greatest locus of control related to direct results, and easiest to attribute marketing results with its outcomes (Hanssens and Pauwels 2016). Consequently, individual customer mindset metrics such as awareness have been found to be the most effective metrics to improve composite marketing-mix performance when managers are making their individual marketing-mix decisions (Mintz, Gilbride, et al. 2021). Yet, customer mindset metrics do not provide a direct financial assessment of performance and also are a marketing-unique term that do not necessarily translate across the firm (Katsikeas et al. 2016).

Marketing assets, such as CLV and brand and customer equity, are designed to provide a measure of the firms' discounted future cash flows accrued based on their relationships with their customers (Schulze, Skiera, and Wiesel 2012) or the value of their brands (Keller 1993). Yet, market asset valuations often are noisy; e.g., the top three brand equity valuators in practice have relatively low correlations (Fischer, Du, and Hornig 2018), and they require not-always straightforward computations and assumptions for practitioners (e.g., McCarthy and Fader 2018). Thus, despite providing financial valuations related to firms' relationships with their customers and their branding activities, Mintz et al. (2021a) and Mintz and Currim (2013) find managers use marketing asset metrics less than other types of metrics when managers are making their individual marketing-mix decisions. Further, marketing asset metrics, like customer mindset metrics, are marketing-unique terms that may not translate across the firm (Katsikeas et al. 2016).

Top-line performance metrics, such as sales and market share, often represent direct financial outcomes of a firm's marketing efforts (Rust et al. 2004). Further, top-line performance is easily understood across the firm and their data is readily available (Hanssens and Pauwels 2016). Hence, Katsikeas et al. (2016) find that top-line performance metrics are the second most often employed performance measure in academic research and Farris et al. (2021) find widespread use of such metrics by managers. However, while marketing's effects on top-line performance metrics are relatively easy to attribute for smaller single-product firms competing in limited markets (Katsikeas et al. 2016), attribution becomes complicated for larger multi-product firms that are conducting multiple actions on multiple products which affect multiple segments (Mintz et al. 2021b). Further, market share has been criticized for its lack of clarity (i.e., what defines a market) and how it relates to financial performance (Edeling and Himme 2018). In addition, top-line performance metrics such as sales and market share do not consider the costs of conducting marketing, potentially limiting its relevance (Farris et al. 2015).

Bottom-line performance metrics, such as ROI and profits, enable managers to assess the financial returns of their marketing efforts when taking into consideration their costs (Rust et al. 2004) using well-understood, standardized, and regularly employed accounting-based measures (Katsikeas et al. 2016). Hence, Mintz et al. (2021a) and Mintz and Currim (2013) find heavy use of these metrics by managers making their individual marketing-mix decisions and Katsikeas et al. (2016) find that bottom-line performance metrics are the most often employed performance measure in academic research. However, ROI and profits typically are reflective of short-term performance outcomes, while marketing initiatives often target longer-term performance outcomes (Farris et al. 2015). Further, similar to top-line metrics, bottom-line performance becomes more difficult to attribute marketing's direct effects if firms compete beyond a single-product in limited markets (Hanssens and Pauwels 2016).

Capital market performance metrics, such as stock return and market value, are normatively the ultimate goal of a public firm (Edeling, Srinivasan, and Hanssens 2021). Further, linking marketing initiatives with capital market performance metrics help establish marketing's value to the firm (Hanssens, Rust, and Srivastava 2009). Hence, Edeling, Srinivasan, and Hanssens (2021) and Katsikeas et al. (2016) both report the increasing use of such performance metrics in academic marketing studies over the last two decades. Yet, attribution of marketing initiatives for a multi-brand multi-product public firm's capital marketing value is an arduous task, in particular due to many confounding and intervening variables that take place between marketing initiatives and capital market performance results (Lehmann 2006). In addition, while capital market performance metrics are generally understood at a broad level, non-financial managers often find it difficult to interpret their results beyond just an increase or decrease (Mintz et al. 2021b), and this problem only grows when trying to understand how those results relate to individual firm efforts (Katsikeas et al. 2016). Consequently, Mintz and Currim (2013) find marketing managers very rarely employ such metrics when making their individual marketing-mix decisions (<1% of the decisions).

Taken together, each of the five performance metric types, e.g., customer mindsets, marketing assets, top-line, bottom-line, and capital market metrics, have certain advantages and disadvantages in how they relate marketing performance assessment. Table 2 summarizes the metric advantages and disadvantages detailed in this Web Appendix.

Web Appendix B. Core Variable Definitions Displayed to Conjoint Respondents

For the next couple of minutes, we will ask you a series of questions where we want to know about your evaluation of different integrated marketing campaigns. Integrated marketing campaigns means that a firm conducted a marketing campaign focusing on the same general goal through all 4 main marketing “P’s” or components, such as promotions, pricing, products, and placements (i.e., distribution).

The situations that you will be asked to evaluate differ in respect to two factors. The first differentiating factor is the firm’s overall strategic orientation and source of competitive advantage, which we specify as either:

1) **Cost-based Oriented Firm:** The firm’s/business unit’s overall strategic orientation and source of competitive advantage is **cost-based**; i.e., its strategy focuses on being a price leader in the majority of its product categories.

2) **Differentiation-based Oriented Firm:** The firm’s overall strategic orientation and source of competitive advantage is more **differentiation-based**; i.e., its strategy focuses on differentiating its product(s) by some attribute other than price.

The second differentiating factor is the goal of the integrated marketing campaign, which we specify as either:

1) **Growth-focused Integrated Marketing Campaign:** Please assume that the goal of all the integrated marketing campaigns provided to you in the following set of questions is **growth focused**. This means that the firm’s objective is mostly aimed towards expansion even if it is at the expense of profits.

2) **Profit-focused Integrated Marketing Campaign:** Please assume that the goal of all the integrated marketing campaigns provided to you in the following set of questions is **profit focused**. This means that the firm’s objective is mostly aimed towards profits even if it is at the expense of growth.

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Further, in the following scenarios, we will show you how different marketing campaigns did in terms of five different types of performance.

These types of performance are characterized as follows:

1. *Customer mindset impact*: this can be thought of how well the marketing campaign affected current and potential customers’ awareness, recall, satisfaction, perception of the firm’s product/service quality, brand perception, loyalty, etc. Measures are typically obtained from surveying customers/buyers.

2. *Marketing assets impact:* this can be thought of as how well the marketing campaign affected customer-based valuations of the firm such as customer lifetime values (CLV), brand equity, customer equity, etc.

3. *Top-line market impact:* this can be thought of how well the marketing campaign affected its success in the marketplace and competitive market position such as the firm’s market share, sales, etc.

4. *Bottom-line financial impact*: this can be thought of how well the marketing campaign affected specific financial returns in terms of net profit, return on investment (ROI), net

present value (NPV), economic value added (EVA), etc. this specific marketing campaign generated.

5. *Capital financial market impact:* this can be thought of how well the marketing campaign affected the firm's financial market position in terms of its impact on stock prices/returns, market value, book-to-market value, Tobin's Q etc.

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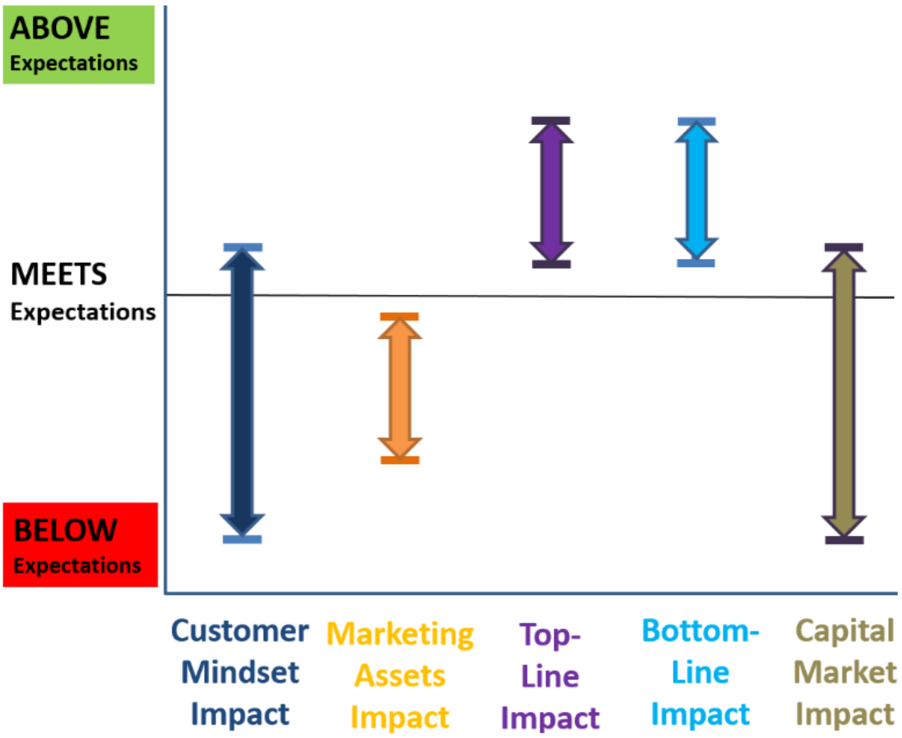
In the following scenarios, the outcome of a campaign is described for each type of performance along the following two dimensions:

Success: A campaign is measured as being above or below expectations.

Accuracy: Performance measurement may be subject to measurement error due to data quality, metric design, etc. Higher accuracy of metric measurement is reflected by a shorter arrow; lower accuracy of metric measurement is reflected by a longer arrow.

Below, we provide an example of a campaign's performance:



In this example, the customer mindset impact and the capital market impact success levels are below expectations and their performance measurements are of low accuracy. In contrast, the top-line impact and bottom-line impact success levels are above expectations and their performance measurements are of high accuracy. Finally, marketing assets impact success level is below expectations and its performance measurements is of high accuracy.

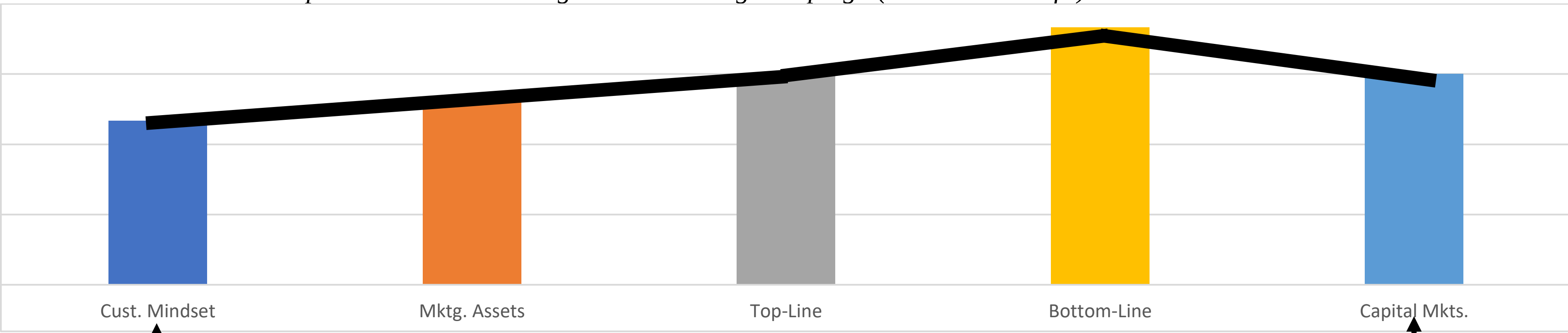
2 Strategic Orientation x 2 Campaign Focus

In your expert opinion, which of the following marketing campaigns would you rank as having the "better" performance for a large S&P 500 firm/business unit that focuses on …

Scenario	Low-Cost Firm Strategy	Differentiated Firm Strategy
Growth Integrated Marketing Campaign Objective	… its **cost advantage** and **growth**? As a reminder, those using a **cost-based strategy** are focused on being a price leader in the majority of its product categories, whilst a **growth focused firm's objective** is mostly aimed towards expansion even if it is at the expense of profits.	… its **differentiation focus** and **growth**? As a reminder, those using a **differentiation-based strategy** are focused on differentiating its product(s) by some attribute other than price, whilst a **growth focused firm's objective** is mostly aimed towards expansion even if it is at the expense of profits.
Profit Integrated Marketing Campaign Objective	… its **cost advantage** and **profits**? As a reminder, those using a cost-based strategy are focused on being a price leader in the majority of its product categories, whilst a **profit focused firm's objective** is mostly aimed towards profits even if it is at the expense of growth.	… its **differentiation focus** and **profits**? As a reminder, those using a **differentiation-based strategy** are focused on differentiating its product(s) by some attribute other than price, whilst a **profit focused firm's objective** is mostly aimed towards profits even if it is at the expense of growth.

Web Appendix Figure 1. Metric Relative Importance based on Integrated Framework

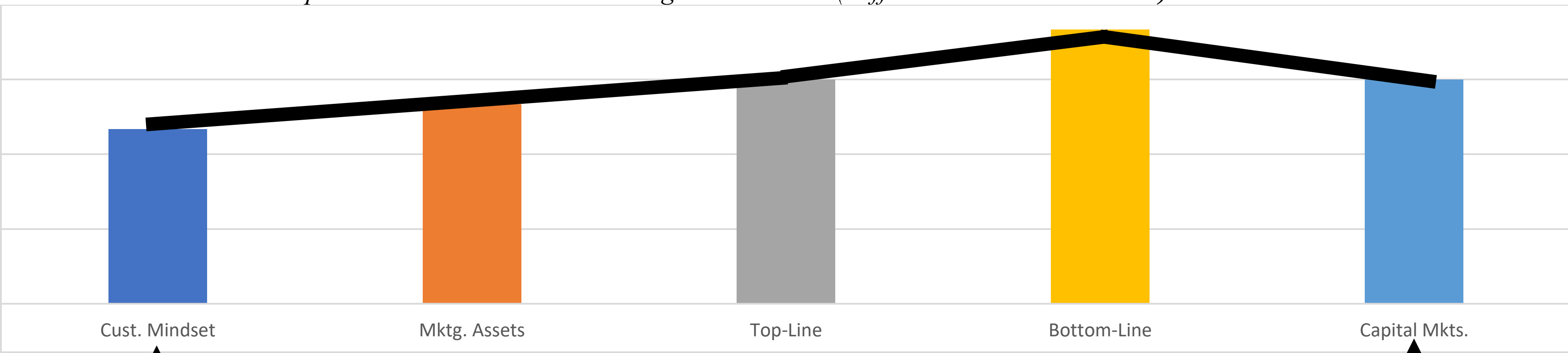
Panel A. Metric Relative Importance based on Integrated Marketing Campaign (Growth vs. Profit)



Most relevant for growth-focused campaigns

Most relevant for profit-focused campaigns

Panel B. Metric Relative Importance based on Firm's Strategic Orientation (Differentiation vs. Low-Cost)



Most relevant for differentiation strategic oriented firms

Most relevant for low-cost strategic oriented firms

Web Appendix Table 1. Managerial Sample Descriptive Statistics

Measure	Outcome	Aggregated Sample (n=431)	Marketing Executives (n=145)	Non-Marketing Executives (n=143)	Investors (n=143)
Number of responses	Percent of sample	100	33.6	33.2	33.2
Age	20 - 39	**48.5**	**62.8**	38.5	44.1
	40 - 59	42.2	30.3	**41.3**	**55.2**
	60+	9.3	6.9	20.3	0.7
Gender	Male	**69.4**	**73.1**	**53.1**	**81.8**
	Not male	30.4	26.2	46.9	18.2
Work experience (yrs in current position)	< 5 years	26.5	24.8	**28.0**	26.6
	6 - 10 years	**37.8**	**42.1**	27.3	**44.1**
	11 - 20 years	22.5	28.3	22.4	16.8
	20+ years	13.2	4.8	22.4	12.6
Firm size (# of employees)	<100	**38.2**	18.6	**58.0**	-
	100-499	22.6	**27.6**	17.5	-
	500-999	17.0	23.4	10.5	-
	1K-10K	20.1	28.3	11.9	-
	>10K	2.1	2.1	2.1	-
Compensation	Short-term commissions or bonuses (1-3)	17.4	14.5	21.0	16.8
	Mixture short/long term (4)	15.8	19.3	23.1	4.9
	Long-term equity (5-7)	**66.8**	**66.2**	**55.9**	**78.3**
Quantitative Background	More Qualitative	**46.6**	**44.8**	40.6	**54.5**
	Mix Qual. & Quant.	36.2	37.2	**46.9**	24.5
	More Quantitative	17.2	17.9	12.6	21.0
Risk orientation	Average of seven questions (1-7 scale); see Table 3 for questions	5.04	5.23	4.59	5.30

All figures listed as proportion (%) within each stakeholder group; bolded figure denotes modal outcome. Investors firm size not shown since this to control for managers firm size that may affect marketing assessments, but investors are evaluating these firms externally and so investors' firm sizes are less relevant or comparable.

Web Appendix Table 2. Conditional Logit Model Full Parameter Estimates

	Without Controls			With Controls		
Variable	**Est. β**	**S.E.**	**Sig.**	**Est. β**	**S.E.**	**Sig.**
Performance (X)						
Cust. Mindset (XCUST)	0.275	0.023	***	0.304	0.026	***
Mktg. Assets (XMKTG)	0.294	0.023	***	0.287	0.025	***
Top-Line (XTOPL)	0.172	0.022	***	0.218	0.026	***
Bottom-Line (XBOTL)	0.461	0.030	***	0.424	0.024	***
Capital Mkts. (XCAPT)	0.311	0.022	***	0.329	0.026	***
Uncertainty (V)						
Cust. Mindset (VCUST)	0.067	0.014	***	0.058	0.014	***
Mktg. Assets (VMKTG)	0.084	0.014	***	0.077	0.014	***
Top-Line (VTOPL)	0.126	0.014	***	0.137	0.014	***
Bottom-Line (VBOTL)	0.123	0.014	***	0.121	0.014	***
Capital Mkts. (VCAPT)	0.058	0.019	**	0.066	0.020	**
Perf x Uncert (X*V)						
Cust. Mindset (XVCUST)	-0.012	0.019		-0.012	0.020	
Mktg. Assets (XVMKTG)	-0.052	0.020	**	-0.057	0.020	**
Top-Line (XVTOPL)	0.033	0.019		0.030	0.020	
Bottom-Line (XVBOTL)	-0.119	0.021	***	-0.128	0.021	***
Capital Mkts. (XVCAPT)	-0.006	0.014		-0.005	0.014	
Marketing Executives						
MktgExecs*XCUST				-0.002	0.032	
MktgExecs*XMKTG				-0.053	0.031	
MktgExecs*XTOPL				-0.056	0.032	
MktgExecs*XBOTL				0.012	0.030	
MktgExecs*XCAPT				-0.043	0.031	
MktgExecs*VCUST				0.030	0.021	
MktgExecs*VMKTG				0.004	0.021	
MktgExecs*VTOPL				-0.014	0.021	
MktgExecs*VBOTL				0.014	0.020	
MktgExecs*VCAPTL				0.013	0.029	
MktgExecs*XVCUST				-0.036	0.028	
MktgExecs*XVMKTG				0.009	0.029	
MktgExecs*XVTOPL				0.042	0.028	
MktgExecs*XVBOTL				0.032	0.030	
MktgExecs*XVCAPT				0.022	0.021	
Non-Marketing Executives						
Non-Mktg*XCUST				0.133	0.034	***
Non-Mktg*XMKTG				0.089	0.033	**
Non-Mktg*XTOPL				0.090	0.034	**
Non-Mktg*XBOTL				0.086	0.031	**
Non-Mktg*XCAPT				0.116	0.033	***
Non-Mktg*VCUST				0.012	0.022	
Non-Mktg*VMKTG				0.003	0.022	
Non-Mktg*VTOPL				0.053	0.022	*
Non-Mktg*VBOTL				0.040	0.021	
Non-Mktg*VCAPTL				0.034	0.030	
Non-Mktg*XVCUST				0.014	0.030	
Non-Mktg*XVMKTG				-0.022	0.030	
Non-Mktg*XVTOPL				0.031	0.029	
Non-Mktg*XVBOTL				-0.079	0.032	*
Non-Mktg*XVCAPT				-0.011	0.022	
Investors						
Investors*XCUST				-0.132	0.029	***
Investors*XMKTG				-0.036	0.029	
Investors*XTOPL				-0.034	0.030	
Investors*XBOTL				-0.098	0.029	**
Investors*XCAPT				-0.073	0.029	*
Investors*VCUST				-0.042	0.019	*

Investors*VMKTG		-0.006	0.019	
Investors*VTOPL		-0.039	0.019	*
Investors*VBOTL		-0.053	0.019	**
Investors*VCAPTL		-0.047	0.027	
Investors*XVCUST		0.022	0.027	
Investors*XVMKTG		0.014	0.027	
Investors*XVTOPL		-0.072	0.027	**
Investors*XVBOTL		0.047	0.028	
Investors*XVCAPT		-0.011	0.019	
Low-Cost (vs. Differentiation) Firm Strategy				
CostStrtgy*XCUST		-0.035	0.020	
CostStrtgy*XMKTG		-0.029	0.020	
CostStrtgy*XTOPL		-0.001	0.020	
CostStrtgy*XBOTL		0.032	0.019	
CostStrtgy*XCAPT		0.047	0.020	*
Growth (vs. Profit) Integrated Marketing Campaign Goal				
GrowStrtgy*XCUST		0.024	0.020	
GrowStrtgy*XMKTG		0.036	0.020	
GrowStrtgy*XTOPL		0.020	0.020	
GrowStrtgy*XBOTL		-0.024	0.019	
GrowStrtgy*XCAPT		-0.014	0.020	
Gender (Male)				
Male*XCUST		-0.011	0.024	
Male*XMKTG		0.001	0.023	
Male*XTOPL		-0.037	0.024	
Male*XBOTL		0.045	0.023	*
Male*XCAPT		-0.002	0.024	
Age				
Age*XCUST		0.023	0.024	
Age*XMKTG		-0.026	0.024	
Age*XTOPL		-0.033	0.025	
Age*XBOTL		0.002	0.024	
Age*XCAPT		-0.036	0.024	
Risk Orientation				
RiskOrient*XCUST		-0.055	0.024	*
RiskOrient*XMKTG		-0.072	0.023	**
RiskOrient*XTOPL		-0.024	0.024	
RiskOrient*XBOTL		-0.131	0.023	***
RiskOrient*XCAPT		-0.045	0.023	
Quantitative Orientation				
QualOrient*XCUST		-0.011	0.020	
QualOrient*XMKTG		-0.029	0.020	
QualOrient*XTOPL		-0.024	0.020	
QualOrient*XBOTL		-0.062	0.020	**
QualOrient*XCAPT		-0.006	0.020	
Long-term Compensation				
LTComp*XCUST		-0.012	0.021	
LTComp*XMKTG		0.022	0.020	
LTComp*XTOPL		-0.013	0.021	
LTComp*XBOTL		-0.010	0.020	
LTComp*XCAPT		-0.003	0.021	
Job Duration				
JobLength*XCUST		0.010	0.024	
JobLength*XMKTG		-0.023	0.023	
JobLength*XTOPL		0.005	0.024	
JobLength*XBOTL		0.035	0.023	
JobLength*XCAPT		0.015	0.024	

*/**/*** = p < .05/.01/.001.

Web Appendix Table 3. Marketing Academic Results

Panel A. Academic Self-Reported Ratings on Performance Metrics Compared to Practitioners

	Aggregate		Marketing		Non-Marketing		Investors		Academics	
Measure	**Est.**	**S.D.**	**Est.**	**S.D.**	**Est.**	**S.D.**	**Est.**	**S.D.**	**Est.**	**S.D.**
Use:										
Cust. Mindset	5.42	1.41	5.48	1.25	5.48	1.51	5.29	1.45	**6.02**	1.01
Mktg. Assets	5.28	1.39	5.48	1.22	5.01	1.43	5.34	1.48	5.98	0.99
Top-Line	5.39	1.39	5.48	1.19	5.00	1.54	**5.68**	1.33	5.94	1.08
Bottom-Line	**5.59**	1.22	**5.62**	1.16	**5.54**	1.32	5.62	1.17	5.95	1.07
Capital Mkts.	5.15	1.59	5.36	1.39	4.48	1.85	5.61	1.27	4.70	1.41
Importance:										
Cust. Mindset	5.71	1.34	5.59	1.43	**6.01**	1.24	5.54	1.31	6.02	1.08
Mktg. Assets	5.48	1.32	5.58	1.22	5.46	1.40	5.40	1.34	**6.12**	1.00
Top-Line	5.57	1.35	5.70	1.21	5.27	1.50	**5.75**	1.28	5.66	1.23
Bottom-Line	**5.75**	1.24	**5.77**	1.14	5.83	1.33	5.64	1.24	5.98	1.20
Capital Mkts.	5.28	1.57	5.48	1.48	4.71	1.81	5.64	1.22	5.14	1.44
Reliability:										
Cust. Mindset	5.48	1.28	5.45	1.37	5.57	1.24	5.41	1.24	4.64	1.31
Mktg. Assets	5.45	1.31	5.57	1.22	5.35	1.36	5.41	1.33	4.85	1.19
Top-Line	5.45	1.35	5.48	1.23	5.14	1.49	**5.73**	1.27	**5.87**	1.23
Bottom-Line	**5.57**	1.17	**5.60**	1.07	**5.57**	1.30	5.54	1.15	5.85	1.14
Capital Mkts.	5.34	1.45	5.55	1.34	4.96	1.64	5.50	1.26	4.98	1.52
Interpretability:										
Cust. Mindset	5.38	1.37	5.43	1.25	5.50	1.39	5.21	1.47	5.29	1.39
Mktg. Assets	5.29	1.33	5.46	1.17	5.12	1.45	5.29	1.36	5.16	1.29
Top-Line	5.54	1.30	5.56	1.10	5.31	1.45	**5.74**	1.30	**6.12**	1.15
Bottom-Line	**5.61**	1.29	**5.66**	1.18	**5.61**	1.47	5.58	1.21	6.06	1.17
Capital Mkts.	5.32	1.46	5.51	1.30	4.85	1.65	5.59	1.30	5.22	1.52

Modal outcome for each stakeholder is bolded.

Panel B. Academic Performance Metrics Relative Importance Compared to Practitioners

	Marketing Academics			Versus Aggregate	Versus Marketers	Versus Non-Marketers	Versus Investors
Metric	**Est. (%)**	**S.E.**	**Sig.[1]**	**p-value [2]**	**p-value [2]**	**p-value [2]**	**p-value [2]**
Cust. Mindset	20.18	2.23	***	.059	0.798	.145	.001[a]
Mktg. Assets	16.49	2.17	***	.405	0.988	.729	.032[b]
Top-Line	17.69	2.20	***	.953	0.443	.910	.891
Bottom-Line	**29.44**	2.29	*base*	.142	0.547	.153	.396
Capital Mkts.	16.19	2.04	***	.007[b]	0.272	.012[b]	.037[b]

Most important metric for marketing academics is bolded;
[1] */**/*** metric significantly less important relative to bottom-line (i.e., *base*) ($p<.05/.01/.001$);
[2] a/b denotes metric is significantly above/below level of importance for all stakeholders (aggregate) or specific stakeholder (e.g., non-marketers) relative to marketing academics ($p<.05$);

Web Appendix Table 4. Mixed Logit Results

	Conditional Logit Model			Mixed Logit Model					
Variable	**Est. β**	**S.E.**	**Sig.**	**Est. β**	**S.E.**	**Sig.**	**Est SD.**	**S.E. (SD)**	**Sig.**
Performance (X)									
Cust. Mindset	0.304	0.026	***	0.295	0.027	***	0.149	0.042	***
Mktg. Assets	0.287	0.025	***	0.291	0.028	***	0.224	0.033	***
Top-Line	0.218	0.026	***	0.210	0.026	***	0.113	0.046	*
Bottom-Line	0.424	0.024	***	0.441	0.033	***	0.372	0.033	***
Capital Mkts.	0.329	0.026	***	0.327	0.026	***	-0.135	0.039	***
Uncertainty (V)									
Cust. Mindset	0.058	0.014	***	0.065	0.014	***	-0.076	0.029	**
Mktg. Assets	0.077	0.014	***	0.079	0.014	***	0.078	0.032	*
Top-Line	0.137	0.014	***	0.126	0.014	***	-0.060	0.039	
Bottom-Line	0.121	0.014	***	0.122	0.014	***	-0.046	0.028	
Capital Mkts.	0.066	0.020	**	0.062	0.019	**	-0.006	0.042	
Perf x Uncert (X*V)									
Cust. Mindset	-0.012	0.020		-0.009	0.019		0.037	0.051	
Mktg. Assets	-0.057	0.020	**	-0.052	0.019	**	-0.022	0.080	
Top-Line	0.030	0.020		0.036	0.018		0.011	0.044	
Bottom-Line	-0.128	0.021	***	-0.120	0.021	***	0.184	0.035	***
Capital Mkts.	-0.005	0.014		-0.009	0.014		0.086	0.027	**

*/**/*** = p < .05/.01/.001; correlation between MIXL and CLM: all estimates = .999; variance parameterized estimates = .999.

Web Appendix Table 5. Academic Sample Descriptive Statistics

Measure	Outcome	%
Age	25 – 44	36.9
	45 – 64	**40.8**
	65+	22.3
Gender	Male	**72.3**
	Not male	27.7
Job Title	Professor	**51.5**
	Associate Professor	19.2
	Assistant Professor	26.9
	Other	2.3
Research focus: Consumer Behavior	Does not describe my research focus well	23.8
	Describes slightly/moderately well	23.8
	Describes very/extremely well	**52.3**
Research focus: Strategy	Does not describe my research focus well	27.7
	Describes slightly/moderately well	**42.3**
	Describes very/extremely well	30.0
Research focus: Modelling	Does not describe my research focus well	**41.5**
	Describes slightly/moderately well	23.1
	Describes very/extremely well	35.4
Risk orientation	Average of seven questions (1-7 scale); see Table 3 for questions	5.04

All figures listed as proportion (%) of academic sample (n=130); bolded figure denotes modal outcome.

Web Appendix References

Bendle, Neil T., Paul W. Farris, Phillip E. Pfeifer, and David J. Reibstein (2021), *Marketing Metrics: The Definitive Guide to Measuring Marketing Performance,* Pearson FT Press.

Edeling, Alexander and Alexander Himme (2018), "When Does Market Share Matter? New Empirical Generalizations from a Meta-Analysis of the Market Share–Performance Relationship," *Journal of Marketing,* 82 (3), 1–24.

---, Shuba Srinivasan, and Dominique M. Hanssens (2021), "The marketing–finance interface: A new integrative review of metrics, methods, and findings and an agenda for future research," *International Journal of Research in Marketing*, 38 (4), 857–76.

Farris, Paul W., Dominique M. Hanssens, James D. Lenskold, and David J. Reibstein (2015), "Marketing Return on Investment: Seeking Clarity for Concept and Measurement," *Applied Marketing Analytics*, 1 (3), 267–82.

Fischer, Marc, Rex Y. Du, and Tobias Hornig (2018), "How Accurate are Commercial Brand Valuation Methods?" Working Paper, University of Cologne.

Fornell, Claes, Forrest V. Morgeson, and G. Tomas M. Hult (2016), "Stock Returns on Customer Satisfaction Do Beat the Market: Gauging the Effect of a Marketing Intangible," *Journal of Marketing*, 80 (5), 92–107.

Hanssens, Dominique M. and Koen H. Pauwels (2016), "Demonstrating the Value of Marketing," *Journal of Marketing*, 80 (6), 173–90.

--- Roland T Rust, and Rajendra K Srivastava (2009), "Marketing Strategy and Wall Street: Nailing Down Marketing's Impact," *Journal of Marketing*, 73 (6), 115–18.

Himme, Alexander and Marc Fischer (2014), "Drivers of the cost of capital: The joint role of non-financial metrics," *International Journal of Research in Marketing,* 31 (2), 224–38.

Hult, G. Tomas M., Forrest V. Morgeson, Neil A. Morgan, Sunil Mithas, and Claes Fornell (2017), "Do managers know what their customers think and why?" *Journal of the Academy of Marketing Science,* 45 (1), 37–54.

Katsikeas, Constantine S., Neil A. Morgan, Leonidas C. Leonidou, and G. Tomas M. Hult (2016), "Assessing Performance Outcomes in Marketing," *Journal of Marketing,* 80 (2), 1–20.

Keller, Kevin Lane (1993), "Conceptualizing, Measuring, and Managing Customer-Based Brand Equity," *Journal of Marketing*, 57 (1), 1–22.

Lehmann, Donald R. (2006), "The Metrics Imperative: Making Marketing Matter," in *Review of Marketing Research*, N. K. Malhotra, ed., Armonk, New York: M.E. Sharpe, 178–202.

McCarthy, Daniel M. and Peter S. Fader (2018), "Customer-Based Corporate Valuation for Publicly Traded Noncontractual Firms," *Journal of Marketing Research*, 55 (5), 617–35.

Mintz, Ofer and Imran S. Currim (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.

---, ---, Jan-Benedict E. M. Steenkamp, and Martijn de Jong (2021a), "Managerial metric use in marketing decisions across 16 countries: A cultural perspective," *Journal of International Business Studies*, 52 (8), 1474–1500.

---, Timothy J. Gilbride, Peter Lenk, and Imran S. Currim (2021b), "The right metrics for marketing-mix decisions," *International Journal of Research in Marketing*, 38 (1), 32–49.

Rust, Roland T., Tim Ambler, Gregory S. Carpenter, V. Kumar, and Rajendra K. Srivastava (2004), "Measuring Marketing Productivity: Current Knowledge and Future Directions," *Journal of Marketing,* 68 (4), 76–89.

Schulze, Christian, Bernd Skiera, and Thorsten Wiesel (2012), "Linking Customer and Financial Metrics to Shareholder Value: The Leverage Effect in Customer-Based Valuation," *Journal of Marketing,* 76 (2), 17–32.