Unlocking the Power of Marketing: Understanding the Links between Customer Mindset Metrics, Behavior, and Profitability

Abstract

Recent evidence about the central role played by perceptual constructs in driving performance outcomes has produced a renewed interest in studying customer mindset metrics (CMMs; e.g., satisfaction, service quality, and loyalty intentions). However, we still lack a proper understanding of how (i.e., *process*) and to what extent (i.e., *magnitude*) these CMMs ultimately translate into profitability at the customer level. In this study, we integrate CMMs into an individual-level framework of customer behavior and profitability and provide a conceptual understanding of the process through which these metrics influence customer profitability. Specifically, we propose three mechanisms through which CMMs affect customer behavior and profitability: *behavioral effect*, *marketing effectiveness effect*, and *marketing efficiency effect*. We empirically test this framework across two distinct contexts, a B2B high-tech firm and a B2C telecommunications firm. The results demonstrate that these unobservable CMMs have a significant and multi-dimensional impact on customer behavior and customer profitability. Furthermore, we compute the increases in customer behavior and customer profitability that each firm can expect due to increases in CMMs to help firms improve resource allocation and make better decisions about how much (and when) to invest in CMMs.

Researchers have long emphasized and demonstrated the importance of customer mindset metrics (CMMs)—summary judgments and overall evaluations that customers make about their relationships with the firm or brand (e.g., customer satisfaction, service quality, commitment, loyalty intentions)—in building successful relationships and creating superior performance outcomes (Bolton, Lemon, and Verhoef 2004; Gupta and Zeithaml 2006; Morgan and Hunt 1994; Srinivasan, Vanhuele, and Pauwels 2010). Despite the accumulated evidence, marketing academics and practitioners have frequently ignored CMMs when building models for customer selection and optimal resource allocation, focusing instead on leveraging actual customer behavior (Reinartz and Kumar 2003; Venkatesan and Kumar 2004). Recent calls for marketing accountability have produced a renewed interest in these metrics and in their impact on the bottom line (Venkatesan, Reinartz, and Ravishanker 2010), leading to a surge of studies that connect CMMs and performance outcomes (Anderson, Fornell, and Lehmann 1994; Fornell, Morgeson III, and Hult 2016; Luo and Homburg 2008). However, these studies have been conducted at an aggregate level, preventing firms from understanding how the return on marketing to an individual customer is influenced by the role of CMMs. With firms investing an increasing amount of resources in improving CMMs and the overall customer experience (Lemon and Verhoef 2016), and CMMs affecting the different components of profitability in multiple and complex ways (Bolton, Lemon, and Verhoef 2004), demonstrating the return on those investments has become a top priority. This study aims to contribute to fill this important gap by providing an understanding of how (i.e., the process) and to what extent (i.e., the magnitude) CMMs affect customer decision making and subsequent behavior and profitability, thus illuminating the deep reasons of marketing success.

Previous research has provided some valuable insights into this domain. While a number of studies have shown a positive effect of CMMs on customer purchase intentions (Anderson and Sullivan 1993; Crosby, Evans, and Cowles 1990; Garbarino and Johnson 1999; Rust, Zahorik, and Keiningham 1995) and behavior (Bolton 1998; Bolton and Lemon 1999; Gustafsson, Johnson, and Roos 2005; Verhoef 2003), another group of studies has investigated the direct link between CMMs and performance outcomes, finding a positive association between these metrics and financial performance (Fornell et al. 2006; Gruca and Rego 2005; Hanssens et al. 2014; Srinivasan, Vanhuele, and Pauwels 2010).

Despite the merit of these studies in demonstrating the importance of CMMs for improving intentions toward the relationship and promoting favorable behaviors as well as for enhancing financial outcomes, they provide a fragmented view of the process through which these metrics translate into profits. Specifically, we lack a proper understanding of the different mechanisms (i.e., the process) through which these metrics impact profitability, their relative importance, and whether different CMMs operate in a similar way in this process. In addition, these metrics reflect an individual's state of mind (Harris 1994), and they have an impact on what customers do in the immediate as well as in the distant future (Palmatier et al. 2013). But for some notable exceptions (Bolton, Lemon, and Verhoef 2004; Bowman and Narayandas 2004; Palmatier et al. 2013; Rust, Lemon, and Zeithaml 2004), studies often do not adopt an individual and/or longitudinal-level framework to the study of CMMs. As a result, we lack an encompassing and integrative individual-level framework that (1) identifies the mechanisms through which CMMs lead to performance outcomes, (2) quantifies their overall and relative impact on profitability at the individual customer level, and (3) enables companies to manage investments in CMMs and to strategically employ these metrics for customer selection and optimal resource allocation.

In this study, we develop an integrative framework to understand the impact of CMMs on customer behavior and customer profitability. Specifically, we build upon traditional individual-level customer profitability models (Gupta et al. 2006; Reinartz and Kumar 2003) and incorporate CMMs. Drawing from social cognition research, we argue that CMMs influence profitability in three distinct ways, through the (1) *behavioral effect*, (2) *marketing effectiveness effect*, and (3) *marketing efficiency effect*. These distinct mechanisms enable us to quantify both the relative and the overall impact of an improvement in different CMMs on individual customer behavior and customer profitability, and to help marketing managers from firms improve their allocation of marketing resources to customers and campaigns to enhance CMMs. We offer an empirical application of the proposed framework using data from two distinct contexts, a B2C telecommunications firm and a B2B high-tech firm.

The proposed framework and its empirical application enable us to contribute to existing knowledge in two critical ways. First, we propose a comprehensive conceptual framework at the individual customer level to understand the central role played by CMMs in the customer profitability model. In this framework, we offer a theoretical understanding of the process (i.e., the different mechanisms) through which CMMs influences individual customer behavior and customer profitability, thus uncovering the path to profitability followed by investments in CMMs and illuminating the (multiple) sources of marketing success. In addition, our study simultaneously considers various CMMs (i.e., satisfaction, service quality, loyalty intentions), which enables us to offer preliminary evidence into their relative importance in driving customer behavior and customer profitability. Second, our proposed framework and empirical application offers managers a practical path to deploying relationship marketing initiatives that influence CMMs and assessing their contribution to business growth. Specifically, our study demonstrates the connections between CMMs and customer behavior and profitability, thus enabling companies to integrate information on customer attitudes and perceptions into their customer management strategies to better explain and predict customer behavior, more effectively discriminate among customers, and allocate resources more efficiently. In doing so, this study responds to recent calls for marketing accountability by building a direct link between CMMs and profitability that can help firms in decisions pertaining to resource allocation and in measuring marketing effectiveness more accurately (Petersen et al. 2009).

Theoretical foundations

Customer mindset metrics (e.g., perceptions, attitudes, and intentions) have been studied extensively since the 1980s under the relationship marketing paradigm. A fundamental reason for this dedicated attention can be found in the benefits that are frequently associated to these metrics: positive CMMs reflect strong relationships, which translate into enhanced (financial and non-financial) performance outcomes (Dwyer, Schurr, and Oh 1987; Gupta and Zeithaml 2006; Morgan and Hunt 1994) and, ultimately, into a distinct competitive advantage for the firm (McKenna 1993). Table 1 offers a summary of relevant research on the consequences of CMMs. As the table demonstrates, existing research tends to be divided into two main areas, studies investigating the impact of CMMs on (1) behavior and (2) performance.

-- Insert Table 1 about here --

Impact of CMMs on behavior

The early work on CMMs focused on understanding the consequences of these metrics on customer behavior (e.g., customer acquisition and retention). Given the lack of actual behavioral data, a first group of studies looked at the effect of customer satisfaction, service quality, trust, and commitment on intentions to repurchase and continue the relationship with the firm. In general, these studies find a positive connection between CMMs and loyalty intentions (e.g., see meta-analytical work on the consequences of customer satisfaction by Szymanski and Henard (2001)). For example, Boulding et al. (1993) show that perceptions of quality relate positively to behavioral intentions. Further, Anderson and Sullivan (1993) demonstrate that repurchase intentions are positively influenced by the level of satisfaction. Garbarino and Johnson (1999) find that satisfaction (for customers maintaining weak relationships), and trust and commitment (for customers with strong relationships), are important drivers of the willingness to engage in future interactions with the company. Recently, the wider availability of extensive behavioral databases together with raising concerns about the true associations between intentions and behavior (Mazursky and Geva 1989; Mittal, Kumar, and Tsiros 1999) has led to a surge of studies looking at the behavioral consequences of CMMs. In general, again, these studies find a positive association between CMMs (mostly satisfaction) and loyal behaviors including retention, cross-buy, or share-of-wallet (e.g., see review on the satisfaction–loyalty relationship by Kumar, Dalla Pozza, and Ganesh (2013)). For example, Bolton (1998) shows a positive impact of customer satisfaction on relationship duration; Verhoef (2003) demonstrates that commitment positively impacts customer retention and customer share; Gustafsson, Johnson, and Roos (2005) find that customer satisfaction and calculative commitment reduce the likelihood of customer churn; and Bolton and Lemon (1999) demonstrate the role of satisfaction as a key precursor of service usage.

Impact of CMMs on performance

With the increasing interest in recent years in making marketing more financially accountable (Kumar and Shah 2009), recent work has shifted the focus toward establishing direct linkages between CMMs and performance outcomes. At the firm level, and using different measures of financial performance (e.g., Tobin's q, return on investment ROI, cash flows, stock price), studies have generally found a positive relationship between CMMs (most frequently customer satisfaction) and firm profitability. For instance, Anderson, Fornell, and Lehmann (1994) demonstrate that the cumulative incremental returns from a continuous one-point increase in customer satisfaction is 11.5% relative to the current ROI, or $7.48 million; Gruca and Rego (2005) find that increasing satisfaction by one point leads to an increase of $55 million in a firm's cash flow; Luo and Homburg (2008) demonstrate that increasing customer satisfaction leads to reductions in the stock value gap (the shortfall of a firm's market value from its optimal value, as measured by the best performing competitors); and more recently, Fornell, Morgeson III, and Hult (2016) demonstrate that in a period of 15 years the recorded cumulative returns on customer satisfaction were 518%, compared with a 31% increase for the S&P 500.

At the customer level, and despite continuous calls for research linking attitudes and behavior and profits (e.g., Bolton, Lemon, and Verhoef [(2004)), there is a considerable lack of empirical studies. Two notable exceptions include Rust, Lemon, and Zeithaml (2004), who provide a strategic framework to project financial return from marketing investments and empirically validate their model by showing the impact of improving customer attitudes toward the relationship (trust and quality) on behavior (self-reported) and CLV; and Bowman and Narayandas (2004), who empirically validate a service profit chain model that links vendor efforts to attribute performance to satisfaction to loyalty (share-of-wallet) and to profitability in a business market (although the main effect of satisfaction is nonsignificant).

Despite the valuable insights into the consequences of CMMs that these studies provide, the previous discussion and the detailed literature review table (Table 1) reveal a number of significant research gaps. First, knowledge on the consequences of CMMs remains highly fragmented, providing only a partial understanding of either their impact on behavior, or their direct effect on performance outcomes. Surprisingly, no research to date has provided a systematic investigation of the *process* through which CMMs impact behavior and profitability, and the mechanisms involved. Second, existing studies looking at the impact of CMMs on profitability have predominantly been conducted at the firm level. However, an investigation of the individual-level effects is necessary to properly understand how the return on marketing to an individual is influenced by CMMs and, thus, promote optimal resource allocation decisions to customers and CMMs campaigns. Third, most studies, particularly those linking CMMs to performance, have focused on only one metric, primarily satisfaction. However, although related, different CMMs capture different aspects of the relationship that, together, determine loyalty behaviors (Agustin and Singh 2005), and they have been shown to differently affect relational outcomes (Garbarino and Johnson 1999). Thus, it is important to broaden the scope and simultaneously consider multiple CMMs to gain a proper understanding of their different impact on behavior as well as their relative importance in driving profitability. Fourth, previous research has mainly looked at one mechanism through which CMMs impact profitability: through changes in behavior (i.e., CMMs → behavior). Even those studies that establish direct linkages between CMMs and profitability (CMMs → performance) assume that their influence goes through changes in behavior. While prior research has suggested other mechanisms through which these metrics can affect profitability (e.g., an improvement in consumers' responsiveness to marketing activities (Dwyer, Schurr, and Oh 1987; Garbarino and Johnson 1999) or an improvement in exchange efficiencies (Anderson, Fornell, and Rust 1997; Rust, Zahorik, and Keiningham 1995; Sheth and Parvatiyar 1995)), they have not been systematically studied to date. Our current understanding of CMMs, and their impact on profitability, will significantly benefit from a simultaneous investigation of the different mechanisms that operate as well as their relative importance. Fifth, most studies measure CMMs at only one point in time (i.e., static snapshot). However, these metrics are dynamic and evolve (Palmatier et al. 2013), requiring a longitudinal approach to properly gauge their effects on behavior and performance over time. Finally, most studies have been conducted either in a B2C (predominantly) or a B2B context. For generalizability purposes, however, it is important to provide an investigation on the consequences of CMMs in multiple contexts. In this study, we aim to address these research gaps, and provide a comprehensive conceptual framework at the individual level to understand the impact of CMMs on customer behavior and profitability.

Conceptual framework and model development

To address these gaps and understand the role played by CMMs in driving performance outcomes, we propose a conceptual framework on the linkages between these metrics, customer behavior, and profitability (see Fig. 1). In developing our framework, we build on previous customer profitability models, which propose that firms strategically invest in marketing efforts to influence customer behavior, which in turn, affects customer profits (i.e., gross margin) (Gupta et al. 2006; Reinartz and Kumar 2003; Venkatesan and Kumar 2004). We extend the customer profitability model to include CMMs. By CMMs we refer to summary judgments and overall evaluations that customers make about their relationships with the firm or brand (Keller 2003; Morgan and Rego 2006), and they include customer satisfaction, perceived quality, commitment, and attitudinal loyalty, among others (Gupta and Zeithaml 2006). They have been formally conceptualized as “high-order mental constructs [that] summarize consumers’ knowledge and experience with a particular firm and guide subsequent actions of the customer” (Garbarino and Johnson 1999). Through direct and indirect interactions and experiences with the firm, the customer’s mind synthesizes and abstracts a generic cognitive representation of the relationship that is captured by these structures of knowledge.

In this study, our focus is on three of the most prominent CMMs: customer satisfaction, perceived quality, and attitudinal loyalty. Satisfaction is defined as “an overall evaluation based on the total purchase and consumption experience with a good or service over time” (Anderson, Fornell, and Lehmann 1994). Perceived quality refers to “the consumer’s judgment about a product’s overall excellence or superiority” (Zeithaml 1988), dependent on the level of product attributes. And attitudinal loyalty refers to “a customer’s stated probability of purchasing from the same product or service provider in the future” (Morgan and Rego 2006). These three constructs have received ample academic attention (Gupta and Zeithaml 2006), are easy to comprehend and communicate (Morgan and Rego 2006), and have been prevalently used in practice to monitor the “hearts and minds” of consumers (de Haan, Verhoef, and Wiesel 2015).

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We argue that CMMs are an integral part of the customer profitability model as they can significantly influence the relationships between its key constituents. Building upon social cognition and information processing (Cohen and Reed 2006; Howard and Renfrow 2006), we offer a conceptual understanding of the way in which CMMs impact individual behavior and profitability. According to this stream of research, the overall evaluations and judgments that individuals create through their interactions and experiences with objects (e.g., the firm) are cognitive structures that represent organized knowledge about that object and function as interpretive frameworks for new information (Howard and Renfrow 2006). These knowledge structures determine the way in which individuals organize the knowledge, beliefs, and experiences about an entity and, thus, condition how they perceive, process, organize, interpret, and respond to information stimuli (Fiske and Taylor 1991). Thus, an individual's overall evaluation of the relationship with the firm (e.g., satisfaction, perceived quality, loyalty) becomes a powerful force in influencing how the customer processes incoming information from the environment and behaves in response to internal (motivations, needs) and external (marketing activities) stimuli.

A fundamental aspect of these summary judgments and evaluations is that they serve a number of key functions (Fazio and Olson 2003). First, they facilitate decision making and enhance the quality of the decisions: the summary judgments that are accessible in the mind enable individuals to make less effortful decision and to increase consistency between beliefs and behaviors. Second, they guide attention: from all stimuli that individuals are exposed to, these evaluations filter what should be attended, noticed, and processed, and what can be ignored and neglected. Third, they free cognitive resources: decision making that uses accessible information on judgments and evaluations is less effortful and save time and energy that otherwise would be required to process and evaluate incoming information.

In our customer profitability model, we argue that these three central features of consumer evaluations and judgments (i.e., CMMs) will materialize in three distinct mechanisms through which CMMs affect customer profitability, through the (1) behavioral effect, (2) marketing effectiveness effect, and (3) marketing efficiency effect.

Next, we specify a set of mathematical models that highlight the three distinct relationships between the customer profitability framework and CMMs. Let $\ln(Mktg_{it})$[1] represent the natural log of marketing efforts of the firm on customer i in time t, $Behavior_{it}$ represent the behavior of customer i in time t, $Profit_{it}$ represent the gross margin provided to the firm by customer i in time t, $Mindset_{it}$ represent the mindset of customer i in time t, $Controls_{it}$ represent a set of control variables for customer i in time t, μ_i represent a customer-specific random effect for customer i, and ε_{it} represent a random error component for customer i in time t. We start by specifying the two main equations for $Behavior_{it}$ and $Profit_{it}$:

$$\begin{aligned} Behavior_{it} &= \alpha_0^B + \alpha_1^B \ln(Mktg_{it}) + \alpha_2^B Mindset_{it} + \alpha_3^B \ln(Mktg_{it}) * Mindset_{it} \\ &+ \alpha_4^B Controls_{it} + \mu_i^B + \varepsilon_{it}^B \end{aligned} \quad (1)$$

$$\begin{aligned} Profit_{it} &= \alpha_0^P + \alpha_1^P \ln(Mktg_{it}) + \alpha_2^P Behavior_{it} + \alpha_3^P Mindset_{it} + \alpha_4^P \ln(Mktg_{it}) * Mindset_{it} \\ &+ \alpha_4^P Controls_{it} + \mu_i^P + \varepsilon_{it}^P \end{aligned} \quad (2)$$

In Eq. 1, we see that a customer's behavior with the firm at time t is a function of the firm's marketing efforts to customer i in time t (α_1^B), customer i's mindset in time t (α_2^B), which we refer to as the *behavioral effect*, and the interaction between the firm's marketing efforts to customer i in time t and customer i's mindset in time t (α_3^B), which we refer to as the *marketing effectiveness effect*. In Eq. 2, we see that a customer's profitability to the firm at time t is a function of the firm's marketing efforts to customer i in time t (α_1^P), customer i's behavior in time t (α_2^P), customer i's mindset in time t (α_3^P)[2], and the interaction between the firm's marketing efforts to customer i in time t and customer i's mindset in time t (α_4^P) which we refer

[1] We transform marketing efforts using the natural log function because we assume that marketing efforts have a positive, but diminishing impact on customer behavior and profitability.

[2] We note here that we do not expect that CMMs will have a direct impact on customer profitability, only a moderating impact on customer profitability directly through the marketing efficiency effect and indirectly through their effects on customer behavior. We do not expect that customers with a more positive mindset will directly provide more profit to the firm just because they have a more positive mindset.

to as the *marketing efficiency effect*. Thus, we expect that CMMs have a direct effect on customer behavior through the behavioral effect (α_2^B) and marketing effectiveness effect (α_3^B), a direct effect on customer profitability through the marketing efficiency effect (α_4^P), and an indirect effect on customer profitability through their impact through changes in customer behaviors ($\alpha_2^P * (\alpha_2^B + \alpha_3^B * \ln(Mktg_{it}))$). This enables us to decompose the impact of CMMs on performance in terms of the three proposed mechanisms and understand their relative influence on firm profitability.

Behavioral effect

The behavioral effect is defined as the process by which positive (negative) evaluations and judgments about the firm leads to an increase (decrease) in customer behavior independent of the firm's marketing efforts. As noted previously, CMMs aid decision making by simplifying purchase decisions, promoting consistency between existing beliefs and behaviors, and increasing the quality of those decisions (Halkias 2015). When confronted with a purchase decision, existing evaluations and judgments help individuals make less effortful decisions (Fazio and Olson 2003). The need for such decision initiates a spontaneous process through which the perceptions and beliefs about the firm (i.e., CMMs) are retrieved from memory. The nature of the evaluation (whether positive or negative) determines the direction of the behavior, such that positive (negative) perceptions lead to approach (avoid) behaviors (Fazio 1990). Thus, CMMs help consumers arrive easily to a decision about how to behave with respect to a firm (e.g., whether to purchase or use more its services, or not) based on the knowledge accumulated in these metrics. Furthermore, social cognition research suggests that customers strive for harmonious relationships in their beliefs, feelings and behaviors, and avoid inconsistencies that generate psychological tension (Meyers-Levy and Tybout 1989). By encouraging behaviors that are aligned with the evaluations stored in memory, CMMs promote consistency between the beliefs held and the behaviors performed, and increase the quality of the decisions by reducing discomfort and mental stress. Therefore, we expect a mental repository of positive (negative) evaluations (CMMs) about a firm will encourage (discourage) the customer to engage in purchase behaviors with that firm.

Marketing effectiveness effect

The marketing effectiveness effect is defined as the process by which the interaction between a customer's evaluation toward the firm and the firm's marketing efforts leads to an increase (or decrease) in customer behavior. Consumers are exposed to vast amounts of stimuli, but due to limited capacity, they attend and process only a relatively small portion of all information they receive (Kardes 1994). As noted previously, CMMs help individuals guide their attention (Cohen and Reed 2006). These cognitive structures serve as selective mechanisms, "a ready aid for sizing up objects and events in the environment" (Smith, Bruner, and White 1956) which determine whether information is attended (Markus 1977), and the amount of cognitive effort that consumers are willing to devote to the acquisition, interpretation and assimilation of that information (Kardes 1994). The nature of the perceptions directs the searches for information. As a perceptual vigilance, consumers will selectively pay more attention to such information and stimuli for whom there is a favorable predisposition and attitude as revealed from the state held in the mind of the customer (Sheth and Parvatiyar 1995). Upon becoming aware of the stimuli, previously-stored evaluations will be retrieved from memory (Fazio et al. 1986). This is more likely to happen when individuals have positive evaluations about a firm, because positive aspects are more salient and easily retrieved (Kiesler and Sproull 1982). Importantly, a positive attitude that has been activated is likely to lead the individual to notice, attend to, and process primarily the positive qualities of the stimuli (Fazio 1990), and even may color one's perceptions of the stimuli such that they are forced to fit with the overall evaluations held in memory (Fazio and Olson 2003). As noted above, the activation of CMMs in memory will therefore prompt customers to engage in attitudinally consistent behaviors (Festinger 1962). Thus, we expect when the customer is exposed to marketing activities, they will be more likely to be noticed, processed and assimilated if they come from a firm for which the consumer holds a favorable evaluation, ultimately leading to a higher likelihood to respond to that stimuli in a manner consistent with the attitude held.

Marketing efficiency effect

The marketing efficiency effect is defined as the process by which the interaction between CMMs and the firm's marketing efforts lead to an increase (or decrease) in customer profit. This is distinct from the marketing effectiveness effect in that the effectiveness of a marketing campaign is a function of whether the customer responds to the marketing campaign (e.g., purchases a product and/or increases usage). However, the efficiency of a marketing campaign is a function of how much profit is obtained for each dollar that is being spent (Anderson, Fornell, and Rust 1997), i.e., this effect is related to the amount of cost that customers with different levels of CMMs necessitate to generate a given profit. As noted previously, CMMs help free cognitive resources. They enable the efficient organization of incoming information, allow individuals to process it more rapidly and effectively, and make "navigating one's environment an easier task" (Fazio and Olson 2003). This is because these cognitive representations held by the customer help reduce the information-processing demands by providing a knowledge system for interpreting and storing information pertaining to the relationship with the firm (Harris 1994; Lord and Foti 1986).

When the customer has a positive representation of the firm (positive CMMs), the cognitive effort required to process information will therefore be reduced and the tasks will be performed automatically and routinely, with minimal effort and, eventually, without conscious control (Alba and Hutchinson 1987). These reductions in cognitive effort will increase the speed at which information processing is performed, making decision making more efficient. At the same time, this increase in the level of automaticity of information processing will reduce the level of information that is required to make inferences, predictions, and engage in relationship behaviors (Halkias 2015). Compared with other customers, those who have a positive evaluation of the relationship with the firm will necessitate a lower level of resources (e.g., communications, information needs) to generate a specific level of profit, given that the positive attitudes held in memory function as a mechanism that enables the customer to more efficiently navigate the relationship with the firm. For example, Morgan and Hunt (1994) stated that successful customer-firm relationships "produce outcomes that promote efficiency, productivity" (p. 22), and Blattberg and Deighton (1996) and Wang and Splegel (1994) further argued that customers with positive attitudes generate higher margins because they are relatively low-maintenance and necessitate lower marketing costs. Thus, we expect customers with positive (negative) CMMs will necessitate a lower (higher) level of marketing resources to generate the same level of profitability.

Methodology

Modeling challenges

The two equations (1 and 2) we specified in the model development section pose several estimation challenges. To choose an appropriate modeling framework for this situation, we need to first account for three key modeling challenges: controlling for the potential endogeneity of marketing efforts, dealing with customer heterogeneity, and accounting for the potential correlation between customer behavior and customer profitability.

Endogeneity The first challenge is related to the strategic allocation of marketing resources by the firm. We expect that both the telecommunications and high-tech firms do not allocate marketing efforts to customers at random. Thus, treating marketing efforts as exogenous is likely to lead to biased model estimates. In order to control for the potential endogeneity of marketing efforts, we use the control function approach. This two-step procedure uses an instrumental variable in an initial marketing model and then after estimation of the instrumental variable regression, uses the computed error as a variable in the main model (in this case the behavior and profit models) to control for the potential endogeneity of marketing efforts by the firm.

Heterogeneity The second challenge is related to the fact that we have panel data from both firms. This means that we observe multiple observations for each customer over time. We take two different approaches in order to control for the potential of within customer effects. We control for observed heterogeneity by introducing a set of demographic (firmographic) for the telecommunications (high-tech) firm. We control for unobserved heterogeneity in both sets of models by allowing for random effects.

Correlation between behavior and gross margin The third challenge is related to the fact that in our main model we want to understand the drivers of customer behavior and customer profitability. It is likely that the errors from these two equations are correlated. Thus, we need a modeling framework, which can jointly estimate these two equations. We note here, though, that a traditional SUR model would not be appropriate as we allow for random effects in both the behavior and gross margin models. To accommodate this issue we chose to estimate the model using a conditional mixed process (CMP). The CMP can be thought of as a flexible SUR framework which allows for multi-equation, multilevel, mixed processes. Here, multi-equation means that it can estimate multiple equations, multilevel means that it allows for random coefficients and effects (intercepts) at various hierarchical levels, and mixed process means that it allows for different equations to have different types of dependent variables.

Modeling steps

Now that we have identified the key challenges in empirically testing our conceptual framework, we now outline the two key steps we follow to estimate our model.

Step 1 The first step of the modeling framework is the instrumental variable model for the control function approach. The instrumental variable model for marketing efforts takes the following format:

$$\ln(\text{Mktg})_{it} = \alpha_0^M + X_{it}^M \alpha_k^M + \mu_i^M + \varepsilon_{it}^M \tag{3}$$

where, ln(.) represents the natural log function, α_0^M is the intercept, μ_i^M is the customer-specific random intercept, ε_{it}^M is normally distributed random error term, X_{it}^M includes the independent variables, which explain marketing efforts as well as the instrumental variable (here we use variables such as past behavior, past profitability, past customer mindsets, and an instrumental variable), and α_k^M is a vector of k parameter estimates. We estimate the model using the xtreg procedure in STATA. Once we estimate the instrumental variable model for marketing efforts, we follow a control function approach and use the predicted error ($\hat{\varepsilon}_{it}^M$) in the main estimation.

Step 2 The main model needs to accommodate the two main equations (1 and 2), Behavior_{it} and Profit_{it}, and accommodate the control function approach from the previous step. Thus, Eq. 1 and Eq. 2 are updated to include the computed error ($\hat{\varepsilon}_{it}^M$) from Eq. 2 and take the following format:

$$\begin{aligned}\text{Behavior}_{it} &= \alpha_0^B + \alpha_1^B \ln(\text{Mktg}_{it}) + \alpha_2^B \text{Mindset}_{it} + \alpha_3^B \ln(\text{Mktg}_{it}) * \text{Mindset}_{it} \\ &+ \alpha_4^B \text{Controls}_{it} + \rho^B \hat{\varepsilon}_{it}^M + \mu_i^B + \varepsilon_{it}^B\end{aligned} \tag{4}$$

$$\begin{aligned}\text{Profit}_{it} &= \alpha_0^P + \alpha_1^P \ln(\text{Mktg}_{it}) + \alpha_2^P \text{Behavior}_{it} + \alpha_3^P \text{Mindset}_{it} + \alpha_4^P \ln(\text{Mktg}_{it}) * \text{Mindset}_{it} \\ &+ \alpha_4^P \text{Controls}_{it} + \rho^P \hat{\varepsilon}_{it}^M + \mu_i^P + \varepsilon_{it}^P\end{aligned} \tag{5}$$

where, ρ^B and ρ^P are the coefficients for the computed errors from the marketing efforts equation to control for the potential endogeneity of marketing efforts made by the firm. We estimate the customer behavior and customer profit models jointly using the conditional mixed process (CMP) procedure in STATA (Roodman 2011).

Empirical application

To empirically test the proposed conceptual framework we used data from two distinct contexts: a B2C telecommunications firm and a B2B high-tech firm. Applying our framework to these two contexts is a strong test to evaluate the external validity of the proposed model and will increase our confidence about the generalizability of the findings to other contexts. Next, we describe the data from the two contexts.

Data

Telecommunications firm A B2C telecommunications firm provided the data to empirically test the conceptual framework. The telecommunications firm offers a wide variety of services in different categories (e.g., landlines, wireless lines, DSL) to individual customers (B2C). For this empirical application, we have monthly data from January 2007 to December 2013 (7 years) for 5,000 customers, which includes measures of marketing efforts by the telecom firm, customer behavior, customer profit, customer demographics, and other exchange characteristics. Further, the 5,000 customers were surveyed once per year during the sampling frame by a third-party research firm that compiled the customer mindset data. The research firm used multi-item scales to measure satisfaction, service quality, and loyalty intentions (see Web Appendix A for details on the customer mindsets).

High-tech firm We also empirically tested the conceptual framework using data from a large multinational high-tech manufacturer. This firm sells computer hardware (personal computers, workstations, servers) and software (applications) to business customers (B2B). For this empirical application, we have monthly data from January 2007 to December 2012 (6 years) for 1,650 customers, which includes measures of marketing efforts by the high-tech firm, customer behavior, customer profit, firmographics, and other exchange characteristics. Further, the 1,650 customers were surveyed once per year during the sampling frame by a third-party research firm that compiled the customer mindset data. The research firm used multi-item scales to measure satisfaction, service quality, and loyalty intentions (see Web Appendix A for details on the customer mindsets).

Variable selection and operationalization

We provide a summary of the variables included in our modeling framework in Table 2 and the descriptive statistics and correlations of the variables in Table 3. In the following sub-sections we provide additional details on the variable selection process.

-- Insert Tables 2 and 3 about here --

Instrumental variable The first variable we needed to identify is an instrumental variable, which can help us control for the potential endogeneity of marketing efforts by the firms. The ideal instrument is one that can help explain why firms are likely to increase (or decrease) marketing efforts to customers, but is unrelated to a customer's behavior or profitability at the specific firm. In this case we obtained the monthly marketing spend from the marketing departments of each firm that were given to allocate on all customers (including those customers not in our sample) for that given month. Next, we selected a set of 5,000 (1,650) customers from the B2C (B2B) who were not in our sample, but exhibited similar past purchase behavior and past profitability as the customers in our sample. We then used the marketing budget spent on these similar customers as an instrument in our marketing effort equation. We believe that this is a good choice for an instrument since we expect that increases in the marketing budget to these similar customers not in our sample is likely to be related to an increase in marketing spending on average across all customers since marketing budgets are set for all customers before allocating marketing efforts to individual customers. But, we believe that increases (or decreases) in the marketing budget for this similar group is not likely to impact the behavior or profitability of a customer in our sample. Further, we can see from Table 2 that the correlation between the marketing budget and the cost of marketing efforts with customers is positively correlated for both firms (0.16 for the B2C firm and 0.14 for the B2B firm). We also see that the marketing budget is unrelated to a given customer's behavior and profitability with either the B2C or B2B firm. This provides some evidence that the marketing budget is a good instrument to use to help control for the potential endogeneity of marketing efforts.

Mindset metrics One of the key contributions of this study is the measurement and integration of customer mindsets into the individual-level customer profitability framework. As noted in the previous section, we collected data from customers from both the B2C telecommunications firm and the B2B high-tech firm on the following three CMMs: *Satisfaction*, *Service Quality*, and *Loyalty Intentions*. As we can see from Table 2, the CMMs are represented by factor scores. Thus, the means and standard deviations are all 0 and 1, respectively. One key concern that we want to address is that the CMMs are often interconnected and have structural relationships, such that the activation of one of them (e.g., satisfactory purchases) increases the probability that other related mindsets (e.g., service quality) are also stimulated and activated to produce a response (Anderson 1983). We do notice that the three CMMs are positively correlated for both the B2C and B2B firms, but that these correlations are all below 0.20. These results are in line with previous work in relationship marketing, which shows that although different mindsets are conceptually distinct, they are related and provide a global view of the quality of the relationship with the firm (De Wulf, Gaby, and Iacobucci 2001; Palmatier et al. 2006). However since all the correlations are less than 0.20, we believe this will not cause issues with multicollinearity in the model estimation.

Exchange and customer characteristics The additional variables selected for the three models (*Marketing*, *Behavior*, and *Profit*) are all individual-level variables that have been shown to be significant predictors of customer buying behavior, customer profitability, and a firm's marketing resource allocation decisions (Venkatesan and Kumar 2004; Venkatesan, Kumar, and Bohling 2007). The intention of this study is to quantify the impact of adding customer mindsets to the general framework and not to identify new exchange characteristics that are drivers of customer behavior and profitability (see Tables 2 and 3 for the list and descriptive statistics of the other variables).

Study findings

Overall model fit

For each of the two firms (B2C telecommunications and B2B high-tech), we estimated two separate sets of models (4 estimations in total): one for each firm with the mindset variables and one for each firm without the mindset variables. We provide the results of this estimation in Tables 4 and 5. To simplify things, the value provided for the intercept is only the general intercept of each equation (α_0) since u_i has a mean of 0 and follows a normal distribution with variance σ^2.

-- Insert Tables 3 and 4 about here --

For the telecommunications (high-tech) firm, we see that in terms of overall fit, adding customer mindsets increases the r-square for the marketing model from 0.088 to 0.099 (0.108 to 0.120). We also see that for the joint estimation of the behavior and gross margin models, the AIC is lowest for the full model for the telecommunications (876,905.36 for the full model and 878,390.06 for the model without customer mindsets) and the high-tech (301,616.33 for the full model and 311,890.49 for the model without customer mindsets) firms. Further, we see that most of the variables included in the models are statistically significant. All of this evidence suggests that the overall model fit is good and that including CMMs is important in helping to explain firm behavior, customer behavior, and customer profitability.

Mindset results by model

Marketing model We find that the coefficients for the main effects of the CMMs of $\text{Satisfaction}_{i,t-1}$, $\text{Service Quality}_{i,t-1}$, and $\text{Loyalty Intentions}_{i,t-1}$, are not statistically significant for either the B2C or B2B firms. However for the telecommunications (high-tech) firm, we find the coefficient for $\text{Gross Margin}_{i,t-1}$*$\text{Satisfaction}_{i,t-1}$ is 0.016 (0.028), the coefficient for Gross $\text{Margin}_{i,t-1}$*$\text{Service Quality}_{i,t-1}$ is 0.029 (0.039), and the coefficient for Gross $\text{Margin}_{i,t-1}$*Loyalty $\text{Intentions}_{i,t-1}$ is 0.025 (0.027). This suggests that having a positive mindset does not directly impact a firm's decision to increase marketing efforts. However, customers who have had more positive mindsets toward the firms and have a higher past profitability are more likely to receive incrementally more marketing efforts from the firms. Thus, when firms actually measure CMMs, it is likely to affect marketing efforts allocated by the firm to customers.

Behavior model For the telecommunications (high-tech) firm, we find the coefficient in the Behavior Model for Satisfaction_{it} is 0.459 (0.746), $\text{Service Quality}_{it}$ is 0.639 (0.984), and Loyalty Intentions_{it} is 0.719 (0.991), providing support for the *Behavioral Effect*. Thus, customers who have a more positive mindset toward the firm are more likely to engage in increasing behavior across categories (revenue per cross-buy) with a firm independent of any marketing efforts. This suggests that firms that invest in increasing overall customer satisfaction, service quality, and loyalty intentions are likely to see increased usage and interaction with customers regardless of direct marketing efforts. With regard to the relative impact of the three CMMs on behavior, the size of the coefficients suggests that the impact of service quality and loyalty intentions is higher than that of satisfaction.

For the telecommunications (high-tech) firm, we find the coefficient in the Behavior Model for $\ln(Mktg_{it})$*$Satisfaction_{it}$ is 0.970 (0.916), $\ln(Mktg_{it})$*Service $Quality_{it}$ is 0.136 (0.169), and $\ln(Mktg_{it})$*Loyalty $Intentions_{it}$ is 0.252 (0.265), providing support for the *Marketing Effectiveness Effect*. This suggests that when firms initiate marketing initiatives to customers, the marketing initiatives are more effective when customers have a more positive mindset toward the firm. In other words, each dollar spent toward encouraging a customer to respond (i.e., make a purchase) is likely to lead to incrementally more customer purchase behavior across product categories when compared to customers who have less positive mindsets. With regard to the relative impact of the three CMMs, the magnitude of the coefficients suggests that customer satisfaction has a stronger moderating effect compared with service quality and loyalty intentions.

Gross margin model We find the coefficients on the main effects of $Satisfaction_{it}$, Service $Quality_{it}$, and Loyalty $Intentions_{it}$ are not statistically significant for either firm. However for the telecommunications (high-tech) firm, we find the coefficient in the Gross Margin Model for $\ln(Mktg_{it})$*$Satisfaction_{it}$ is 1.359 (0.871), $\ln(Mktg_{it})$*Service $Quality_{it}$ is 1.787 (0.960), $\ln(Mktg_{it})$*Loyalty $Intentions_{it}$ is 2.892 (2.041), providing support for the *Marketing Efficiency Effect*. This suggests that customers with positive mindsets are not necessarily more profitable than customers with less positive mindsets. However when firms spend marketing efforts on customers with positive mindsets, there is an increase in profit efficiency. In other words, each dollar spent on marketing efforts on customers with positive mindsets brings a higher return on marketing investment (ROMI) for both the telecommunications and high-tech firms. Again, we find differences in the relative impact of the three studied CMMs. The size of the parameters reveals that loyalty intentions have a stronger impact on improving the efficiency of marketing activities compared with service quality and satisfaction.

The impact of CMMs on profitability: two applications of our framework

In this section, we present two applications of our framework. In the first application, we explore the impact of changes in CMMs on customer behavior and customer profitability. In the second application, we explore how including (or excluding) CMMs from customer selection impacts firm profitability.

For the first application, we need to understand the marginal and conditional impact of changes in CMMs on customer behavior through the behavioral effect and marketing effectiveness effect and on customer profitability directly through the marketing efficiency effect and indirectly through changes in customer behavior due to changes in CMMs. We summarize the key coefficients related to CMMs from our Behavior_{it} and Profit_{it} models in Table 6.

--- Insert Table 6 about here ---

We can see from Table 6 the marginal impact of Satisfaction, Service Quality, and Loyalty Intentions for the behavioral, marketing effectiveness, and marketing efficiency effects for both the B2C telecommunications and B2B high-tech firms. These numbers were obtained from the estimation results in Table 5. Next, we have to determine how changes in these CMMs are likely to impact customer behavior and customer profitability.

Customer behavior The impact of CMMs on customer behavior comes from both the behavioral effect and the marketing effectiveness effect. If we take the marginal of Eq. 3 with respect to each CMM, we see that the behavioral effect is α_2^B and the marketing effectiveness effect is $\alpha_3^B * Mktg_{it}$. Thus, the impact of each CMM on customer behavior is equal to $\alpha_2^B + \alpha_3^B * Mktg_{it}$. Next, we compute the increase in customer behavior due to a 1 standard deviation increase in each CMM (see Table 7).

--- Insert Table 7 about here ---

We see from Table 7 that a 1 standard deviation increase in Satisfaction, Service Quality, or Loyalty Intentions leads to a corresponding increase in customer behavior by $0.65 ($0.79), $0.67 ($1.02), $0.77 ($1.04) for the B2C Telecommunications (B2B High-tech) firm respectively. These results provide the firm a direct link between making investments in CMMs to how those investments will lead to an average increase in each customer's behavior (i.e., revenue per cross-buy) per month.

Customer profitability The impact of CMMs on customer profitability comes from two different effects. First, customer profitability is directly impacted by CMMs through the marketing efficiency effect. Second, customer profitability is indirectly impacted by the change in customer behavior that was due to the behavioral effect and marketing effectiveness effect. So, we start by substituting Eq. 3 into the $Behavior_{it}$ variable in Eq. 4 and then take the marginal of Eq. 4 with respect to each of the CMMs. We find that the direct impact of CMMs on customer profitability from the marketing efficiency effect is $\alpha_4^P * Mktg_{it}$ and the indirect impact of CMMs from their effect on customer behavior is $\alpha_2^P * (\alpha_2^B + \alpha_3^B * Mktg_{it})$. If we combine these two terms and simplify, we get the marginal impact of CMMs on customer profitability as

$(\alpha_4^P + \alpha_2^P * \alpha_3^B) * Mktg_{it} + \alpha_2^P * \alpha_2^B$. Next, we compute the increase in customer profitability due to a 1 standard deviation increase in each CMM (see Table 7).

We see from Table 7 that a 1 standard deviation increase in Satisfaction, Service Quality, or Loyalty Intentions leads to a corresponding increase in customer profitability by $1.73 ($1.94), $1.85 ($2.47), $2.30 ($2.74) for the B2C telecommunications (B2B high-tech) firm. These results provide the firm a direct link between making investments in CMMs to how those investments will lead to an average increase in each customer's profitability per month.

For the second application, we want to see how customer selection to maximize profitability will be affected if the firms take into account (or ignore) CMMs. To do this, we again used the data from the telecommunications and high-tech firm. This time we used only the first six (five) years of data from the telecommunications (high-tech) firm, leaving one year of data for the holdout. We estimate the same models on each of the two subsamples. Then, we predicted the profitability of each of the customers in the holdout year—in one case using the model without the CMMs and in the other case using the model with the CMMs. We then rank-ordered the customers in each sample by their predicted profitability. Next, we selected the top 10%, 15%, and 20% of customers based on their predicted profitability. We chose 10%, 15%, and 20% as many firms only have marketing budgets that allow them to reach out to a portion of their total customer base. Finally, we summarized the actual average monthly profit for each of the groups of customers across the telecommunications and high-tech firms and provide the results in Table 8.

--- Insert Table 8 about here ---

As we can see from Table 8, both models (with and without CMMs) are able to sort customers well based on their expected profitability. This suggests that the models are effective at helping firms predict future customer profitability. But, we see that by not considering CMMs, both the telecommunications and high-tech firms are unable to maximize their profitability. When selecting the top 10%, 15%, 20% of customers, by considering CMMs the telecommunications (high-tech) firm was able to select customers which, on average, was able to generate $340.20 vs. $308.99 ($273.25 vs. $244.11), $269.03 vs. $250.80 ($214.29 vs. $203.15), $225.20 vs. $212.77 ($187.40 vs. $174.80).

These two applications show the value firms can generate when they either make investments in increasing CMMs (Application 1) or make better customer selection and resource allocation decisions to customers using CMMs (Application 2).

Discussion

Theoretical implications: CMMs as an integral part of the customer profitability model

Recent calls for marketing accountability, together with the need for a better understanding of the connection between CMMs and performance, have produced a renewed interest in the academic community in the study of CMMs (Hanssens et al. 2014). Despite the merit of previous studies in advancing knowledge about the consequences of CMMs (see Table 1), a proper understanding of the role played by these CMMs in the individual customer profitability model was still lacking. This study is aimed at filling this important gap by proposing an integrative and comprehensive framework about the impact of CMMs on performance and developing an empirical application of the framework to demonstrate the central role played by CMMs in customer behavior and profitability. This enables us to contribute to existing knowledge in several important ways.

First, this study bridges two important streams of research in the domain of customer relationship management. One pertains to understanding the ROI of marketing, and focuses on identifying the direct linkages between marketing activities and financial outcomes (Lehmann 2004; Pauwels et al. 2004; Srinivasan and Hanssens 2009), but notably ignores the multi-faceted role played by CMMs in explaining ROMI. The other concerns understanding the impact of mindset metrics on financial outcomes (Fornell et al. 2006; Gruca and Rego 2005; Luo and Homburg 2008; Srinivasan, Vanhuele, and Pauwels 2010), but importantly it ignores the implications of these metrics with regard to marketing investments and resource allocation decisions. In this study we integrate CMMs into the individual customer profitability model to provide a comprehensive understanding of the central role played by these metrics in driving firm performance. Specifically, drawing from social cognition and information processing theories, this study offers a conceptual understanding of the different ways in which CMMs influence customer behavior and profitability: through the *behavioral*, *marketing effectiveness*, and *marketing efficiency effects*. With an application to both B2C (telecom firm) and B2B (high-tech firm), the empirical analyses demonstrate the various routes through which CMMs impact behavior and profitability, as well as their relative importance. In doing so, this study integrates two central streams of research to provide a unified understanding of the extent to which, and the reasons why, the return on marketing investments is affected by CMMs. Importantly, this research underscores the central role of CMMs as an integral part of the customer profitability model, to help have a more accurate understanding of their impact on performance and improve acquisition and retention strategies and resource allocation decisions.

Second, this study offers novel insights into the different impact of different CMMs on behavior and profitability. Most studies, particularly those linking CMMs to performance, have focused on only one metric, primarily satisfaction. However, different CMMs capture different aspects of the relationship, and they present different properties (i.e., prospective vs. retrospective; specific vs. generic), which might translate into different effects on behavior and profitability (Garbarino and Johnson 1999). Our results offer preliminary evidence on the extent to which different CMMs, which differ in their time span or the extent to which they provide a retrospective (e.g., satisfaction) vs. prospective (e.g., loyalty intentions) view of the relationship, and the degree of concreteness or whether they represent evaluations of more general (e.g., satisfaction) vs. concrete (e.g., perceived quality) aspects of the relationship (de Haan, Verhoef, and Wiesel 2015; Lemon, White, and Winer 2002), differently influence customer behavior and profitability through the behavioral, marketing effectiveness, and marketing efficiency effects. Specifically, in our studied contexts, service quality and loyalty intentions have a stronger direct effect on behavior compared with satisfaction, but satisfaction has the strongest impact when it comes to improving the effectiveness of marketing activities. Also, loyalty intentions is the metric that has the strongest impact on the efficiency of marketing activities (i.e., profit obtained for each dollar spent). These results offer an interesting starting point for future studies that may want to look at the differential impact of different CMMs on explaining customer decision making and profitability.

This study also responds to the call for financial accountability of marketing (Kumar and Shah 2009) by establishing the linkages between CMMs and customer profitability. With firms competing intensely for the hearts and minds of consumers (Hanssens et al. 2014), and investing large amounts of resources in improving customer mindsets and experiences (Lemon and

Verhoef 2016), demonstrating ROMI has become a top priority. Our study offers a better understanding of the connections between investments in the state of mind of the consumer and profitability, and into how these investments ultimately translate into financial performance. Importantly, it demonstrates that the role of CMMs in driving performance goes beyond their direct impact on behavior (behavioral effect), as they also impact profitability through improving the efficiency and effectiveness of marketing. Failing to account for these effects would likely result in an underestimation of the economic value of investments in CMMs. Thus, by decomposing the impact of CMMs on profitability into its different mechanisms, we enable firms to connect the investments made on building relationships with their customers to the different components of customer profitability, thus illuminating the deep sources of marketing success and enabling companies to unlock the power of marketing.

Managerial implications: managing customers for profit based on mindsets

In this study we developed and tested a conceptual framework that empirically identifies the relationships among CMMs, customer behavior, and customer profitability. This framework enables companies to build a link between the customer mindset and customer profitability, and assess whether, and to what extent, a customer's behavior and profitability to the firm changes based on investments in programs to improve customer mindsets. By doing this, managers can determine the investment appeal of different marketing actions and, thus, improve their effectiveness, the allocation of resources, and the return on those investments. Table 9 summarizes the main managerial takeaways from our study.

--- Insert Table 9 about here ---

Firms spend significant amounts of resources in relationship building programs to improve consumer perceptions and attitudes under the assumption that they will lead to enhanced performance outcomes. However, the need for marketing accountability requires that the return on these investments should be accurately determined to help demonstrate the contribution of marketing to business growth (Kumar and Shah 2009). This study offers firms a framework to identify the ROMIs in CMMs that can help them make better decisions about the implementation of programs that improve CMMs as well as the evaluation of the effectiveness of various CMM campaigns. Specifically, in addition to demonstrating the economic impact of investments on CMMs, our framework can offer managers practical guidance on whether, and how much, to invest in programs that improve customer attitudes by projecting the contribution to profitability of these investments and comparing it with the cost of implementing the program. Importantly, and contrary to previous studies, which look at the profitability implications of customer perceptions and attitudes at an aggregated level, our study offers an individual-level framework. This enables firms make decisions at the customer level to improve the relationships with the best customers and maximize each customer's lifetime value. In the empirical part of the study we presented an application of our framework (Application 1) and demonstrated how to derive the economic contribution of improvements in CMMs for two firms in B2C and B2B markets.

Our framework can also be useful for firms who want to better understand how investments in CMMs can lead to changes in customer behavior and customer profitability (Hanssens et al. 2014). By decomposing the total impact of CMMs on profitability into the three effects (behavioral effect, marketing effectiveness effect, and marketing efficiency effect), firms can identify the multiple ways in which their investments ultimately translate into customer profitability. Therefore, integrating CMMs into the customer profitability model can help firms improve customer selection and resource allocation decisions, which are currently based solely on information about actual customer behavior (Reinartz and Kumar 2003; Venkatesan and Kumar 2004). For example, our study demonstrates that customers who have more positive predispositions toward the firm (score higher in CMMs) are more responsive to marketing activities (marketing effectiveness effect) and necessitate a lower level of marketing resources to generate the same profit level (marketing efficiency effect). Thus, knowing the state of the mind of each customer represents an important indicator to improve targeted marketing activities and identify opportunities for growth. In the empirical part of the study, we presented an application of our framework (Application 2) and demonstrated how information on CMMs can help companies more accurately predict future customer profitability and improve their resource allocation decisions.

Also, our framework demonstrates that different CMMs, with their different properties (i.e., prospective vs. retrospective; general vs. specific), exert different effects on profitability through their distinct impact on the three proposed mechanisms. Thus, firms can strategically invest in programs that build specific CMMs in order to improve specific aspects or components of the customer profitability model. For example, if firms want to improve the effectiveness of their marketing activities, programs that improve customer satisfaction will be more effective. However, if the firm pursues efficiencies in managing the relationships with its customers, improving loyalty intentions will yield greater return. This knowledge will also help firms further refine their customer selection and resource allocation decisions discussed before. For example, using satisfaction as the criterion to target a marketing campaign will result in better responses compared with using loyalty or quality.

Limitations and future research

This research addresses a phenomenon of great academic and managerial interest: the integration of CMMs into the individual-level customer profitability framework. However, we recognize that our study has several limitations, which suggest possible directions for future research. Using data from two large and established companies, we validated the proposed conceptual framework across two distinct contexts. While this test increases our confidence in the robustness of the conceptual framework, the validity of our findings and the generalizability of our results, these two contexts represent only a small portion of the total population of industries and, thus, further applications of our proposed framework to other product categories and industries should yield more insights.

The support we obtained for the key role of mindsets in customer profitability offers an opportunity to solve other issues that we have not addressed in this research such as (1) what the most critical drivers of the CMMs are or (2) how much it costs the firm to increase each CMMs. Further, it would be interesting to integrate transaction-specific mindsets in our model, which account for transient evaluations and emotions, and examine whether they have an impact (and how much) on CMMs and, ultimately, on customer profitability.

Finally, we measured three mindset variables to examine their impact on customer profitability: satisfaction, service quality, and loyalty intentions. While these three relational constructs have received a great deal of attention in prior research and they have been prevalently used in practice to monitor the "hearts and minds" of consumers (de Haan, Verhoef, and Wiesel 2015), other relational constructs that capture different aspects of the relationship may also relevant in influencing a customer's present and future profitability. Drawing on information processing theories, our framework offers conceptual arguments to understand the differential impact of different CMMs. Thus, building on our framework, future research might empirically examine the role of other relevant relational constructs such as trust and commitment (Morgan and Hunt 1994) and quantify their financial implications.

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Figure 1: The Link between Customer Mindsets, Behavior, and Profitability

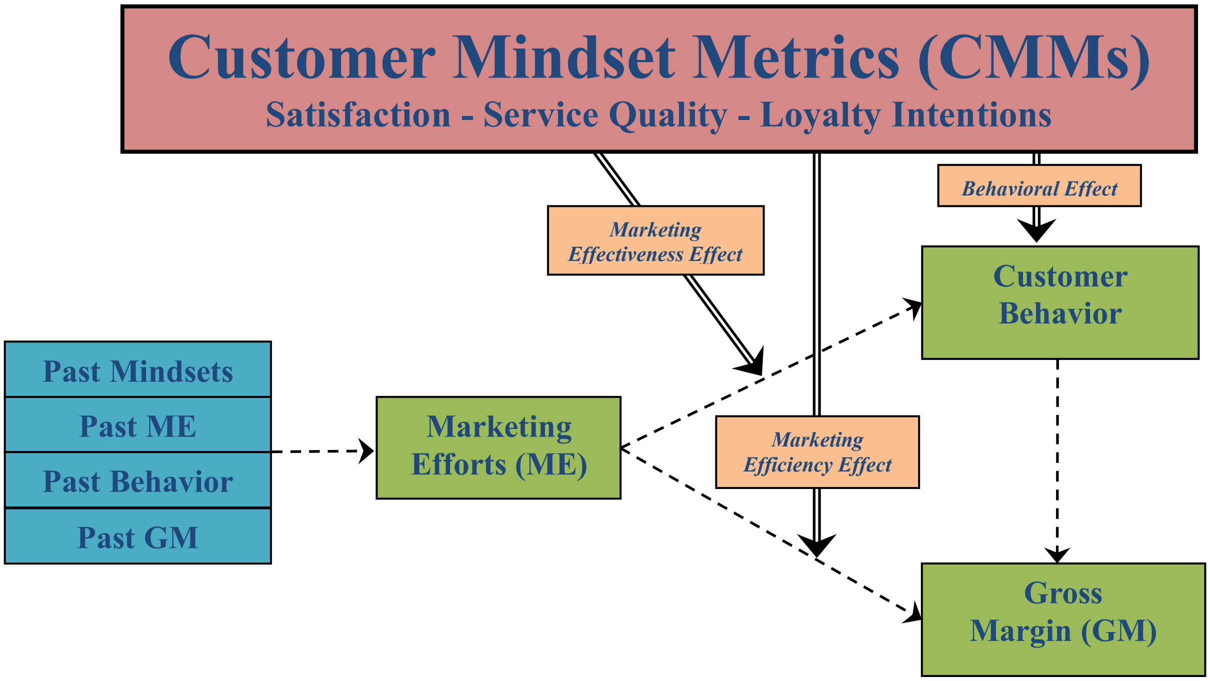

Table 1: Literature Review on the Consequences of CMMs

Study	CMMs considered	Outcome/s (behavior and/or performance)	Mechanisms	Level of analysis (customer vs. firm)	Study design (cross-section vs. longitudinal)	Study context: (Industry, B2C vs. B2B)	Key findings
Impact on behavior (intentions)							
Anderson and Weitz (1989)	Trust	Behavior *(Perceived continuity of the relationship)*	CMMs → Behavior	Customer level	Cross-sectional	Independent sales agents (B2B)	High levels of trust lead business customers expect the relationship to continue in the future.
Crosby, Evans, and Cowles (1990)	Relationship quality (customer satisfaction and trust)	Behavior *(anticipation of future interactions)* and Performance *(sales effectiveness)*	CMMs → Behavior	Customer level	Cross-sectional	Life insurance (B2C)	Relationship quality (satisfaction and trust) has a positive influence on a customer's anticipation of future interaction with the salesperson. It does not have an impact on sales effectiveness.
Bolton and Drew (1991)	Service quality	Behavior *(Perceived service value and utility)*	CMMs → Behavior	Customer level	Cross-sectional	Telecommunications (B2C)	Service quality has a strong positive impact on perceived service value.
Cronin and Taylor (1992)	Customer satisfaction and service quality	Behavior *(purchase intentions)*	CMMs → Behavior	Customer level	Cross-sectional	Various: Banking, pest control, dry cleaning and fast food (B2C)	Customer satisfaction has a positive impact on purchase intentions; service quality does not have a significant impact on purchase intentions.
Anderson and Sullivan (1993)	Customer satisfaction and service quality	Behavior *(Repurchase intentions)*	CMMs → Behavior	Customer level	Cross-sectional	Various: Swedish Customer Satisfaction Barometer (B2C)	Repurchase intentions are positively influenced by the level of customer satisfaction and by service quality (through satisfaction). High satisfaction insulates firms from changes in quality and satisfaction.
Boulding, Kalra, Staelin, and Zeithaml (1993)	Service quality	Behavior *(Behavioral intentions: word of mouth, willingness to pay)*	CMMs → Behavior	Customer level	Cross-sectional	Education (B2C)	Perceptions of quality have a positive impact on behavioral intentions.
Zeithaml, Berry, and Parasuraman (1996)	Service quality	Behavior *(Word-of-mouth communications, purchase intentions, price sensitivity and complaining behavior)*	CMMs → Behavior	Customer level	Cross-sectional	Computer manufacturer (B2B). Retailing, automobile insurer and life insurer (B2C)	Service quality has a positive impact on favorable behavioral intentions (word of mouth and willingness to pay) and a negative impact for unfavorable behavioral intentions (switching intentions and complaints).
Garbarino and Johnson (1999)	Customer satisfaction, trust and commitment	Behavior *(Intentions to continue the relationship in the future)*	CMMs → Behavior	Customer level	Cross-sectional	Entertainment (B2C)	Customer satisfaction, trust, and commitment differentially impact future intentions depending on the relational orientation of the customer. For high relational oriented customers, trust and commitment are the most important drivers of future behavior. For low relational oriented customers, satisfaction is the main driver of future behavior.
De Wulf, Odekerken-Schröder, and Iacobucci (2001)	Relationship quality (customer satisfaction, trust and commitment)	Behavior *(share of wallet, purchase frequency, and loyalty)*	CMMs → Behavior	Customer level	Cross-sectional	Food and apparel industries (B2C)	Relationship quality (as measured by satisfaction, trust, and commitment) has a positive and strong effect on behavioral intentions.

Olsen (2002)	Customer satisfaction and service quality	Behavior *(Repurchase loyalty)*	CMMs → Behavior	Customer level	Cross-sectional	Seafood products (B2C)	There is a strong positive relationship between customer satisfaction and loyalty. Service quality influences loyalty through its impact on satisfaction.
Capraro, Broniarczyk, and Srivastava (2003)	Customer satisfaction	Behavior *(Customer defection)*	CMMs → Behavior	Customer level	Cross-sectional	Health insurance (B2C)	Satisfaction is negatively related to the likelihood of defection.
Agustin and Singh (2005)	Customer satisfaction, trust, and relational value	Behavior *(share of wallet, repeat purchase and spending)*	CMMs → Behavior	Customer level	Cross-sectional	Retail clothing and airline travel (B2C)	Customer satisfaction and trust have positive effects on loyalty. Satisfaction presents a decreasing rate of return, while trust is associated with an increasing rate of return.
Impact on behavior (actual)							
Bolton (1998)	Customer satisfaction	Behavior *(Relationship duration)*	CMMs → Behavior	Customer level	Longitudinal (satisfaction measured in two points)	Cellular telephone industry (B2C)	Customers with higher levels of satisfaction tend to have longer duration times.
Bolton and Lemon (1999)	Customer satisfaction	Behavior *(Service usage)*	CMMs → Behavior	Customer level	Longitudinal (attitudes also longitudinal, in two moments)	Interactive television entertainment service and cellular communications service (B2C)	High levels of customer satisfaction lead consumers to have higher usage levels of the service.
Bolton, Kannan, and Bramlett (2000)	Customer satisfaction	Behavior *(Repurchase behavior and service usage)*	CMMs → Behavior	Customer level	Longitudinal (attitudes measured only once)	Credit card (B2C)	Having a lower satisfaction level than the competitor leads to a lower likelihood of repurchase. Having a higher satisfaction level than the competitor leads to a higher level of service usage. These effects differ depending on loyalty program membership.
Bowman and Narayandas (2001)	Customer satisfaction	Behavior *(Share of category requirements and word of mouth)*	CMMs → Behavior	Customer level	Cross-sectional	Frequently purchased consumer goods (B2C)	Higher levels of customer satisfaction lead to a higher share of category requirements (decreasing returns), but to lower propensity to engage in word-of-mouth activity.
Mittal and Kamakura (2001)	Customer satisfaction	Behavior *(Repurchase intentions and repurchase behavior)*	CMMs → Behavior	Customer level	Longitudinal (satisfaction measured only once)	Automotive industry (B2C)	Customer satisfaction has a positive effect on repurchase intentions and repurchase behavior. The effects vary depending on customer characteristics.
Verhoef, Franses, and Hoekstra (2001)	Customer satisfaction and payment equity	Behavior *(Cross-buy)*	CMMs → Behavior	Customer level	Longitudinal (attitudes measured only once)	Insurance (B2C)	Customer satisfaction and payment equity do not have a main effect on cross-buy. The effect of satisfaction is moderated by relationship length.
Verhoef, Franses, and Hoekstra (2002)	Customer satisfaction, trust, commitment, and payment equity	Behavior *(Customer referrals and cross-buy)*	CMMs → Behavior	Customer level	Longitudinal (attitudes measured only once)	Insurance (B2C)	Trust, customer satisfaction, affective commitment and payment equity all have a positive effect on willingness to recommend (referrals), while only the last two positively and significantly impact cross-buy.
Keiningham, Perkins-Munn, and Evans (2005)	Customer satisfaction	Behavior *(Share of wallet)*	CMMs → Behavior	Customer level	Cross-sectional	Financial services (B2B)	Satisfaction has a positive impact on share of wallet. This effect is stronger for higher values of customer satisfaction.
Verhoef (2003)	Customer satisfaction, affective	Behavior *(Customer retention and share of wallet)*	CMMs → Behavior	Customer level	Longitudinal (attitudes	Insurance (B2C)	Among the studied constructs, only affective commitment had a positive and significant effect on retention and share of wallet.

	commitment, and payment equity				measure only one time)		
Gustafsson, Johnson, and Roos (2005)	Customer satisfaction and commitment	Behavior *(Customer retention)*	CMMs → Behavior	Customer level	Longitudinal	Telecommunications (B2C)	Customer satisfaction and calculative commitment have a negative influence on customer switching behavior (churn). Affective commitment does not significantly affect churn.
Homburg, Koschate, and Hoyer (2005)	Customer satisfaction	Behavior *(Willingness to pay)*	CMMs → Behavior	Customer level	Cross-sectional	Restaurant and education (B2C)	Customer satisfaction has a positive effect on willingness to pay. The relationship is non-linear (concave for low levels of satisfaction, convex for high levels of satisfaction).
Seiders et al. (2005)	Customer satisfaction	Behavior *(Repurchase intentions and repurchase behavior –purchase frequency and amount)*	CMMs → Behavior	Customer level	Cross-sectional	Retailing –women's apparel and home furnishing (B2C)	Satisfaction has a strong positive effect on repurchase intentions, but no direct effect on repurchase behavior.
Impact on performance (firm level)							
Rust and Zahorik (1993)	Customer satisfaction	Behavior *(Customer retention)* and Performance *(Market share)*	CMMs → Behavior → Performance	Firm level	Cross-sectional	Banking services (B2C)	Customer satisfaction is a driver of individual customer retention, which affects the aggregated retention rates and market share of the company.
Anderson, Fornell, and Lehmann (1994)	Customer satisfaction and service quality	Performance *(Return on Investment ROI)*	CMMs → Performance	Firm level	Longitudinal	Various: Swedish Customer Satisfaction Barometer (B2C)	Customer satisfaction strongly and positively affects ROI. The cumulative incremental returns from a continuous one-point increase in customer satisfaction over five years is 11.5%, or $7.48 million. In addition, the short-run elasticity of ROI with respect to quality is 0.196.
Rust, Zahorik, and Keiningham (1995)	Service quality	Behavior *(Repurchase intentions)* and Performance *(Market share and Return on investment ROI)*	CMMs → Behavior → Performance	Firm level	Cross-sectional	Hotel (B2C)	Framework to evaluate the financial impact of quality improvement efforts. With an example application, the authors demonstrate that the model helps managers identify opportunities to make profitable quality investments: e.g. an investment of $1 million on improving quality in one important service attribute for customers can lead to a return on quality (ROQ) of 44.6%.
Anderson, Fornell, and Rust (1997)	Customer satisfaction	Performance *(Productivity –sales per employee, and Return on investment ROI)*	CMMs → Performance	Firm level	Longitudinal	Various: Swedish Customer Satisfaction Barometer (B2C)	Customer satisfaction has a positive effect on productivity (only for goods) and on ROI. An increase in 1% in satisfaction and productivity simultaneously leads to an increase of 0.365% in ROI for goods, and 0.22% in ROI for services.
Ittner and Larcker (1998)	Customer satisfaction	Performance *(Revenues and Shareholder value – market value of equity)*	CMMs → Performance	Firm level	Longitudinal	Various: American Customer Satisfaction Index (B2C)	Customer satisfaction is positively associated to market value of equity (a one unit increase in the satisfaction index leads to an increase in the market value of equity of $236 to $243 million). In addition, the results show that the release of customer satisfaction information is associated with abnormal returns over a ten-day period.
Anderson, Fornell, and Mazvancheryl (2004)	Customer satisfaction	Performance *(Shareholder value – Tobin's q)*	CMMs → Performance	Firm level	Longitudinal	Various: American Customer Satisfaction Index (B2C)	Customer satisfaction has a positive and strong relationship with shareholder value, as measured by Tobin's q. A 1% increase in satisfaction leads to a 1.016% increase in shareholder value (or $275

							million for an average BusinessWeek 1000 company).
Gruca and Rego (2005)	Customer satisfaction	Performance *(Shareholder value – growth and variability of cash flows)*	CMMs → Performance	Firm level	Longitudinal	Various: American Customer Satisfaction Index (B2C)	Customer satisfaction has a positive impact on future cash flow growth and a negative effect on cash flow variability. For an average firm in the data, a one-point increase in customer satisfaction translates into an increase in future cash flows of $55 million, and reduces the variability of cash flows by more than 4%.
Fornell, et al. (2006)	Customer satisfaction	Performance *(Shareholder value – market value of equity, stock return, cumulative returns)*	CMMs → Performance	Firm level	Longitudinal	Various: American Customer Satisfaction Index (B2C)	Customer satisfaction has a positive effect on market value of equity (1% increase in satisfaction leads to a 4.6% increase in market value). Customer satisfaction information does not have an immediate impact on stock prices. However, the cumulative returns for firms in the top 20% of ACSI outperformed the DJIA index by 93%, the S&P 500 by 201%, and the NASDAQ by 335%.
Aksoy et al. (2008)	Customer satisfaction	Performance *(Shareholder value – abnormal returns, valuation rations, cumulative returns)*	CMMs → Performance	Firm level	Longitudinal	Various: American Customer Satisfaction Index (B2C)	Higher customer satisfaction leads to higher excess and abnormal returns. A portfolio formed by companies with above average ACSI and positive trend has an average excess return of 0.78% per month. An investment of $100 at the beginning of the observation period in 1996 triples to $312 in 2006, compared with the $205 in the S&P 500.
Luo and Homburg (2008)	Customer satisfaction	Performance *(Shareholder value – stock value gap)*	CMMs → Performance	Firm level	Longitudinal	Airline industry (B2C)	Customer satisfaction has a negative and significant impact on the stock value gap: the shortfall of a firm's market value from its benchmarked optimal value.
Anderson and Mansi (2009)	Customer satisfaction	Performance *(Credit ratings and cost of debt)*	CMMs → Performance	Firm level	Longitudinal	Various: American Customer Satisfaction Index (B2C)	Higher customer satisfaction is associated with higher credit rating (a 1% increase in the satisfaction index leads to a 6% increase in credit rating) and lower cost of debt (firms with high customer satisfaction have a 2% lower cost of debt, or savings of about $5 million).
Jacobson and Mizik (2009)	Customer satisfaction	Performance *(Shareholder value – abnormal returns)*	CMMs → Performance	Firm level	Longitudinal	Various: American Customer Satisfaction Index (B2C)	Firms that have been rated with higher customer satisfaction tend to obtain abnormal returns, but only in some industries (i.e. computer and Internet sectors).
Tuli and Bharadwaj (2009)	Customer satisfaction	Performance *(Shareholder value – stock returns risk: systematic and idiosyncratic risk)*	CMMs → Performance	Firm level	Longitudinal	Various: American Customer Satisfaction Index (B2C)	A positive change in customer satisfaction results in negative changes in overall and downside systematic risk and overall and downside idiosyncratic risk.
Luo, Homburg, and Wieseke (2010)	Customer satisfaction	Performance *(Firm value –abnormal return, systematic risk, idiosyncratic risk)*	CMMs → Performance	Firm level	Longitudinal	Various: American Customer Satisfaction Index (B2C)	Customer satisfaction has a direct and positive effect on abnormal returns and a direct and negative effect on risk. Customer satisfaction also leads to better and less dispersed analyst recommendations, which again improve firm value.
Fornell, Morgeson III, and Hult (2016)	Customer satisfaction	Performance *(Shareholder value – stock returns)*	CMMs → Performance	Firm level	Longitudinal	Various: American Customer Satisfaction Index (B2C)	Stock returns on customer satisfaction are significantly above the market. During a period of 15 years, the cumulative returns on satisfaction were 518%, compared with 31% for the S&P 500.
Impact on performance (customer-level)							

Bowman and Narayandas (2004)	Customer satisfaction	Behavior *(Share of wallet)* and Performance *(Customer profitability)*	CMMs → Behavior → Performance	Customer level	Cross-sectional	Processed metal industry (B2B)	Chain of effects framework to link customer management efforts to profitability. Satisfaction is found to positively impact share of wallet (increasing returns), which drives profitability.
Rust, Lemon, and Zeithaml (2004)	Service quality and trust (and others: value and relationship-related constructs)	Behavior *(Customer retention)* and Performance *(CLV and customer equity)*	CMMs → Behavior → Performance	Customer level	Cross-sectional	Airline industry (B2C)	Strategic framework to identify how marketing actions link to customer equity and financial return. Customer perceptions (including quality and trust) positively impact behavior (retention) which in turn affects CLV and customer equity. Using a simulated scenario, the authors project the financial impact of an improvement in service quality: an increase in quality of 0.2 points (in a 5-points scale) will improve customer equity by 1.39%, or $101.3 million.

Table 2: Variable Operationalization

Variable	**Operationalization**
Profit (Gross Margin)	Profit (gross margin) from customer i at time t (‘000s for high-tech)
Behavior*	Behavior observed from customer i at time t, in this case average revenue per cross-buy (‘000s for high-tech)
Marketing Cost	Log of marketing cost spent on customer i at time t (‘000s for high-tech)
Tenure	Total tenure of customer i at time t (in days)
Customer-initiated Contacts	Number of customer-initiated contacts by customer i at time t
Multichannel	Total number of channels purchased by customer i up to time t
Instrumental Variable	
Marketing Budget	Budget allocated to marketing at time t for a sample of customers of the same size at the firm with similar past spending levels as those in the focal sample (‘000s for high-tech)
Customer Mindset Metrics (CMMs) (See Web Appendix A for details of the scales and items)	
Satisfaction	Satisfaction level of customer i at time t (surveyed once per year)
Service Quality	Service Quality level of customer i at time t (surveyed once per year)
Loyalty Intentions	Loyalty Intentions level of customer i at time t (surveyed once per year)
B2C Telecommunications Firm Customers	
Age	Age (in years) of customer i at time t
Income	Income of customer i at time t
Residence	1 if the customer lives in an urban area (0 if rural) at time t
Gender	1 if the customer is male (0 if female)
B2B High-tech Firm Customers	
Years	Number of years in existence of the client firm
Revenue	Annual Revenue of the client firm
Industry	Industry of the client firm (1 if B2B, 0 if B2C)

* We use revenue per cross-buy to measure a customer’s behavior with the telecommunications and high-tech firms. Anytime a firm sells products that are related (e.g., data, voice, and TV in telecommunications or hardware, software, and services in high-tech), the most watched metric by managers is revenue per cross-buy. The metric stems from the fact some cross-buys may not be profitable, hence firms like to maximize the average contribution from each cross-buy.

Table 3: Descriptive Statistics and Correlations
B2C Telecommunications Firm (B2B High-tech firm)

	Mean	Std. Dev.	1	2	3	4	5	6	7	8	9	10	11	12	13
1. Profit (Gross Margin)	69.48 (58.63)	134.43 (90.21)	1 (1)												
2. Behavior	17.02 (30.24)	19.64 (28.61)	0.34 (0.29)	1 (1)											
3. Marketing Cost	0.20 (5.28)	0.41 (4.91)	0.16 (0.17)	0.09 (0.08)	1 (1)										
4. Marketing Budget	571.34 (8,711)	325.52 (2,365)	*0.00*^{ns} *(0.00*^{ns}*)*	*0.00*^{ns} *(0.00*^{ns}*)*	0.16 (0.14)	1 (1)									
5. Satisfaction	0 (0)	1 (1)	0.05 (0.06)	0.06 (0.06)	0.05 (0.06)	*0.00*^{ns} *(0.00*^{ns}*)*	1 (1)								
6. Service Quality	0 (0)	1 (1)	0.03 (0.03)	0.04 (0.05)	0.03 (0.04)	*0.00*^{ns} *(0.00*^{ns}*)*	0.16 (0.14)	1 (1)							
7. Loyalty Intentions	0 (0)	1 (1)	0.07 (0.08)	0.03 (0.03)	0.04 (0.05)	*0.00*^{ns} *(0.00*^{ns}*)*	0.10 (0.13)	0.08 (0.09)	1 (1)						
8. Tenure	931.22 (1281.19)	144.76 (212.58)	0.05 (0.06)	0.04 (0.05)	*0.00*^{ns} *(0.00*^{ns}*)*	0.01 (0.02)	0.02 (0.03)	0.01 (0.03)	0.02 (0.03)	1 (1)					
9. Customer-initiated Contacts	9.42 (14.61)	24.71 (21.70)	0.15 (0.13)	0.10 (0.09)	0.10 (0.08)	0.06 (0.05)	0.05 (0.07)	0.01 (0.02)	0.01 (0.03)	*0.00*^{ns} *(0.00*^{ns}*)*	1 (1)				
10. Multichannel	1.09 (1.82)	0.79 (0.68)	0.16 (0.17)	0.03 (0.04)	0.13 (0.12)	0.05 (0.04)	0.02 (0.02)	0.02 (0.04)	0.02 (0.02)	*0.00*^{ns} *(0.00*^{ns}*)*	0.28 (0.30)	1 (1)			
11. Age (Years)	59.94 (10.60)	10.12 (9.92)	*0.00*^{ns} *(0.00*^{ns}*)*	0.05 (0.04)	0.05 (0.06)	-0.01 (-0.01)	-0.04 (-0.03)	0.03 (0.05)	0.03 (0.04)	0.16 (0.17)	-0.14 (-0.12)	-0.17 (-0.15)	1 (1)		
12. Income (Revenue)	2.18 (42.73)	1.13 (20.31)	0.08 (0.07)	0.12 (0.13)	0.15 (0.13)	0.01 (0.03)	0.05 (0.06)	*0.00*^{ns} *(0.00*^{ns}*)*	*0.00*^{ns} *(0.00*^{ns}*)*	0.01 (0.02)	0.19 (0.17)	0.16 (0.16)	-0.10 (-0.11)	1 (1)	
13. Residence (Industry)	0.61 (0.36)	0.39 (0.64)	-0.06 (-0.05)	-0.04 (-0.05)	*0.00*^{ns} *(0.00*^{ns}*)*	0.01 (0.02)	0.04 (0.03)	0.01 (0.02)	0.01 (0.02)	-0.22 (-0.18)	0.01 (0.02)	0.08 (0.07)	-0.04 (-0.03)	0.05 (0.04)	1 (1)

* see description of variables in Table 1
** non-significant correlations are noted with ^{ns} and are italicized

Table 4: Results from the Estimation – Marketing Model

	B2C Telecommunications firm		B2B High-tech firm	
	No Mindsets* *α (std. err.)	***w/ Mindsets* *α (std. err.)***	***No Mindsets* *α (std. err.)***	***w/ Mindsets* *α (std. err.)***
Dependent Variable: ln($Marketing_t$)				
Intercept (α)	0.084 (0.011)	0.093 (0.014)	0.078 (0.021)	0.093 (0.022)
Gross $Margin_{i,t-1}$	0.0002 (0.00002)	0.0002 (0.00002)	0.003 (0.0004)	0.003 (0.0004)
$Behavior_{i,t-1}$	0.0003 (0.0001)	0.0004 (0.0001)	0.006 (0.002)	0.006 (0.002)
Marketing $Budget_t$	0.0001 (0.00002)	0.0002 (0.00002)	0.006 (0.0004)	0.006 (0.0004)
Satisfaction $_{i,t-1}$	---	*0.016 (0.017)^{ns}*	---	*0.028 (0.041)^{ns}*
Service Quality $_{i,t-1}$	---	*0.015 (0.014)^{ns}*	---	*0.024 (0.027)^{ns}*
Loyalty $Intentions_{i,t-1}$	---	*0.038 (0.021)^{ns}*	---	*0.021 (0.025)^{ns}*
Gross $Margin_{i,t-1}$*$Satisfaction_{i,t-1}$	---	0.016 (0.003)	---	0.028 (0.003)
Gross $Margin_{i,t-1}$*Service $Quality_{i,t-1}$	---	0.029 (0.007)	---	0.039 (0.011)
Gross $Margin_{i,t-1}$*Loyalty $Intentions_{i,t-1}$	---	0.025 (0.004)	---	0.027 (0.008)
$Age_{i,t-1}$ / $Year_{i,t-1}$	-0.0003 (0.0001)	-0.0004 (0.0001)	-0.0026 (0.0005)	-0.0025 (0.0005)
$Income_{i,t-1}$ / $Revenue_{i,t-1}$	0.032 (0.002)	0.030 (0.002)	0.021 (0.001)	0.022 (0.001)
$Residence_{i,t-1}$	*-0.005 (0.003)^{ns}*	*-0.005 (0.003)^{ns}*	---	---
$Gender_i$ / $Industry_i$	-0.059 (0.003)	-0.059 (0.003)	-0.061 (0.004)	-0.065 (0.004)
Model Fit				
Overall R-Square	0.088	0.099	0.108	0.120

^{ns} denotes not significant (all other variables significant at $p < 0.01$)

Table 5: Results from the Estimation – Behavior and Gross Margin Models

	B2C Telecommunications firm		B2B High-tech firm	
	No Mindsets α (std. err.)	*w/ Mindsets α (std. err.)*	*No Mindsets α (std. err.)*	*w/ Mindsets α (std. err.)*
Dependent Variable: Behavior$_{it}$				
Intercept (α_0)	-3.190 (0.755)	-3.161 (0.754)	-3.670 (0.962)	-3.638 (0.958)
ln(Marketing$_{it}$)	2.830 (0.319)	2.802 (0.318)	5.628 (1.023)	5.530 (1.019)
Tenure$_{it}$	0.001 (0.0003)	0.002 (0.0004)	0.004 (0.0008)	0.004 (0.0008)
CIContacts$_{it}$	0.031 (0.003)	0.030 (0.004)	0.015 (0.005)	0.016 (0.005)
Multichannel$_{it}$	0.196 (0.066)	0.204 (0.67)	0.302 (0.052)	0.304 (0.051)
Satisfaction$_{it}$ *(Behavioral Effect)*	---	0.459 (0.092)	---	0.746 (0.076)
Service Quality$_{it}$ *(Behavioral Effect)*	---	0.639 (0.059)	---	0.984 (0.091)
Loyalty Intentions$_{it}$ *(Behavioral Effect)*	---	0.719 (0.092)	---	0.991 (0.221)
ln(Marketing$_{it}$)*Satisfaction$_{it}$ (*Marketing Effectiveness effect*)	---	0.970 (0.209)	---	0.916 (0.136)
ln(Marketing$_{it}$)*Service Quality$_{it}$ (*Marketing Effectiveness effect*)	---	0.136 (0.019)	---	0.169 (0.035)
ln(Marketing$_{it}$)*Loyalty Intentions$_{it}$ (*Marketing Effectiveness effect*)	---	0.252 (0.012)	---	0.265 (0.041)
Age$_{it}$ / Years$_{it}$	0.176 (0.008)	0.174 (0.008)	0.157 (0.013)	0.153 (0.012)
Income$_{it}$ / Revenue$_{it}$	2.518 (0.074)	2.513 (0.075)	0.351 (0.105)	0.362 (0.118)
Residence$_{it}$	-0.823 (0.175)	-0.805 (0.173)	---	---
Gender$_i$ / Industry$_i$	-0.477 (0.170)	-0.489 (0.169)	-0.822 (0.238)	-0.908 (0.248)
Computed Error$_{it}$ ($\hat{\varepsilon}_{it}^{M}$)	0.575 (0.058)	0.564 (0.051)	0.463 (0.145)	0.466 (0.146)
Dependent Variable: Gross Margin$_{it}$				
Intercept (α_0)	-20.062 (4.843)	-20.997 (4.804)	-12.413 (4.125)	-12.581 (4.219)
Behavior$_{it}$	2.252 (0.305)	2.236 (0.298)	0.975 (0.277)	0.945 (0.265)
ln(Marketing$_{it}$)	10.612 (2.108)	16.075 (2.045)	3.066 (0.664)	3.083 (0.672)
Tenure$_{it}$	0.024 (0.004)	0.026 (0.004)	0.026 (0.008)	0.026 (0.008)
CIContacts$_{it}$	0.712 (0.024)	0.781 (0.023)	0.461 (0.013)	0.446 (0.012)
Multichannel$_{it}$	2.543 (0.578)	2.042 (0.551)	2.801 (0.644)	2.819 (0.645)
Satisfaction$_{it}$	---	*0.522 (0.594)^{ns}*	---	*0.292 (0.361)^{ns}*
Service Quality$_{it}$	---	*0.327 (0.592)^{ns}*	---	*0.083 (0.401)^{ns}*
Loyalty Intentions$_{it}$	---	*0.107 (0.583)^{ns}*	---	*0.218 (0.453)^{ns}*
ln(Marketing$_{it}$)*Satisfaction$_{it}$ (*Marketing Efficiency Effect*)	---	1.359 (0.384)	---	0.871 (0.210)
ln(Marketing$_{it}$)*Service Quality$_{it}$ (*Marketing Efficiency Effect*)	---	1.787 (0.388)	---	0.960 (0.312)
ln(Marketing$_{it}$)*Loyalty Intentions$_{it}$ (*Marketing Efficiency Effect*)	---	2.892 (0.596)	---	2.041 (0.624)
Age$_{it}$ / Years$_{it}$	*0.070 (0.055)^{ns}*	*0.071 (0.054)^{ns}*	*0.035 (0.037)^{ns}*	*0.036 (0.038)^{ns}*
Income$_{it}$ / Revenue$_{it}$	10.395 (0.551)	10.274 (0.519)	0.756 (0.032)	0.708 (0.028)
Residence$_{it}$	-5.527 (0.534)	-5.445 (0.516)	---	---
Gender$_i$ / Industry$_i$	-11.527 (1.064)	-11.799 (1.096)	-10.946 (0.746)	-10.650 (0.735)
Computed Error$_{it}$ ($\hat{\varepsilon}_{it}^{M}$)	0.575 (0.108)	0.505 (.102)	0.940 (0.194)	0.935 (0.191)
Overall Model Fit				
-2*Log-Likelihood	878,348.06	876,835.36	311,846.49	301,548.33
AIC	878,390.06	876,905.36	311,890.49	301,616.33

^{ns} *denotes not significant (all other variables significant at $p < 0.01$)*

Table 6: Summary of Behavioral, Marketing Effectiveness, and Marketing Efficiency Effects

B2C (B2B)	Behavioral	Marketing Effectiveness	Marketing Efficiency
Satisfaction	0.459 (0.746)	0.970 (0.209)	1.359 (0.871)
Service Quality	0.639 (0.984)	0.136 (0.169)	1.787 (0.960)
Loyalty Intentions	0.719 (0.991)	0.252 (0.265)	2.892 (2.041)

Table 7: Change in Behavior and Gross Margin Due to Change in Mindset (+1 Std. Dev.)
(At Mean-level of Marketing Efforts)

B2C (B2B*)	Behavior (Revenue/Cross-buy)	Gross Margin
Satisfaction	\$0.65 (\$0.79)	\$1.73 (\$1.94)
Service Quality	\$0.67 (\$1.02)	\$1.85 (\$2.47)
Loyalty Intentions	\$0.77 (\$1.04)	\$2.30 (\$2.74)

* B2B results are in 000s of dollars

Table 8: Customer Selection to Maximize Profitability with and without CMMs
(Average Monthly Customer Profit for 1 Year)

B2C (B2B*)	Without CMMs	With CMMs
Top 10% of Customers	\$308. 99 (\$244.11)	\$340.20 (\$273.25)
Top 15% of Customers	\$250.80 (\$203.15)	\$269.03 (\$214.29)
Top 20% of Customers	\$212.77 (\$174.80)	\$225.20 (\$187.40)

* B2B results are in 000s of dollars

Table 9: Summary of Managerial Takeaways

Strategic decision	Managerial implications from the proposed framework
Marketing accountability	The application of the proposed framework enables firms make investments in programs to build CMMs more accountable by deriving their contribution to customer profitability and business growth.
Investments in programs to build CMMs	The proposed framework helps firms evaluate the investment appeal of different relationship building programs by projecting the contribution to profitability of these investments and comparing it with the cost of implementing the program.
Leveraging CMMs to improve profitability	Through the decomposition of the impact of CMMs on profitability, firms can identify the extent to which their investments in CMMs affect profitability through the three proposed mechanisms as well as their relative importance. This can help them understand the sources of marketing success and promote activities that leverage the impact of CMMs on profitability.
Which CMMs to invest in	An improved understanding of the different impact on profitability of different CMMs may help firms better design their relationship building programs to improve specific aspects or components of the customer profitability model (e.g., marketing effectiveness, behavior, or marketing efficiency).
Customer selection and resource allocation	The proposed framework demonstrates the need to integrate CMMs into the customer profitability model to improve customer selection and resource allocation decisions (e.g., customers with higher CMMs are more responsive to marketing activities and necessitate a lower level of marketing resources).
Managing customer relationships at the individual level	Our individual-level framework enables firms make decisions at the customer-level to improve the relationships with the best customers and maximize each customer's lifetime value.