Linking Customer Behaviors to Cash Flow Level and Volatility: Implications for Marketing Practices

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Marketing affects customer behavior, and customer behavior in turn drives a firm's cash flows and, ultimately, valuation. In this sequence of relationships, a commonly overlooked factor by marketers is the volatility of customers' cash flows. This study links different recurring customer behaviors to the future level *and* volatility of a customer's cash flows. Empirical analyses of the large customer database of a *Fortune* 500 retailer reveal that a 1% desired change in the different types of recurring customer behaviors corresponds to a future quarterly 4.61% decrease in the cash flow volatility and $39.42 million increase in the future cash flow level of the firm. Furthermore, firm-initiated marketing is 1.9–3.2 times more effective at managing the future cash flow level and volatility when it is selectively targeted to customers with certain characteristics. Overall, the study enables marketers to manage different customer behaviors that influence customers' future cash flow level and volatility and ultimately quantify the impact of these behaviors on the shareholder value of the firm.

Keywords: cash flow volatility, cash flow level, shareholder value, customer habits

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Linking Customer Behaviors to Cash Flow Level and Volatility: Implications for Marketing Practices

One of the fundamental drivers of firm valuation is the cash flow of the firm (Dechow 1994). The cash flow is usually evaluated in terms of its level and volatility (Rountree, Weston, and Allayannis 2008). In general, all else being equal, (1) the higher the firm's cash flow levels, the higher the firm's value (Vuolteenaho 2002), and (2) the higher the firm's cash flow volatility (or variability of cash flow over time), the lower the firm's value (Froot, Scharfstein, and Stein 1993; Vuolteenaho 2002; Zhang 2006). This is because an increase in the volatility of a firm's cash flow increases the uncertainty or risks associated with the firm's future cash flow stream, thereby increasing the likelihood of the firm to incur an internal cash flow shortfall and thus raising the cost of capital for the firm (Francis et al. 2004; Minton and Schrand 1999). For example, Rountree, Weston, and Allayannis (2008) find that a 1% increase in the cash flow volatility of the firm results in a .15% decrease in firm value.

Customers are typically one of the fundamental and most important sources of a firm's cash flows. Therefore, a proper management of customers' cash flow levels and volatility will bear substantive implications for firm valuation. However, managing customers' cash flow volatility has not been a major concern for marketers to date (Fischer, Shin, and Hanssens 2015). Much of the empirical work in marketing has focused on analyzing how marketing influences firm value by affecting

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the *level* of future customer cash flows (e.g., Gupta, Lehmann, and Stuart 2004; Rust, Lemon, and Zeithaml 2004) while ignoring the potential consequences of marketing on the *volatility* of customers' future cash flows.

In the widely cited market-based assets framework, Srivastava, Shervani, and Fahey (1998) argue that firms can decrease the cash flow volatility (and thus increase the shareholder value) of the firm by structuring their marketing around activities that help stabilize customers' spending behavior. However, while this has been conceptually discussed as a necessary marketing imperative, Srivastava, Shervani, and Fahey (1998, p. 12) contend that "such assessments of marketing strategy are rare." To the best of our knowledge, no empirical study to date has assessed the relative importance of customer-level behavioral factors on the future cash flow volatility of the firm, and therefore this is the main research focus of the current study. Because cash flow level also governs firm valuation, the overall objective of this study is to analyze customer-level data to evaluate how marketers can increase the overall value of a firm by managing both customer cash flow level and volatility through implementation of differentiated marketing initiatives. From a research standpoint, investigating "how individual-level data should be used to build more powerful customer-level marketing programs" has been listed among the tier-one research priorities of the Marketing Science Institute (2014, p. 5) for 2014–2016.

MAPPING INDIVIDUAL CUSTOMER BEHAVIOR TO FUTURE CASH FLOW VOLATILITY AND LEVEL

Our research takes place in the context of a large publicly listed *Fortune* 500 retailer. The business context is important because it represents a noncontractual situation in which customers are free to transact of their own accord, encounter low switching costs, and typically exhibit polygamous loyalty (Dowling and Uncles 1997; Reinartz and Kumar 2000). Consequently, individual customers of the firm are likely to exhibit widely varying revenue streams in terms of both cash flow levels and volatility over time. It is of particular relevance to marketers to shed light on (1) which type(s) of customer behaviors affect the cash flow level and volatility of a firm and (2) the extent to which they do so.

Theoretically, any customer behavior(s) bearing a profit or cost implication for the firm could be included in an analysis of the customer's cash flow level and volatility. For example, a customer's purchase behavior would qualify as a relevant behavioral measure. Thus, how should such customer-level behavioral measures be operationalized given the empirical objective of linking them to a customer's cash flow level and volatility?

Empirical studies from extant research have utilized different types of customer behavioral measures. These may be broadly classified as (1) single-period measures such as contemporaneous measures (e.g., customer purchase behavior in time t) or one-period-lagged measures (e.g., customer purchase behavior in time $t - 1$) (Blattberg et al. 1978), (2) summary measures such as average frequency of customer behavior in the past (East and Hammond 1996; Malthouse and Blattberg 2005), and (3) habit-based measures that quantify the frequency and temporal consistency of past behavior (Liu-Thompkins and Tam 2013; Shah, Kumar, and Kim 2014).

Intuitively, the degree to which a customer frequently and consistently repeats a behavior (i.e., habit-based measure) is likely to relate better to the level and volatility of the customer's cash flows compared with the other aforementioned measures. In the business context, customers' habits have been widely acknowledged as powerful drivers of shopping behavior and, thus, firm performance (Duhigg 2012). Articles in popular news outlets such as *The Wall Street Journal*, *USA Today*, and *Reuters* have often attributed the stock price and/or financial performance of firms such as Walmart, Tesco, Mattel, and J.C. Penney to customers' (changing) shopping habits (Anderson 2014; Associated Press 2014; Davey 2014; Evans and Erheriene 2014; Malcolm 2014; Mattioli 2013). Therefore, we propose to study habit-based measures in this study as drivers of future customer cash flow level and volatility and, ultimately, the shareholder value of the firm.

A related research question is whether the empirical analyses may include *different* aspects of a customer's recurring behavior with the firm. Given the business context of our research (i.e., a retailer), we analyze four aspects of a customer's repetitive behavior: (1) purchasing regularly priced items ("purchase habit"), (2) purchasing items on promotion ("promotion habit"), (3) returning previously purchased items ("return habit"), and (4) purchasing steeply priced loss-leader items and/or items marked on clearance ("low-margin habit"). Our choice of these four repetitive behaviors is primarily motivated by firms' contemporary marketing practices that are known to be mindful of customers who consistently purchase (Kaye 2015; Trefis Team 2015), respond to promotions (Bawa and Shoemaker 1987; Davis 2015), purchase low-margin items (Tuttle 2011; Walters and MacKenzie 1988), or return previously purchased items (Kerr 2013; McWilliams 2004) while planning marketing campaigns and/or changes in marketing policies. For a brief definition of the four habits and the associated rationale for their inclusion, see Table 1.

Each of the four aforementioned recurring behaviors has an associated cost/profit implication. Therefore, the habit strength measures may serve as a behavioral proxy for both the cash flow level and volatility of the customer. In a recent study, Shah, Kumar, and Kim (2014) find that the changes in habit-based measures, compared with other customer-level measures, relate better with the customer profits. We build on this study to address several research questions that have not been investigated by extant research:

1. Can habit-based measures help explain the variation in the future cash flow volatility of each customer? If so, how (in terms of the direction of the relationship)?
2. What is the relative importance of different habitual customer behaviors in driving the future cash flow volatility (and level) of each customer and, ultimately, the firm?
3. Can marketing result in conflicting outcomes (i.e., improving the cash flow level while also increasing the cash flow volatility)? If so, how and why?
4. How and to what extent can implementation of systematic customer-level differentiated marketing (vs. random, untargeted marketing) interventions help improve the effectiveness of marketing in terms of influencing the future cash flow level and volatility of each customer?
5. How can firms apply these findings to implement appropriate marketing policies and practices for customer acquisition and retention with the overarching objective of maximizing the shareholder value of the firm?

We address these questions by empirically analyzing the customer data set of a large retailer. The data set contains rich

Table 1
DEFINITIONS AND THE BUSINESS RATIONALE FOR THE FOUR HABIT-BASED MEASURES

Habit Measure	*Definition*[a]	*Business Rationale*
Purchase habit	A customer's general tendency to repeatedly and regularly buy products from the firm regardless of whether they are on promotion or are low-margin items.	Virtually all marketing practices are directed toward encouraging customers to buy repeatedly from the firm, given the obvious financial benefits. Customers with strong purchase behavior can generate high revenue for the firm by purchasing the most recent or fully priced products rather than searching for bargains (Kaye 2015).
Promotion habit	A customer's general tendency to repeatedly and regularly buy items that are offered through marketing and sales promotions.	According to a study conducted by AgilOne Inc., which works with 150 retailers to analyze customers' purchase behaviors, approximately 20% of shoppers can be classified as promotion shoppers or customers that make a purchase only when they see a promotion deal (Banjo 2014). Large retailers such as J.C. Penney, Kohl's, and Macy's heavily rely on promotion deals to drive their in-store traffic, and it is important for retailers to identify the cherry pickers with strong promotion habit (Fox and Hoch 2005).
Return habit	A customer's general tendency to repeatedly and regularly return previously purchased products.	Customers return $264 billion worth of products, or almost 9% of total sales, each year (Kerr 2013). From a retailer's standpoint, it is necessary to allow customers to return products to lower customers' perceived risk in current and future purchases. However, product returns become a serious concern for retailers when customers consistently return previously purchased products (Shah et al. 2012), as in the cases of national electronics retailer Best Buy (McWilliams 2004) and apparel retailer Filene's Basement (Zbar 2003).
Low-margin habit	A customer's general tendency to repeatedly and regularly buy steeply discounted products of the firm.	Retailers are known to steeply discount their products for a variety of reasons (Kapner 2013; Lichtenstein, Netemeyer, and Burton 1990; Walters and MacKenzie 1988).The shoe brand Donald J Pliner identifies "discount shoppers" who buy only clearance items and/or products priced at more than 25% off as one of its three important customer segments (Banjo 2014).

[a]Adapted from Shah, Kumar, and Kim (2014).

information consisting of customer-level daily transactions, marketing and communication interventions, and customer characteristics for approximately 700,000 customers over an observation period of four years. The longitudinal data help us construct the stock variables pertaining to the four aforementioned customer habits as well as analyze the trend of cash flow levels and volatility over time.

We find that (1) all four habit measures serve as statistically reliable and theoretically grounded behavioral proxies for explaining the future cash flow volatility and level of the customer as well as the firm, (2) the relative importance of the four habits varies in terms of both magnitude and direction of relationship with respect to driving the future cash flow level and volatility, (3) firm-initiated marketing can amplify adverse outcomes (i.e., decrease cash flow levels and increase cash flow volatility) or result in conflicting outcomes (i.e., increase cash flow level at the expense of increasing cash flow volatility), (4) differences in customer-level characteristics may be leveraged to significantly increase the efficiencies of customer-level marketing programs, and (5) the firm's acquisition and retention programs may be strategically tailored to increase (decrease) the cash flow level (volatility) of the firm.

The overarching goal is to enable marketers to manage both cash flow level and volatility simultaneously in an efficient manner by implementing differentiated customer-level marketing practices and/or policies. We elaborate on this further in a subsection related to the managerial implications of our findings.

The rest of the article is organized as follows. First, we discuss the relevant literature and develop a conceptual framework. Then, we describe the data, key measures, and methodology for the operationalization of the conceptual framework. Subsequently, we discuss the results and managerial implications of the research and conclude with limitations and future directions.

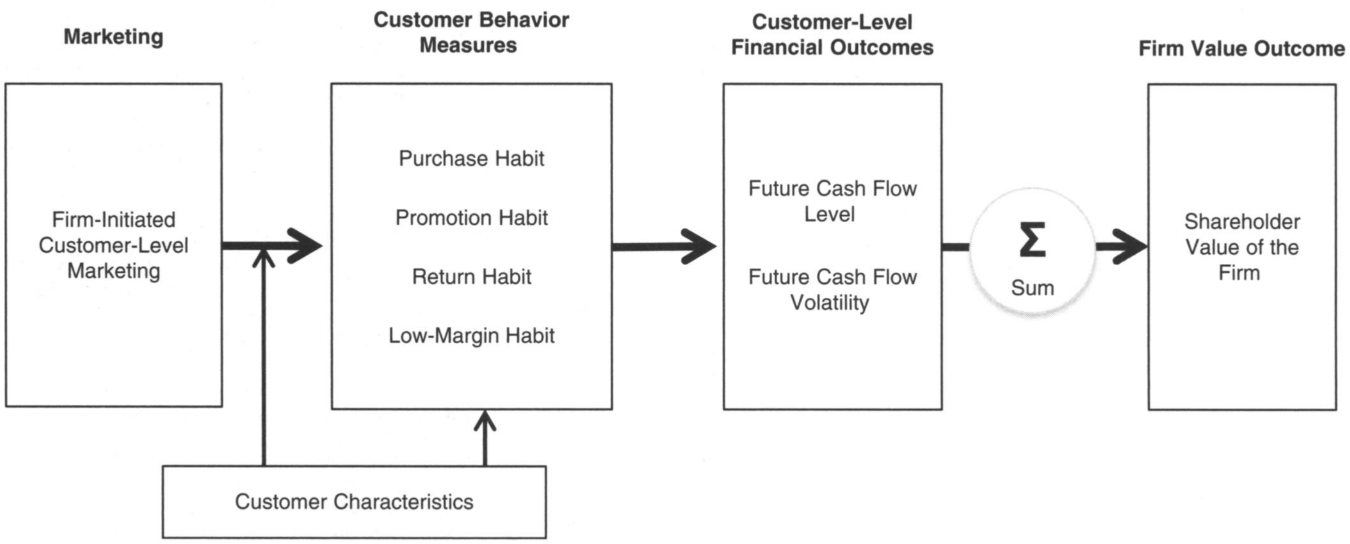
THEORY AND CONCEPTUAL FRAMEWORK

The objective of our research is to empirically link (1) marketing to customer behavior and (2) customer behavior to the future cash flow level and volatility of the customer and, eventually, the shareholder value of the firm (see Figure 1). Toward this endeavor, we draw on multiple streams of research to conceptually clarify the rationale underlying the key linkages.

Marketing and Customer Behavior

Several studies from the customer relationship management literature have firmly established the link between marketing and individual customer behavior (e.g., Fader, Hardie, and Lee 2005; Reinartz and Kumar 2000; Shah, Kumar, and Kim 2014; Tarasi et al. 2011; Venkatesan and Kumar 2004; Verhoef 2003) by employing different types of customer-level

Figure 1
CONCEPTUAL FRAMEWORK



Notes: Summation indicates aggregation across all customers of the firm.

behavioral measures. As we have discussed, our choice of behavioral measure is the habit-based measure.

A habit is defined as a person's tendency to repeat past behavior (e.g., Neal et al. 2012). Notably, the human brain is designed to develop habitual routines. When people perform a particular behavior in a given situation (with a satisfactory outcome) over time, they become cognitively hardwired to repeat that behavior consistently in the same or a similar situation (Marchette, Bakker, and Shelton 2011; Muraven and Baumeister 2000). Once habitual routines are established, the associated behavior is typically triggered by an extrinsic cue (Wood and Neal 2009). In the business context, firm-initiated marketing may serve as the extrinsic cue to trigger or influence the customer's related recurring behavior. For example, sales promotion communication from a firm is likely to consistently motivate customers with a strong promotion focus to visit the respective store and buy items that are marked on promotion. In general, firm-initiated marketing may serve as a reminder to customers to visit the store and, thus, exhibit their respective habitual behaviors. Therefore, we expect marketing to have a significant positive effect on the four aforementioned habitual behaviors of the customers, as illustrated in Figure 1.

We draw our proposed habit-based measures and the linkage between marketing and habit-based measures from Shah, Kumar, and Kim (2014). However, unlike Shah, Kumar, and Kim's study, the main focus of this research is not to develop habit-based measures and correlate them with customer profits; rather, it is to apply the habit-based measures as drivers of future cash flow volatility and level for each customer and, ultimately, the shareholder value of the firm. By doing so, we address several unanswered research questions of managerial importance (as discussed previously). Furthermore, we introduce methodological refinements to the approach of Shah, Kumar, and Kim by explicitly accounting for the heterogeneity of customers' habit formation and the relative effectiveness of marketing as well as by addressing the issue of endogeneity bias.

Prior research studies have suggested (but have not empirically shown) that certain characteristics can increase people's likelihood of developing routinized behaviors relatively faster. For example, Yoon, Cole, and Lee (2009) find that older consumers are prone to exhibiting repetitive behaviors because they rely more on existing knowledge and have limited physical mobility and skills. Likewise, customers with a higher level of education and higher income are considered more likely to exhibit consumption behaviors based on a habitual (rather than an extended) decision process because they tend to be employed and thus experience increased time pressure (Engel, Kollat, and Blackwell 1968). In contrast, Raju (1980) shows that homemakers are more variety seeking and thus are less likely to repeat the same behavior over time, while Quinn and Wood (2005) propose that customers with large households are less prone to exhibiting repetitive habitual behaviors. Furthermore, customers with certain characteristics are likely to differ in their responsiveness to firm-initiated marketing actions. For example, Rust and Verhoef (2005) show that customers with a higher income are more responsive to marketing interventions. Consequently, we allow the relative effectiveness of marketing and habit strength formation to vary for each customer on the basis of observed customer characteristics (see Figure 1).

Analyzing Customer-Level Cash Flow Volatility Along with Cash Flow Level

In the extant marketing literature, several empirical studies have acknowledged the importance of the volatility of customer cash flows in driving firm performance (Grewal, Chandrashekaran, and Citrin 2010; Kumar and Shah 2009; Srinivasan and Hanssens 2009). However, only a handful of marketing studies have attempted to uncover the drivers of cash flow volatility. The few exceptions include Fischer, Shin, and Hanssens (2015), who show that a firm's and competitors' marketing spending patterns and responses can affect cash flow volatility; in addition, Gruca and Rego (2005) find that improvement in customer satisfaction can reduce the variability in a firm's cash flow because firms with high customer satisfaction rates carry lower risk of losing the existing customers. However, both empirical studies employ aggregate (brand- or firm-level) drivers of cash flow volatility and are not suitable for helping firms understand customer-level behavioral difference and/or implement a differentiated customer-level marketing program, which is the focus of the current study.

Furthermore, we propose to evaluate the relative importance (in terms of magnitude and direction) of four different habit-based measures on the customer's future cash flow level and volatility. Following the definitions of the habit measures (as we discuss in Table 1), we expect purchase and promotion habits to have a positive impact, and low-margin and return habits to have a negative impact, on customers' future cash flow levels. This is consistent with the direction of the relationship between customer habits and customer profits reported by Shah, Kumar, and Kim (2014).

A strong purchase habit should help stabilize a customer's cash flow stream (particularly in noncontractual settings) and, thus, should negatively affect his or her future cash flow volatility. In contrast, a strong return habit is likely to increase the variability of the customer's revenue stream by virtue of the customer purchasing and returning items. Consequently, a customer's return habit should positively contribute to his or her future cash flow volatility. Similarly, customers' promotion and low-margin habits are likely to positively contribute to their future cash flow volatility because they are likely to purchase selectively and intermittently only when there is a promotion and/or when the relevant item is steeply discounted by the firm.

The cash flow level and volatility of each customer may be aggregated to evaluate the overall impact at the firm level. Consequently, marketers can implement such a framework to determine which individual customer to target for which habit-based measure to create the desired change in future cash flow level and volatility and, thus, overall firm value. In the next section, we describe the data employed to operationalize the conceptual framework illustrated in Figure 1.

RESEARCH METHODOLOGY

Data

The data set employed for the empirical analyses comes from a *Fortune* 500 retailer[1] that sells a wide assortment of products related to home improvement goods, furniture, home appliances, and gardening needs. The firm is one of the major retail store chains in the United States, operating more than 900 stores across the nation. Typical retail stores of this chain stock more than 15,000 items, with prices that range from a few cents to several thousands of dollars.

For this retailer, we obtain the following five types of data corresponding to the observation period of four years from 2005 to 2008:

- Customer transaction data: These consist of daily transaction data for a large representative sample of customers who made purchases from one of the firm's 900+ stores and/or the firm's website during the observation period of four years. The transaction data contain rich customer-level information in terms of the time of purchase, store location, purchase amount, number of items purchased, number of products returned, amount of products returned, and so on.
- Customer marketing data: These consist of all firm-initiated promotion and direct mail communications (including e-mail, coupons, and other direct marketing campaigns) implemented by the firm at the individual customer level during the observation period.
- Product margin data: These consist of a list of product margins associated with each stockkeeping unit sold by the retailer in the observation period. Given the wide assortment of products sold, the product margin varies from −18% to 133%. The average product margin is 39%.
- Customer characteristics data: We obtain customer characteristics data for several variables such as age, income, financial score, marital status, education level, home value, number of people in the household, and so on through the generous research collaboration support from Acxiom Corporation.
- Macroeconomic data: We obtain macroeconomic variables such as housing starts information corresponding to the observation period from Federal Reserve Economic Data.

We combine the customer-level transaction and marketing data based on the unique customer identifiers to track each customer's transaction activities and marketing communications received. We also apply the product margin data to determine the proportion of low-margin items the customers purchased during the observation period. Then, we append customer characteristics data from Acxiom by first name, last name, and other available identifiable information in the customer data set. The merged data set represents rich details in terms of all firm-initiated marketing, customer characteristics, product purchases, and product returns at the individual customer level across the observation period of four years (2005–2008). Consequently, the data contain a large representative sample of the retailer's customers who either already existed or initiated a relationship with the firm from 2005 onward.

Given the objective of our research (i.e., analyzing customer habits), we exclude customers with a single purchase occasion during the observation period. Because the study is conducted in a noncontractual setting, extreme data points for cash flow volatility can be generated that would lead to a potential misrepresentation of the impact of customer behavioral drivers on future cash flow volatility. Therefore, to minimize the impact of extreme data points, we remove customers with extremely high levels of volatility (i.e., customers with the top 1% of cash flow volatility). The final data set consists of 666,992 customers who account for approximately 86% of the total firm revenue from customers in the observation period. We employ this customer data set to derive the key habit measures and estimate the econometric models as detailed subsequently.

Key Variables and Measures

Habit-based measures. The extent to which a recurring behavior is habitual may be quantified along a continuum of habit strength using self-reported habit measures (e.g., Verplanken and Orbell 2003) or inferred empirically using observed transaction behavior (Shah, Kumar, and Kim 2014). We

[1]A nondisclosure agreement stipulates that we cannot reveal the name of the firm.

follow the approach proposed by Shah, Kumar, and Kim (2014) to empirically determine the strength of purchase, promotion, return habit, and low margin for each customer. Basically, the habit-based measure that corresponds to each recurring behavior may be computed as the ratio of the average frequency and temporal consistency of the behavior. For a brief description of how the habit-based measures (identified along a continuum of habit strength) are computed, refer to the Web Appendix; for a more detailed description, see Shah, Kumar and Kim.

Measuring cash flow volatility and level. In this study, "cash flow" refers to the level of cash flow generated by an individual customer i at time t (quarter). We have accounted for the product return cost, individual marketing cost, and the profit margin of each product sold when deriving the cash flow at the individual level. To test the impact of customers' different behavioral characteristics on the variance of future cash flows, we compute the individual future cash flow volatility by dividing the standard deviation of individual cash flow level by the absolute value of the mean level of cash flow over the same period. This is a widely used measure in many studies (Gruca and Rego 2005; Minton and Schrand 1999; Minton, Schrand, and Walther 2002; Morgan and Rego 2009). Consistent with the approach employed in the extant literature, we derive the cash flow volatility at the customer level as the standard deviation of each customer's cash flow divided by the absolute value of the mean of cash flow over the same period. The cash flow volatility measures the stability of an individual customer's cash flow. We measure the level of cash flow data over four quarters[2] to obtain the standard deviation and the absolute mean.

Other variables. In addition to the habit strength and cash flow volatility measures, we employ customer-level transaction, marketing, and characteristics data. The firm implements three types of customer-level marketing programs: e-mail campaigns, coupons, and direct mail. The marketing decision variable (herein also referred to as "firm-initiated marketing" or simply "marketing") is operationalized in the data (by the firm) as a composite-weighted measure of the number of e-mails, coupons, and direct mail pieces the firm sent to each customer in a given time period. In addition, we use macroeconomic variables corresponding to the observation period. Table 2 lists the key variables employed for the empirical analyses.

The correlation of habit strength measures is generally low (as indicated in Table 3), thereby implying that the respective habits are independent. The correlation is the lowest ($\rho = .01$, $p < .01$) for the purchase and promotion habits and the highest ($\rho = .30$, $p < .01$) for the purchase and low-margin habits.

MODEL SPECIFICATION AND ESTIMATION

We need to model (1) the effect of customer-level marketing on the habit strength of each customer and (2) the effect of habit strengths (i.e., purchase, promotion, return, and low-margin habit) on the future cash flow levels and volatility of each customer (as depicted in the conceptual framework of Figure 1). The habit strength measure (for each of the four habits) that corresponds to the recurring behavior j of customer i at time t may be specified as

$$\text{Habit}_{jit} = \gamma_{j0} + \gamma_{j1}\text{Marketing}_{it} + \upsilon_{jit}, \tag{1}$$

and the future cash flow volatility and level for customer i at time t may be specified as

$$\begin{aligned}\text{Cash Flow Volatility}_{it+1} = \beta_0 &+ \beta_1 \text{ Purchase Habit}_{it} \\ &+ \beta_2 \text{ Promotion Habit}_{it} \\ &+ \beta_3 \text{ Return Habit}_{it} \\ &+ \beta_4 \text{ Low-Margin Habit}_{it} \\ &+ \varepsilon_{it}, \text{ and}\end{aligned} \tag{2}$$

$$\begin{aligned}\text{Cash Flow Level}_{it+1} = \delta_0 &+ \delta_1 \text{ Purchase Habit}_{it} \\ &+ \delta_2 \text{ Promotion Habit}_{it} \\ &+ \delta_3 \text{ Return Habit}_{it} \\ &+ \delta_4 \text{ Low-Margin Habit}_{it} + \eta_{it},\end{aligned} \tag{3}$$

where υ_{jit}, ε_{it}, and η_{it} represent the error terms or the unexplained variations in habit strength, cash flow volatility, and cash flow level, respectively. Customer-level marketing is subsumed by the corresponding habit strength measures, as observed in Equation 1, and is not specified as a separate covariate in Equations 2 and 3.

The basic model specifications of Equations 1, 2, and 3 suffer from potential issues. First, other variables of interest besides the key covariates (i.e., habit strength measures and marketing) could affect the respective dependent variables. Omission of the relevant variables in the model specification contributes to an omitted variable bias and, consequently, creates issues of endogeneity with the covariates of interest (i.e., marketing in Equation 1 and habit strength measures in Equations 2 and 3). Second, the endogeneity issue may also arise from the notion that the customer-level marketing specified in Equation 1 is likely to be a nonrandom decision of the firm to manage the relationship and/or behavior of the respective customer.

To remove these biases, we would need to get additional information pertaining to (1) additional relevant exogenous control variables and (2) factors underlying the firm's marketing decision process. Failure to address the endogeneity issue will render the causal effect of marketing in Equation 1 to be unidentified and will bias the effect size of the habit strength measures in Equations 2 and 3.

Given the panel structure of our data, we follow the recommendation of Germann, Ebbes, and Grewal (2015) to discuss and evaluate different model specifications before choosing the best alternative to minimize the aforementioned issues. More specifically, we consider the following three model specifications: (1) a rich data model, (2) an unobserved-effects model, and (3) an instrument variable (IV) model.

Rich Data Model Approach

The rich data model specification strives to account for all relevant omitted variables to minimize the omitted variable bias. In the context of our research, this would entail augmenting the right-hand side of Equations 1, 2, and 3 with a set of relevant control variables that are assumed to be exogenous. These could include customer-level behavioral variables, customer characteristics, environmental shocks, and macroeconomic factors.

Given the panel structure of our data, customers continue to transact with the firm over time. Therefore, it would be unrealistic to assume that the error terms for the same set of customers from different time periods will be uncorrelated.

[2]We tested different time horizons (two, three, and five quarters) for calculating the volatility of cash flows. (For details, refer to the "Robustness Check" subsection.)

Table 2
SUMMARY OF MEASURES AND DATA SOURCES

Variable	*Operational Measure*	*Data Source*
Cash Flow $Level_{it}$	Level of cash flow for customer i at time t	Derived from the firm's customer database
Cash Flow $Volatility_{it}$	Coefficient of variation of customer i's cash flow level at time t	Derived from the firm's customer database
Behavioral $Intensity_{jit}$	Frequency of behavior j conditional on the total number of purchase incidences for a customer i at time t	Derived from the firm's customer database
$Habit_{jit}$	Strength of temporally recurring behavior j for a customer i at time t is operationalized as the Mean(Behavioral $Intensity_{jit}$)$/(1+\sigma_{jit})$	Derived from the firm's customer database
σ_{jit}	Temporal consistency of behavior j of a customer i at time t	Derived from the firm's customer database
$Marketing_{it}$	Level of firm-initiated marketing (direct mail, e-mail, and coupons) for customer i at time t, which is a weighted sum obtained by multiplying the unit cost–based weight (assigned by the firm) with the frequency of the respective marketing medium: the firm's outbound direct mail, e-mail, and coupons to the customers.	The firm's customer database
Cross-Buy_{it}	Number of cross-buy for customer i at time t	The firm's customer database
Control Variables: Customer Characteristics and Macroeconomic Factors		
Age	Whether customer i is over 65 years old (1, and 0 otherwise)	Acxiom
Children	Whether customer i has children (1, and 0 otherwise)	Acxiom
Homemaker	Whether customer i is a homemaker (1, and 0 otherwise)	Acxiom
College education	Whether customer i has postgraduate education (1, and 0 otherwise)	Acxiom
Income	Whether customer i has top 50% income level (median split; 1, and 0 otherwise)	Acxiom
Store card holder	Whether customer i has the store credit card (1, and 0 otherwise)	The firm's customer database
Housing starts	Number of privately owned new housing units in a given period t (in thousands of units)	Federal Reserve Economic Data

A popular way to address this issue is to specify the respective models as random-effects panel data models where the error term is decomposed into two parts (Germann, Ebbes, and Grewal 2015). For example, the error term for Equation 1 would be specified as $\varepsilon_{it} = \beta_{0i} + \zeta_{it}$, where β_{0i} would be the customer-specific random error term (usually assumed to be i.i.d. and to follow a normal distribution) and would help account for the correlation of the error terms for each customer over time; ζ_{it} would be the random component that varies across customers and over time. Similar treatment would apply to Equations 2 and 3.

Table 3
INTERCORRELATION OF HABIT MEASURES

	Purchase Habit	*Promotion Habit*	*Return Habit*	*Low-Margin Habit*
Purchase habit	1			
Promotion habit	.012***	1		
Return habit	.199***	.178***	1	
Low-margin habit	.302***	.112***	.160***	1

***$p < .01$.

In the context of our research, the rich data model approach may help address the potential omitted variable bias in Equations 2 and 3. However, this approach may not be sufficient to rule out the endogeneity bias arising from the nonrandom customer-level marketing in Equation 1.

Unobserved Effects Model Approach

Another popular alternative is to specify the three equations as an unobserved effects model where a proxy variable may be inserted to represent the effect of the omitted variables. For example, customer-level intercepts ($\alpha_{1i}, \alpha_{2i}, \alpha_{3i}$) may be inserted in Equations 1–3, where α_{1i}, α_{2i}, and α_{3i} would represent fixed unknown constants as well as all time-invariant unobserved factors. One of the major identifying assumptions with this specification is that the omitted variables and/or the process causing the endogeneity bias do not vary over time. This identifying assumption is likely to be violated in the context of our research because customer-level marketing may be influenced by time-varying factors that are not observed in the data and thus are not included in the model specification. Alternatively, a one-period lag of the dependent variable may be included to represent time-varying unobserved factors. However, inclusion of a lagged dependent variable to control for time-varying unobserved effects requires a strong identifying assumption that there is no serial correlation in the panel data set. In any case, a lagged dependent variable will not be adequate to account for the firm's underlying nonrandom customer-level marketing decisions in Equation 1 in the context of our research.

IV Model Approach

The third alternative is to pursue an IV approach. This entails finding one or more relevant IVs that will correlate with the customer-level marketing decision of the firm in Equation 1 but not with the respective error term of the equation.

Theoretically, firms implement customer-level marketing to influence desired behavior (e.g., purchase) and/or manage relationships for select customers. In an effort to maximize this objective, firms are likely to strategically focus their marketing efforts on the basis of a customer's past value and/or tactically direct their marketing campaigns to customers who are more likely to respond to marketing offers.

As discussed previously, the firm implements three types of customer-level marketing programs: e-mail campaigns, coupons, and direct mail. The marketing decision variable is operationalized as a composite weighted measure of number of e-mails, coupons, and direct mailings sent by a firm to each customer in a given time period. The transaction data set records every customer's response to these programs in terms of the number of e-mails opened or clicked, coupons redeemed, and/or purchases made related to an item promoted in the direct mail. Furthermore, we have full access to the profit and revenue stream of each customer. We also have information on the channel preferences and lifestyle clusters of each customer, which can be employed to infer marketing communication preferences for each customer. Consequently, we choose the following variables as instruments for the marketing decision variable: (1) number of e-mails opened, (2) number of e-mails clicked, (3) dollar value of product(s) purchased from a direct mail promotion, and (4) dollar value of coupon(s) redeemed in the previous time period (or quarter). Furthermore, we also include the value of customer profit in the previous year and the channel preferences (e.g., online order preference) and/or lifestyle clusters (e.g., high-tech living) as additional instruments. For new customers, we replace the values of the instruments (for the previous period) with the average values corresponding to all customers of the firm. By doing so, we have a reasonable set of IVs that theoretically meet the relevance criterion, given our data and understanding of the institutional setting.

Instruments should also meet the exclusion criterion (i.e., be uncorrelated with the omitted variables). The customer-level marketing action(s) of competing retailer(s) is a major category of omitted variables. Because the focal firm does not observe what direct mail promotion, e-mail, and/or coupon offers are sent out to which customers at what time by competing retailer(s), it is unlikely that the instruments will correlate with the omitted variables (i.e., the error term containing the omitted variables), thereby meeting the exclusion criterion.

We follow the control function methodology to fix the endogeneity problem (for details, see Wooldridge [2002] or Petrin and Train [2010]) with the aforementioned instruments. Consequently, we add the endogeneity correction residuals in Equation 1 to alleviate the endogeneity bias pertaining to customer-level marketing.

Final Model Specifications

In this section, we describe the final model specifications after addressing the endogeneity issue and adding relevant control variables and random effects in the basic model specifications of Equations 1, 2, and 3.

Habit strength model. We expect the habit strength of a customer to be influenced by firm-initiated marketing and past frequency of the habitual behavior (Shah, Kumar, and Kim 2014). Given the panel structure of the data, the habit strength (on average) may systematically evolve over time for all customers of the firm. Consequently, the habit strength measure[3] corresponding to the recurring behavior j of customer i at time t may be specified as

$$\text{(4)}\quad \text{Level 1: Habit}^*_{jit} = \gamma_{j0i} + \gamma_{j1i}\text{Marketing}_{it} + \gamma_{j2i}\ln\left(\text{Behavioral Intensity}_{jit-1}\right) + \gamma_{j3}\text{Time}_{it} + \gamma_{j4}\xi_{it} + \upsilon_{jit},$$

where

j = 1, 2, 3, 4 (i.e., purchase habit, promotion habit, return habit, and low-margin habit);
t = quarter (four-month time interval);
Marketing_{it} = the level of firm-initiated marketing effort for customer i at time t;
$\text{Behavioral Intensity}_{jit-1}$ = intensity of behavior j for customer i at time $t - 1$;
Time_{it} = continuous time indicator for customer i at time t;
ξ_{it} = endogeneity correction residuals that influence the level of marketing efforts for customer i at time t;
γ_{j0i} = parameter estimates for intrinsic habit strength of behavior j for customer i;
γ_{j1i} = parameter estimates for the effect of marketing efforts on habit j for customer i;
γ_{j2i} = parameter estimates for the nonlinear effect of prior behavior j on habit j for customer i;
γ_{j3} = parameter estimates for the time effect on habit j;
γ_{j4} = parameter estimates for endogeneity correction residual on habit j; and
υ_{jit} = error term representing the variation within individuals at time t for habit j.

The log transformation of the behavioral intensity measure (i.e., $\text{Behavioral Intensity}_{jit-1}$) helps capture the diminishing (nonlinear) effect of the past behavior on the habit strength of the customer over time.[4] The time variable (Time) ranging from 0 to 14 quarters captures the average growth in customers' habit strength over time. For all four habit strength models (j = 1, 2, 3, 4), we included a set of

[3]The habit measure (as described in Table 2) is a bounded measure ranging from 0 to 1. However, Equation 4 is specified as a linear model where υ_{jit} is assumed to be i.i.d. normal. Therefore, we apply a logit transformation to the habit strength measure as $\text{Habit}_{jit}{}^* = \ln[(\text{Habit}_{jit})/(1 - \text{Habit}_{jit})]$ and the transformed (continuous and unbounded) measure is used as the dependent variable in Equation 4.

[4]We add a small constant to the behavioral intensity measure before taking the log transformation to prevent taking the log of zero.

endogeneity correction residuals (ξ_{it}) to alleviate the endogeneity bias pertaining to customer-level marketing.

As discussed previously, customer-level differences (identified on the basis of differences in observed characteristics) may (1) accelerate or inhibit habit formation across customers and (2) influence the relative effectiveness of marketing on habit formation. Therefore, we employ a hierarchical linear modeling (HLM) framework by allowing the customer-specific random coefficients in Equation 4 to be a function of customer-specific characteristics:

$$(5)\quad \text{Level 2: } \gamma_{j0i} = \theta_{j00} + \theta_{j01}\text{Customer Characteristics}_i + \mu_{j0i},$$
$$\gamma_{j1i} = \theta_{j10} + \theta_{j11}\text{Customer Characteristics}_i + \mu_{j1i},$$
$$\gamma_{j2i} = \theta_{j20} + \theta_{j21}\text{Customer Characteristics}_i + \mu_{j2i},$$

where

Customer Characteristics$_i$ = a matrix of individual characteristics for customer i;
θ_{j00} = intercept of habit j;
θ_{j01} = a vector of parameter estimates for the impact of customer characteristics on habit j;
θ_{j10} = fixed effect of marketing on habit j;
θ_{j11} = a vector of parameter estimates for the differential impact of marketing by customer characteristics on habit j;
θ_{j20} = fixed effect of past behavior j on habit j;
θ_{j21} = a vector of parameter estimates for the differential impact of past behavior by customer characteristics on habit j;
μ_{j0i} = error term representing the variation in intercepts between individuals for j;
μ_{j1i} = error term representing the variation in the effect of marketing for habit j; and
μ_{j2i} = error term representing the variation in the effect of behavior intensity between individuals for habit j.

Consequently, in Equation 4, γ_{j0i} allows the baseline level of habit strength to vary by individual customers, while γ_{j1i} and γ_{j2i} allow firm-initiated marketing and the customer's past behavioral intensity to have differential effects on the habit strength of each customer. The intercepts (θ_{j00}, θ_{j10}, and θ_{j20}) capture the mean level of habit strength j, the mean effect of marketing on habit strength, and the mean effect of prior behavior j on habit strength, respectively, across all customers of the firm. The coefficients for customer characteristics (θ_{j01}, θ_{j11}, and θ_{j21}) help capture the average level of habit strength, the effect of marketing on habit strength, and the effect of prior behavior on habit strength on the basis of different customer characteristics.

The error terms (μ_{j0i}, μ_{j1i}, and μ_{j2i}) help capture the unobserved heterogeneity of habit strength, effects of marketing, and behavioral intensity, respectively on the habit strength for each customer of the firm. The error term υ_{jit} is assumed to be normally distributed with mean 0 and variance σ_j^2, and the error terms in the second level (μ_{j0i}, μ_{j1i}, and μ_{j2i}) are assumed to follow a multivariate normal distribution with a mean vector 0 and a variance–covariance matrix Σ. We estimate the HLM as specified in Equations 4 and 5 by applying a maximum likelihood estimation procedure.

Future cash flow volatility and level model. Following the basic specification of Equations 2 and 3 and our previous discussion, we add the following control variables: (1) the level of cross-buy (Cross-Buy$_{it}$), which controls for an additional dimension of customer behavior that the habit-based behavioral measures may not have captured, and (2) the macroeconomic and seasonality factors (Seasonality$_{t+1}$, Housing Starts$_{t+1}$), which help account for the exogenous environmental shocks. Therefore, the future cash flow volatility and level of each customer (i.e., in time t + 1), may be specified as

$$(6)\quad \text{Cash Flow Volatility}_{it+1} = \beta_1 \text{ Purchase Habit}_{it} + \beta_2 \text{ Promotion Habit}_{it} + \beta_3 \text{ Return Habit}_{it} + \beta_4 \text{ Low-Margin Habit}_{it} + \beta_6 \text{ Cross-Buy}_{it} + \beta_7 \text{ Seasonality}_{t+1} + \beta_8 \text{ Housing Starts}_{t+1} + \beta_{00} + \beta_{0i} + \varepsilon_{it},$$

$$(7)\quad \text{Cash Flow Level}_{it+1} = \delta_1 \text{ Purchase Habit}_{it} + \delta_2 \text{ Promotion Habit}_{it} + \delta_3 \text{ Return Habit}_{it} + \delta_4 \text{ Low-Margin Habit}_{it} + \delta_6 \text{ Cross-Buy}_{it} + \delta_7 \text{ Seasonality}_{t+1} + \delta_8 \text{ Housing Starts}_{t+1} + \delta_{00} + \delta_{0i} + \eta_{it},$$

where

Cash Flow Volatility$_{it+1}$ = cash flow volatility of customer i at time t + 1;
Cash Flow Level$_{it+1}$ = cash flow volatility of cash flow of customer i at time t + 1;
Purchase Habit$_{it}$ = purchase habit strength of customer i at time t;
Promotion Habit$_{it}$ = promotion habit strength of customer i at time t;
Return Habit$_{it}$ = return habit strength of customer i at time t;
Low-Margin Habit$_{it}$ = low-margin habit strength of customer i at time t;
Cross-Buy$_t$ = cross-buy level (i.e., the total number of different product categories purchased by a customer) at time t
Seasonality$_{t+1}$ = spring and summer seasons of a year indicator at time t + 1;
Housing Starts$_{t+1}$ = number of new privately owned housing units started in the United States at time t + 1;
β, δ = parameters to be estimated;
β_{00}, δ_{00} = mean-level intercepts;
β_{0i}, δ_{0i} = individual-specific unobserved time-invariant random effects;
ε_{it}, η_{it} = error terms; and
t = quarter (four-month time interval).

The customer-specific random intercepts (β_{0i} and δ_{0i}) allow the error terms for the same set of customers transacting with the firm (given the panel structure of our data) to be correlated across time, help capture the unobserved customer-level heterogeneity, and are assumed to be normally distributed with mean 0 and variance σ_v^2 and σ_φ^2. The intercepts (β_{00} and δ_{00}) capture the mean level of volatility and level of cash flows. The

Table 4
PARAMETER ESTIMATES FOR HABIT STRENGTH MODEL

	Purchase Habit (j = 1)		*Promotion Habit (j = 2)*		*Return Habit (j = 3)*		*Low-Margin Habit (j = 4)*	
Independent Variables	*Est.*	*t-Value*	*Est.*	*t-Value*	*Est.*	*t-Value*	*Est.*	*t-Value*
Intercept	−4.05	−1,607.0***	−14.29	−1,350.0***	−10.61	−798.5***	−2.29	−562.7***
Marketing_{it}	.10	49.5***	.54	27.7***	.29	16.9***	.43	59.3***
$\ln(\text{Behavioral Intensity}_{it-1} + 1)$	9.85	576.7***	10.37	334.5***	6.23	333.2***	1.94	330.1***
Time	−.02	−693.3***	.30	1370.4***	.24	1,118.1***	.02	147.7***
Customer Characteristics								
Age_i	.03	11.2***	.02	1.4	.26	17.9***	.07	16.3***
Children_i	.002	.7	−.02	−1.7**	−.05	−4.0***	−.04	−11.1***
Homemaker_i	−.08	−12.7***	.05	2.0**	−.14	−4.4***	−.06	−6.3***
$\text{College Education}_i$	.01	4.9***	.11	11.6***	.33	28.6***	.04	11.7***
Income_i	.13	59.6***	.43	47.2***	.87	75.2***	.10	28.9***
$\text{Store Card Holder}_i$	.05	23.2***	1.67	182.3***	1.64	142.0***	.32	92.5***
Differential Effects of Marketing								
$\text{Marketing}_{it-1} \times \text{Age}_i$	.005	2.2	.10	5.2***	−.02	−1.0	−.04	−5.4***
$\text{Marketing}_{it-1} \times \text{Children}_i$	−.003	−1.5***	−.11	−6.6***	−.02	−1.5	.03	5.3***
$\text{Marketing}_{it-1} \times \text{Homemaker}_i$	−.03	−6.8***	.03	.6	−.07	−1.6	.01	.5
$\text{Marketing}_{it-1} \times \text{College Education}_i$	−.01	−3.2***	.14	8.7***	−.05	−3.5***	−.04	−7.5***
$\text{Marketing}_{it-1} \times \text{Income}_i$	.02	12.9***	.46	28.6***	−.03	−1.9*	−.07	−11.3***
$\text{Marketing}_{it-1} \times \text{Store Card Holder}_i$	.04	21.0***	1.91	115.7***	.61	41.7***	−.24	−39.4***
$\ln(\text{BI}_{it-1} + 1) \times \text{Age}_i$	−.17	−9.1***	.16	6.0***	−.08	−4.4***	−.03	−4.6***
$\ln(\text{BI}_{it-1} + 1) \times \text{Children}_i$	.05	3.2**	.02	1.0	.03	2.0**	.02	4.4***
$\ln(\text{BI}_{it-1} + 1) \times \text{Homemaker}_i$	.44	10.5***	−.39	−6.8***	−.003	−.1	.05	3.3***
$\ln(\text{BI}_{it-1} + 1) \times \text{College Education}_i$	−.14	−9.4***	−.08	−3.8***	−.19	−13.1***	−.05	−9.0***
$\ln(\text{BI}_{it-1} + 1) \times \text{Income}_i$	−.69	−46.9***	−.15	−7.2***	−.41	−27.9***	−.09	−17.7***
$\ln(\text{BI}_{it-1} + 1) \times \text{Store Card Holder}_i$	−.63	−42.5***	−2.49	−92.2***	−.61	−38.9***	−.42	−81.7***
Endogeneity correction residual	.14	45.4***	1.33	53.2***	.99	40.2***	.47	38.2***
Covariance Parameters								
Variance component (intercept)	.76	562.3***	12.71	544.2***	20.58	559.4***	1.63	503.7***
Variance component (marketing)	.13	169.5***	15.06	233.0***	9.00	180.8***	.18	23.1***
Variance component (ln[BI + 1])	23.26	306.8***	3.24	52.1***	2.62	63.8***	1.24	190.4***
Level 1 residual variance	.08	1,867.9***	5.72	1,918.2***	5.60	1,892.3***	1.56	1,814.9***
Model Fit								
Deviance (−2 log-likelihood)	6,555,345		42,256,321		42,315,877		30,455,179	

*$p < .1$.
**$p < .05$.
***$p < .01$.

error terms ε_{it} and η_{it} are assumed to be normally distributed with mean 0 and variance σ^2_ε and σ^2_η.

RESULTS AND DISCUSSION

Habit Strength Model Results

The results of model for habit strengths (Equations 4 and 5) are reported in Table 4 for purchase, promotion, return, and low-margin habits. We find that customer-level marketing has a significant and positive effect on the purchase ($\theta_{110} = .10$, $p < .01$), promotion ($\theta_{210} = .54$, $p < .01$), return ($\theta_{310} = .29$ $p < .01$), and low-margin ($\theta_{410} = .43, p < .01$) habits strengths. In addition, past behavior positively reinforces the strength of all four habitual behaviors ($\gamma_{120} = 9.85, p < .01; \gamma_{220} = 10.37$, $p < .01$; $\gamma_{320} = 6.23$, $p < .01; \gamma_{420} = 1.94$, $p < .01$). These results are consistent with the findings of Shah, Kumar, and Kim (2014). However, we obtain four additional novel insights related to the variation in customer habit strength.

First, we find that, on average, the habit strength does not increase (over time) for all four habitual behaviors, as indicated by the growth parameter. More specifically, the growth parameter is negative for the purchase habit ($\gamma_{13} = -.02, p < .01$) and positive for the promotion, return, and low-margin habits (respectively, $\gamma_{23} = .30$, $p < .01$; $\gamma_{33} = .24$, $p < .01; \gamma_{43} = .02$, $p < .01$).

Second, customer characteristics significantly influence the relative level of habit strength of each customer. For instance, we find that a customer's age (Age_i) is positively correlated with each of the four habit strengths, thereby implying that as customers get older, they are relatively more likely to develop routine behaviors. However, we find that customers with children (Children_i) are less likely to form shopping habits such as promotion, return, and low-margin habits. This is consistent with the notion that customers with larger households are less likely to exhibit repetitive behaviors (Quinn and Wood 2005), which could occur as a result of heterogeneous preferences within a large household. Homemakers have weaker purchase, return, and, low-margin habits. This could be because homemakers have relatively more shopping time at their disposal and are thus less likely to develop a shopping routine compared with people with greater time constraints, who are more likely to develop shopping routines (Wood and Neal 2009). However, homemakers are more likely to exhibit strong promotion habit as compared with other customers, implying that homemakers are more deal prone. We also find that customers with a college education and a high level of income are more prone to develop the four shopping habits. This could be related to the influence of time constraints on the development of routine behavior. That is, customers with a college education and a high level of income are likely to be employed and have less (shopping) time at their disposal; thus, they are more likely to develop a routinized shopping behavior (Wood and Neal 2009). Finally, we find that ownership of store card has a positive effect on all four habitual behaviors. This is consistent with prior literature that has investigated the role of store cards in motivating customers to shop more frequently (Karimi 2014; Seiders and Voss 2004).

Third, we find that individual customer characteristics significantly influence the extent to which past behavior (operationalized as past behavioral intensity) contributes to the customer's habit strength. The results indicate that prior behavioral intensity has a relatively weaker impact on the purchase habit ($\theta_{121,1} = -.17, p < .01$), return habit ($\theta_{321,1} = -.08$, $p < .01$), and low-margin habit ($\theta_{421,1} = -.03$, $p < .01$) for customers who are older, whereas it has a relatively stronger impact on purchase habit ($\theta_{121,2} = .05, p < .05$) and return habit ($\theta_{321,2} = .03$, $p < .05$) for customers who have children. Collectively, these empirical results support the notion that people typically vary in their ability to learn a behavior and retrieve memories from past experiences (Chylinski, Roberts, and Hardie 2012; Marchette, Bakker, and Shelton 2011).

Finally, we find that customer-level characteristics significantly influence the effect of marketing on the habit strength of each customer. The results indicate that marketing has a significantly stronger impact on the purchase habit ($\theta_{111,5}$ = .02, $p < .01$) and promotion habit ($\theta_{211,5} = .46$, $p < .01$) of customers with a higher income. This could be because higher-income customers are in general expected to be more responsive to marketing interventions (Rust and Verhoef 2005). The results also indicate that marketing is more effective (has a significant positive effect) for older customers ($\theta_{211,1} = .10, p <$ .01) and store card holders ($\theta_{211,6} = 1.91$, $p < .01$) but less effective (has a significant negative effect) for customers with children ($\theta_{211,2} = -.11$, $p < .01$) in changing promotion habit strength. The effect of marketing on the return habit does not vary for older customers, homemakers, and households with children. In contrast, marketing is less effective on the strength of the return habit for customers with a college degree and a high income ($\theta_{311,4} = -.05, p < .01$; $\theta_{311,5} = -.03, p < .10$). We also observe in our results that for older customers, the positive effect of marketing is weak for the low-margin habit ($\theta_{411,1} = -.04$, $p < .01$), indicating that when the habit is formed, there is a relatively lesser need for a marketing cue for older customers given their limited ability to process information in short periods of time. For store card holders, the positive effect of marketing is weak for the low-margin habit ($\theta_{411,6} = -.24$, $p < .01$). Meanwhile, marketing has a stronger positive effect on the low-margin habit for customers with children ($\theta_{411,2} = .03$, $p < .01$).

The statistical significance of the estimates for the variance component of the intercept for all four habits implies that there is a statistically significant random variation of habit strength across customers. Similarly, estimates for the variance component of the slopes for all four habits indicate the presence of a systematic variance in the effects of marketing and prior behavior. Thus, the HLM framework or the addition of the level 2 estimates is justified in the model setup. The endogeneity correction residuals are significant in all four habit strength models. Overall, the results from the habit strength model bear implications for implementing a differentiated marketing strategy to selectively influence the strength of the desired habitual behavior of each customer.

Cash Flow Volatility and Level Model Results

Table 5 summarizes the results for the models corresponding to the future volatility (Equation 6) and the level of cash flows (Equation 7). The results indicate that purchase habit ($\beta_1 = -439.65, p < .01$) decreases—whereas promotion ($\beta_2 = 75.78$, $p < .01$), return ($\beta_3 = 96.01$, $p < .01$), and low-margin ($\beta_4 = 93.39, p < .01$) habits increase—the future cash flow volatility of individual customers. In contrast, purchase ($\delta_1 = 1{,}149$, $p < .01$) and promotion ($\delta_2 = 55.40$, $p < .01$) habits increase, whereas return ($\delta_3 = -41.83$, $p < .01$) and low-margin ($\delta_4 = -44.16, p < .01$) habits decrease, the future cash flow levels of individual customers. The estimates for the variance component of the intercept for both future cash flow volatility and level of cash flow imply that there is a significant random variation across customers.

Table 5

PARAMETER ESTIMATES FOR INDIVIDUAL CASH FLOW VOLATILITY AND LEVEL MODELS

	Cash Flow Volatility		*Cash Flow Level*	
Independent Variables	*Estimate*	*t-Value*	*Estimate*	*t-Value*
Intercept	82.53	2.80***	−7.10	−24.18***
Purchase $Habit_{it}$	−439.65	30.76***	1,149	306.04***
Promotion $Habit_{it}$	75.78	18.98***	55.40	24.86***
Return $Habit_{it}$	96.01	11.29***	−41.83	−31.03***
Low-Margin $Habit_{it}$	93.39	6.73***	−44.16	−56.12***
$Seasonality_{t+1}$	8.41	1.94***	26.94	143.13***
$Cross\text{-}Buy_{it}$	−1.96	.38***	12.11	309.17***
Housing $Starts_t$	.04	.003***	.04	113.61***
Covariance Parameters				
Variance component (intercept)	17,829	862.53***	3,564	259.82***
Residual	5,222,103	2,742.47***	48,741	1,911***
Deviance (−2 log-likelihood)	146,150,000		109,230,000	

***$p < .01$.

Notes: Cash flow volatility variable is rescaled (i.e., multiplied by 100) to make the two equations comparable.

Overall, the results suggest that the promotion habit has a conflicting effect on firm performance by contributing to increases in the customer's future cash flow level (a desired outcome) and volatility (an undesired outcome). Increasing customers' regular purchase habit is the best bet for enhancing the financial performance of the firm, whereas the return and low-margin habits have a double whammy effect by adversely influencing both customers' future cash flow level and volatility.

Robustness Check

We perform three robustness checks to evaluate the appropriateness of the model specification and the associated measures. First, we assess different time horizons for calculating the volatility of cash flows at the customer and firm levels (in addition to the time horizon of four quarters used in this study). That is, we recalculate the cash flow volatility with time horizons of two, three, and five quarters for each customer. We assess the quality of prediction by computing the mean absolute percentage error (MAPE) for each of the four models (including our model using four quarters of data). We find that the MAPE increases by 86% when two quarters of data are used, by 18% when three quarters of data are used, and by 32% when five quarters of data are used, as compared with the proposed model. Therefore, our results indicate that the time horizon of four quarters gives the customer-level cash flow volatility model the best fit with the data (i.e., lowest mean squared error).

Second, following the recommendation of Germann, Ebbes, and Grewal (2015), and echoing our previous discussion, we assess whether the results pertaining to the key variables of interest (i.e., marketing and the habit strength measures) are convergent under varying identifying assumptions. That is, we evaluate (1) the rich data, unobserved effects, and IV approach to assess the impact of customer-level marketing on the habit strength measures of each customer and (2) the rich data and unobserved effects approach to assess the impact of habit strength measures on the future cash flow level and volatility of the customer. Our results (as summarized in Table 6, Panels A and B) indicate that the statistical significance and direction of the relationship pertaining to the aforementioned variables of interest are consistent and, thus, robust to varying identifying assumptions.

Third, we evaluate the relative stability of the habit strength measures to predict customers' future cash flow level and volatility by comparing the in-sample and out-of-sample predictions. For out-of-sample predictions, we reestimate the model by holding out the last quarter to test our model. We find that the MAPE (mean average percentage error) for the out-of-sample prediction is marginally higher than the in-sample MAPE (see Table 6, Panel C). Nevertheless, the difference between the two MAPE values is approximately 3%, thereby implying stability of the model performance.

Quantifying the Relative Importance of Different Habits and Differentiated Marketing

Changes in the cash flow of each customer will ultimately affect a firm's overall cash flow levels. In the context of this study, the relatively large sample of customers (included in the analyses) may be regarded as a true representative sample of all customers of the firm. In addition, the customers of the firm are likely to be primary generators of the firm's cash flows, given the context of the retail business. Therefore, the overall change in the cash flows of all customers included in our sample is likely to correspond with the firm's overall cash flow levels.

To empirically validate this notion, we aggregated the observed cash flows of all customers in our sample to obtain a single aggregated measure of customer cash flow

Table 6

ROBUSTNESS CHECK RESULTS AND MODEL FIT

A: Robustness Check for Habit Strength Model

		Marketing Effect (DV: Habit Strengths)			
Model Type	*Model*	*Purchase Habit*	*Promotion Habit*	*Return Habit*	*Low-Margin Habit*
Rich data model	Random effects	.13 (.01)***	.33 (.11)***	.32 (.09)***	.49 (.04)***
Unobserved effects model	Fixed effects	.17 (.004)***	1.01 (.03)***	.64 (.03)***	.22 (.017)***
IV model	Random effects with control function	.10 (.002)***	.54 (.019)***	.29 (.02)***	.43 (.007)***

B: Robustness Check Results for Cash Flow Volatility and Cash Flow Level Models

Model Type	*Model*	*Habit*	*DV: Cash Flow Volatility*	*DV: Cash Flow Level*
Rich data model	Random effects	Purchase	−439.65 (30.76)***	1,149 (3.75)***
		Promotion	75.78 (18.98)***	55.40 (2.22)***
		Return	96.01 (11.29)***	−41.83 (1.34)***
		Low margin	93.39 (6.73)***	−44.16 (.78)***
Unobserved effects model	Fixed effects	Purchase	−117.20 (12.26)***	1,198 (47.68)***
		Promotion	109.78 (5.70)***	329.65 (22.18)***
		Return	72.31 (3.47)***	−155.21 (13.49)***
		Low margin	65.37 (1.82)***	−38.72 (7.10)***

C: Model Fit

Goodness-of-Fit	*MAPE*
In-sample	25.1%
Out-of-sample	28.2%

***$p < .01$.

Notes: DV = dependent variable. Parameter estimates are followed by standard errors in parentheses.

corresponding to each quarter in the observation period. Then, for the same time range, we obtain firm-level quarterly cash flow level from the firm's financial statements (available through Compustat). For the firm-level cash flow, we compute the "operating cash flow" from the earnings before interest and taxes (EBIT). The EBIT is a measure of the firm's profit and represents the difference between operating revenues and operating expenses. We compute the operating cash flow of the firm for each quarter of the observation period as Operating Cash Flow = EBIT + Depreciation – Taxes (Morgan and Rego 2009). We find that the aggregated measures (obtained from customers in our data sample) and the firm-level measures (obtained from Compustat) are strongly correlated ($\rho = .76$, $p < .01$) even with an observation window of 16 quarters. Thus, in this section, we regard the simulated aggregated (from customer-level) outcomes as a proxy for firm-level outcomes.

Quantifying the Relative Importance of Different Customer Habits

What is the relative importance of different habits on customers' future cash flow level and volatility? We apply the parameter estimates of Table 4 to simulate the change in the future volatility and level of each customer's cash flows corresponding to a 1% change in each customer's habit strength during the observation period. We assess the firm-level outcome by calculating the sum of cash flows (to get the total cash flow level) and weighted (by the proportion of the firm's total cash flow level) sum of the volatility of cash flows of all customers, as summarized in Table 7.

We find that a 1% increase in customers' purchase habit corresponds to a 1.83% decrease in the future cash flow volatility and a 4.62% ($28.46 million) increase in the future level of the cash flows; a 1% increase in promotion habit strength increases the future cash flow volatility by .15% while also increasing the future cash flow levels by .14% ($.86 million); for the return and low-margin habits, a 1% decrease in habit strength corresponds to a .57% and 2.36% decrease in the future cash flow volatility and .32% ($1.97 million) and 1.32% ($8.13 million) increase in the firm's future cash flow level, respectively.

In terms of the relative importance, the change (or 1% decrease) in low-margin habit has the strongest impact on decreasing the firm's future cash flow volatility while the change (or 1% increase) in purchase habit has the strongest impact on increasing the firm's future cash flow level. Overall, a 1% desired change in the strength of each of the four habits (i.e., increase in purchase and promotion habits and decrease in return and low-margin habits) corresponds to a 4.61% reduction in future cash flow volatility and a 6.40% ($39.42 million) increase in the future level of the firm's operating cash flows over an observation period of four years.

In the next subsection, we discuss how the change in habit strength can be effectively achieved through customer-level marketing and acquisition efforts.

Quantifying the Effectiveness of Differentiated Marketing

To what extent can firms increase the effectiveness of their marketing efforts by selectively targeting (or not targeting) customers on the basis of certain customer characteristics? We quantify this in the context of (1) marketing to existing customers of the firm with the objective of changing their habit strength and (2) acquiring new customers who are prone to developing habit strength with respect to certain behaviors.

Changing the habit strength of existing customers. As we have discussed, firm-initiated marketing serves as an effective cue for customers to strengthen their habitual behaviors (see the results in Table 4). Consequently, to what extent can the effectiveness of marketing (for changing customers' habit strength) be improved by selectively targeting (on the basis of certain customer characteristics) versus randomly targeting customers?

We quantify this by simulating a 20% increase (decrease) in marketing across different samples of customers and measuring the corresponding changes in habit strength. We first randomly choose a sample of 50,000 customers of the firm and simulate the effect of a 20% increase in marketing communications on the purchase and promotion habit strengths. We find that, on average, the purchase and promotion habit strengths increase by .16% and 4.98%, respectively, over the observation period. We repeat the simulation to evaluate the effect of a 20% decrease in marketing communication on customers' return and low-margin habit strengths. We find that, on average, the return and low-margin habit strengths decrease by 1.61% and 1.78%, respectively, over the observation period.

In the second part of our simulation, we choose a sample of 50,000 customers with one or more of the desired customer characteristics (e.g., age, store card holder, college education, income) that help improve the effectiveness of marketing and/or assist in the desired increase (or decrease) of the respective four habits. In other words, we draw a select sample of 50,000 customers with the desired characteristics corresponding to each of the four habits. Consequently, we simulate the effect of a 20% increase (decrease) in marketing communications on the purchase and promotion (return and low-margin) habit strengths. We find that, on average, the purchase and promotion habit strengths increase by .51% and 10.48%, respectively, and the return and low-margin habit strengths decrease by 3.48% and 3.52%, respectively, as we summarize in Table 8. When we compare the habit strength outcomes from the two marketing intervention simulations, we find that marketing interventions directed at increasing (decreasing) customers' habit strength are 1.9–3.2 times more effective when they are selectively targeted to customers with specific

Table 7
THE IMPACT OF CUSTOMER HABITS ON THE FUTURE CASH FLOW VOLATILITY AND CASH FLOW LEVEL OF CUSTOMERS

	Weighted Sum of Cash Flow Volatility of Customers	*Total Cash Flow Level of Customers*
1% increase in purchase habits	−1.83%	4.62% ($28.46 million)
1% increase in promotion habits	.15%	.14% ($.86 million)
1% decrease in return habits	−.57%	.32% ($1.97 million)
1% decrease in low-margin habits	−2.36%	1.32% ($8.13 million)
1% change in all customer shopping habits	−4.61%	6.40% ($39.42 million)

Table 8
THE IMPACT OF MARKETING ON CHANGE IN HABIT STRENGTH

	Randomly Select 50,000 Customers	*Select 50,000 with Desirable Characteristics*
Increased Marketing by 20%		
Change in purchase habit strength	.16%	.51%
Change in promotion habit strength	4.98%	10.48%
Reduced Marketing by 20%		
Change in return habit strength	−1.61%	−3.48%
Change in low-margin habit strength	−1.78%	−3.52%

customer characteristics as opposed to a random selection of customers.

Selectively acquiring customers. As discussed previously, the presence of purchase and promotion habits is beneficial for the firm, and customers with certain characteristics are prone to developing habitual behavior faster than others. In such a scenario, all else being equal, we evaluate the extent to which acquired customers with desirable customer characteristics can form stronger purchase and promotion habits over the observation period.

First, we randomly select 10,000 customers and evaluate the actual habit formation for these customers in the observation period. Thereafter, we selectively choose two samples of 10,000 customers with one or more of the desired customer characteristics as listed in Table 4 that could help accelerate the formation of the purchase and promotion habits. We compare the three samples of customers on the basis of (1) the change in habit strengths from the end of the first year to the end of the fourth year of the observation period, (2) the average cash flow volatility levels, and (3) the average cash flow levels (as shown in Table 9).

On comparing the different cohorts, we find that (all else being equal) the selectively acquired cohort of customers can develop positive shopping habits (i.e., purchase and promotion) that are 35%–62% stronger, with cash flow levels that are 16%–50% higher, than the randomly acquired cohort of customers. The cash flow volatilities are 41% lower for the purchase habit cohort and 14% higher for the promotion habit cohort as compared with the randomly acquired cohort of customers.

These results underscore the importance of gaining customer-level insights and, thus, of implementing customer-level marketing programs for customer acquisition and retention to improve the efficiency and effectiveness of the firm's marketing resources. However, there are two caveats underlying these results. First, these simulations and results are specific to a single retailer and may not be readily generalizable to other firms. Second, we do not have competitor data. Therefore, in our simulations, we assume no systematic change in marketing from competitors.

IMPLICATIONS

For Research

In customer relationship management settings, it is important to focus on customers' enduring behavioral constructs rather than on contemporaneous or single-period-lag behavioral variables. The theory of habit offers a theoretical framework to quantify customers' recurring behavior along the continuum of habit strength. In addition, there has been a major resurgence of research interest in analyzing the habit construct in the social psychology literature (Neal et al. 2012; Wood, Quinn, and Kashy 2002) and the marketing literature, in which the business implications of customer habits are being revisited (Liu-Thompkins and Tam 2013; Shah, Kumar, and Kim 2014).

In this study, we evaluate the relative importance of different types of recurring customer behavior (quantified along the continuum of habit strength) in driving the future cash flow level and volatility (or shareholder value) of the firm. Our findings show that habit strength is the fundamental driver underlying a customer's future repeat behavior. Yet empirical applications of different routinized behaviors of customers are limited. Further research can greatly benefit by incorporating the habit construct to better understand customer behaviors over time (especially in noncontractual settings).

Table 9
SIMULATING THE IMPACT OF SELECTIVE CUSTOMER ACQUISITION ON HABIT STRENGTH

	Randomly Acquired 10,000 Customers	*Selectively Acquire 10,000 Customers with Desirable Characteristics for Purchase Habit*	*Selectively Acquire 10,000 Customers with Desirable Characteristics for Promotion Habit*
Purchase habit strength	.066	.089	.064
Promotion habit strength	.021	.020	.034
Return habit strength	.079	.088	.092
Low-margin habit strength	.307	.311	.305
Avg. cash flow volatility	1.35	.79	1.54
Avg. cash flow levels	$2,749.34	$4,113.20	$3,200.18

Implications for Marketing Practices and Policies

How can firms identify customer segments to strategically manage the future cash flow levels and volatilities of their customers? One possible approach is to divide the customers into discrete segments on the basis of their characteristics and/or covariance in cash flows and, thus, manage the customer segments by employing a portfolio approach (Tarasi et al. 2011).

In this study, we propose to divide the customers into discrete segments on the basis of the relative strength of the recurring behavior and, thus, determine the levels of cash flows and volatilities in those segments. More specifically, we do a median split of customers' habit strengths to distinguish between relatively low and high habit strengths. We then choose the high–habit strength customers who correspond to the four habits and map them on a two-dimensional grid representing cash flow level and volatility (see Figure 2).

In Figure 2, the size of the circle indicates the number of customers with relatively high levels of the respective habit strength. The relative position of the circle on the grid is determined by the average level of cash flow level and volatility of the customers who belong to the respective habit groups. Because the intercorrelation of different habits is relatively weak, most customers with a relatively high level of the respective habit strength do not necessarily have other habits that are strong. More specifically, less than 15% of the customers represented in Figure 2 have two or more habits of relatively high strength. Consequently, Figure 2 can serve as a guiding framework for managers to manage the relative position and size of individual customer segments through implementation of customized marketing practices and/or broad changes in marketing policies.

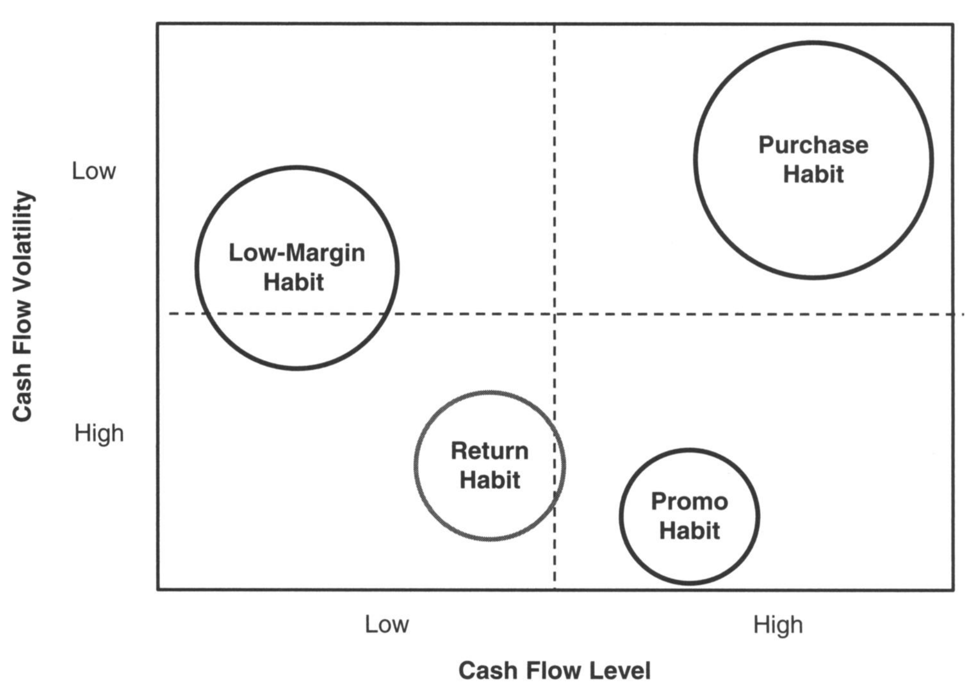
For example, firms may try to nudge the relative position of customer segments in the direction of the upper-right quadrant (representing high future cash flow level and low future cash flow volatility) by implementing differentiated marketing practices directed at increasing the purchase habit and decreasing the return and low-margin habits, as discussed previously. Alternatively, firms may expand (contract) the relative size of purchase habit (return and low-margin habits) segment (i.e., increase [decrease] the number of customers with high habit strength) by implementing broad policy changes such as (1) introducing a loyalty program with bigger rewards for customers who make regular purchases, (2) developing a stringent return policy for serial returners, and/or (3) demarketing to customers who purchase only low-margin items.

CONCLUSION AND FUTURE DIRECTIONS

The methodology discussed in this study is applicable for firms in which customers are the primary sources of the firm's cash flows. If the firm's cash flows are primarily due to other sources (e.g., trading, sale of major assets, income from investments, currency hedging, fluctuation in commodity prices), then customer habits may not be strong predictors of the shareholder value of the firm.

The results presented in this study are from a single retail firm and thus may not be readily generalizable to all retail firms. In addition, we do not have proprietary customer databases of competing retail firms. Therefore, although we do know the habitual behavior of each customer at the retailer included in this research, we do not have data on how these

Figure 2
MAPPING CUSTOMER SEGMENTS ON THE BASIS OF HABIT, CASH FLOW LEVEL, AND CASH FLOW VOLATILITY



Notes: The size of each circle indicates the number of customers with relatively high levels of the respective habit strength.

customers behave at competing retailers and whether the marketing activities of competing retailers can affect the habitual behavior of customers at the focal firm. This limitation is hard to overcome because it is difficult to obtain customer-level transaction data of all possible firms at which customers are likely to transact. However, this presents an excellent opportunity for further research to conduct a multifirm customer-level study to analyze habitual behavior and its impact on firm performance.

The observation period for the empirical analyses is four years. During this time, the retail firm included in this study did not undertake any major policy shifts. Sometimes ad hoc policy shifts, as in the case of J.C. Penney, which discontinued its long-standing practice of promotions in early 2012 (Mattioli 2013; O'Toole 2013); however, this strategy proved disastrous when the firm lost business from habitual promotion shoppers. Therefore, firms need to exercise caution. Further research can empirically analyze this phenomenon by employing an observation period that includes a major marketing policy change of a firm.

In conclusion, this is the first empirical study to link marketing to the future level and volatility of customer cash flows by analyzing customer-level behavioral factors. The findings of this research and the associated managerial implications are directed at enabling marketers to expand their influence in the organization through their ability to enhance the firm's shareholder value.

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