Cross-buying refers to the customer behavior of buying additional products and/or services from the same firm (e.g., Ngobo 2004). When customers purchase more products or services from the same firm, they are known to extend the duration of their relationship with the firm (Kamakura et al. 2003; Li 1995; Reinartz and Kumar 2003), increase purchase frequency (Reinartz, Thomas, and Bascoul 2008; Venkatesan and Kumar 2004), and/or increase their contribution margin per order (Kumar, George, and Pancras 2008), which directly or indirectly results in an increase in customer profitability (Kumar, Shah, and Venkatesan 2006; Kumar et al. 2008). In such a scenario, what should a firm do when it encounters a customer who is likely to purchase additional products/services from the firm? The question seems redundant given the obvious positive financial consequence to the firm.

However, marketplace realities present a significantly different view. A Wall Street Journal article reports that Best Buy (an electronics retailer operating a chain of retail stores across the United States) has identified approximately 20% of its customers (infamously labeled “demon customers” by the company) as unprofitable despite making multiple purchases from its stores (McWilliams 2004). Filene’s Basement (a discount clothing store) banned two of its most frequent customers from entering the retailer’s 21 outlets after discovering that they were highly unprofitable (Zbar 2003). Financial services firms have repeatedly reported highly unprofitable customers despite cross-buy (Brown 2003; Weissman 2006). These examples of marketplace evidence are intriguing and raise important research questions such as the following: Can customers who willingly purchase additional products and/or services of a firm be unprofitable? If so, what factors can potentially characterize customers with unprofitable cross-buy? Can the collective actions of such customers substantially affect the firm’s bottom line over time? In such a scenario, what are the implications for the firm’s current marketing practices and policies, which are typically directed at maximizing cross-buy opportunities across all the firm’s customers?

We address these questions through theoretical reasoning and empirical analyses of customer transaction data. A related issue is whether our findings from data analyses would hold for firms in both consumer and business markets having a contractual (or stream) rather than noncontractual (or nonstream) business revenue. To ensure generalizability of the findings, we analyze customer databases of five firms from different industries and business settings, serving consumer and business markets. Our results offer...
novel insights into an age-old and widely prevalent marketing practice of encouraging customers to cross-buy:

1. Contrary to conventional wisdom, customer cross-buy is not necessarily profitable for all customers of the firm and can adversely affect a firm’s bottom line. Across all five firms, approximately 10%–35% of the customers who cross-buy are unprofitable and account for 39%–88% of the firms’ total loss from its customers.

2. It is the persistence of adverse customer behavior that drives unprofitable customer cross-buying over time. Across all five firms, we find that customers who exhibit persistent adverse behavioral traits (as discussed in the next section) generate more losses as they purchase more products and/or services from the firm over time. In contrast, customers with nonpersistent adverse behavioral traits tend to eliminate their initial losses (if any) and generate more profits with an increase in cross-buy over time.

3. A company’s marketing policies and practices may serve to facilitate (or deter) the persistence of adverse customer behavioral traits associated with unprofitable cross-buying. In our analyses, we observe a strong relationship between a firm’s marketing policies and practices and the relative importance of certain adverse behavioral traits of the respective firm’s customers. For example, we find that the adverse customer behavioral trait of excessive product returns has the highest level of relative importance in the firm with the most liberal product return policy.

Overall, to the best of our knowledge, this is the first study to explore, empirically test, and generalize the phenomenon of unprofitable cross-buying across multiple firms from different industries and business settings. Furthermore, we demonstrate the problem as a systemic issue that managers can diagnose by analyzing the persistence of customer-specific adverse behavioral traits in the firms’ customer database. The importance of these findings is twofold: (1) They serve to draw attention to a negative consequence of customer cross-buy—an area that has received minimal attention in the marketing literature to date; and (2) the findings call for managers to rethink their current managerial practice of maximizing cross-buy opportunities for all customers of the firm. This is imperative given that firms typically hope to increase profits by encouraging customers to cross-buy. Our study shows that for certain customers, such actions can actually result in losses.

The rest of the article is organized as follows. We discuss relevant theory and empirical analyses pertaining to the phenomenon of unprofitable cross-buy. The analyses are divided into two parts. In the first part, we explore the phenomenon of unprofitable cross-buying, empirically determine the extent to which it poses a problem across firms, and evaluate whether the problem is significant enough to warrant managerial attention. In the second part of the analyses, we focus on quantifying the factors underlying unprofitable cross-buying across different firms and its relationship (if any) with the respective firms’ marketing practices and policies. Thereafter, we discuss the implications of our findings for both theory and practice of marketing. We conclude with limitations and future directions of this research.

Background and Theory

Extant literature to date implies a positive relationship between customer cross-buy and profitability (as discussed previously). Consequently, our understanding is based on the premise that as customers buy more products/services from the firm, they will (on average) generate more profit for the firm. Managerial practices and decisions are often based on intuition derived from (easy to observe) aggregate-level outcomes (Dane and Pratt 2007). Consistent with the expected positive relationship between cross-buy and profitability (on average), contemporary marketing practices are typically designed to maximize cross-buy opportunities across all a firm’s customers. For example, Wells Fargo (a Fortune 500 financial services firm) has consistently placed great emphasis on increasing the cross-buy ratio of all its customers (Wells Fargo Annual Reports 2006–2010).

To get a more holistic view of marketing practices (pertaining to encouraging customers to cross-buy) across different firms, we conducted an exploratory open-ended survey during a three-month period in 2008 in the form of face-to-face interviews with marketing executives from 22 firms from the financial services, telecommunications, retail, and high-technology sectors (at least three firms from each industry), serving consumer and business markets. The responses from the survey indicated that marketing practices across all firms surveyed were directed toward maximizing cross-buy across all customers of the firms. In such a scenario, if there was a customer with unprofitable cross-buy in the database, virtually all managers reported that they would aggressively offer additional products to such a customer. The managers were unanimous in defending their actions by reiterating the conventional wisdom that customer cross-buy leads to higher profits; their beliefs were further reinforced by the observed (at the aggregate customer level) success of their past cross-sell campaigns, in which the total customer profits had always increased in response to an average increase in the number of products purchased by the respective firms’ customers. Therefore, given the aggregate-level favorable outcome, it made managerial sense to maximize cross-buy opportunities for all the firms’ customers.

Previous empirical studies have found that the relationship observed at the aggregate customer base level need not hold true for every customer of the firm due to the inherent differences in customers, commonly referred to as “customer heterogeneity” in the research literature (e.g., Bell and Latin 2000; Kumar and Shah 2009). Therefore, it may be worthwhile to test whether the relationship between profit and cross-buy is necessarily positive for all customers of the firm. In other words, is customer cross-buy profitable for all customers of the firm? If not, to what extent does the phenomenon of unprofitable cross-buy exist across firms?1 Is the problem serious enough to warrant managerial action? If so, can managers identify and quantify the underlying factors related to unprofitable cross-buy so they can take the necessary corrective actions?

1Note that unprofitable cross-buying is conceptually different from unprofitable cross-selling, as we explain subsequently.
We know from past literature that unprofitable customers exhibit one or more of the following behaviors: They (1) make excessive (and often unreasonable) demands for customer service (Dowling and Uncles 1997; Reinartz and Kumar 2000), (2) generate revenue reversals for the firm by defaulting on loans or excessively returning previously purchased products (Petersen and Kumar 2009; Reinartz and Kumar 2003), (3) spend a limited amount due to small size and/or share of wallet (Du, Kamakura, and Mela 2007; Kumar et al. 2008), and (4) purchase a loss-leader product (Blattberg et al. 1978; Cao and Grucu 2005; Webster 1965). It is known from extant literature that in general, these adverse behavioral characteristics are associated with unprofitable customers who are highly undesired by any firm (e.g., Cao and Grucu 2005); however, what is not known is whether these behavioral characteristics necessarily relate to customers who augment the firm revenue and deepen their relationship with the firm by willingly purchasing additional products or services of the firm (i.e., cross-buy) over time. Our ability to relate adverse behavior (and the consequent unprofitable outcome) to customers who cross-buy is further complicated by the finding that extant research has already shown several positive outcomes associated with customer cross-buy, such as increased purchase frequency (Reinartz, Thomas, and Bascoul 2008; Venkatesan and Kumar 2004), increased contribution margin per order (Kumar, George, and Pancras 2008), and increased customer profitability (Kumar, Shah, and Venkatesan 2006; Kumar et al. 2008). In such a scenario, customer cross-buy could be viewed as the means to overcome an unprofitable outcome (due to the adverse customer behavior) rather than being associated with the unprofitable outcome.

A fundamental distinction between an unprofitable customer and a customer who is unprofitable with cross-buy can be made on the basis of time. Customer cross-buying is usually observed as a sequential activity that typically spans over time (Knott, Hayes, and Neslin 2002). For example, Li, Sun, and Wilcox (2005) show that in the context of banking services, consumer demand for multiple products naturally evolve over time. Similarly, Reinartz, Thomas, and Bascoul (2008) contend that customer cross-buying is a consequence of an extended relationship of the customer with the firm. Therefore, for a customer to be unprofitable despite cross-buying products/services over time, the adverse customer behavior (as discussed previously) must not only be present but also persist over time. Social and behavioral science literature can help shed light on why and how adverse customer behavior may persist in certain customers.

The concept of habit has a long history of research in social psychology dating back to the nineteenth century (e.g., James 1890). In simple terms, habits represent a person’s behavioral tendency (Aarts, Verplanken, and Knippenberg 1998; Wood, Quinn, and Kashy 2002). Previous researchers have advanced the concept of habit to explain why and how the frequency of past behavior contributes to habit formation and thus directly influences subsequent behavior that is temporally consistent (Ronis, Yates, and Kirscht 1989; Triandis 1980). This could pertain to a variety of behaviors such as physical exercise or travel mode choice behavior (for a comprehensive meta-analysis, see Ouellette and Wood 1998) as well as habitual consumer behavior, which bears implications for marketers in terms of understanding consumer-level differences due to cross-national differences in consumption habits (Green and Langeard 1975), relationship proneness (Odekerken-Schröder, De Wulf, and Schumacher 2003), and habit-determined brand loyalty (Woods 1960). Notably, econometricians have widely employed the concept of consumer habits and the potential consequences to explain nonintuitive and often puzzling outcomes observed in the marketplace (e.g., Abel 1990; Campbell and Cochrane 1999; Constantinides 1990; Martin and Harald 2000).

In the context of our research, if the aforementioned adverse behavior of a customer is observed repeatedly over time and purchase occasions, the temporal consistency (if present) of such adverse customer behavior may be characterized as adverse behavioral traits that stem from the underlying habits of the customer involved (Allport 1927). Furthermore, habits by definition help establish a routine through which future customer behavior becomes consistent with the past behavior (Aarts, Verplanken, and Knippenberg 1998; Ouellette and Wood 1998). Thus, a customer with adverse habits or persistent adverse behavioral traits is likely to continue to exhibit similar behavior in the future and thereby increase the likelihood of sustaining an unprofitable outcome. In such a scenario, if the firm in question was to make additional investments to encourage such a customer to cross-buy, the customer’s adverse behavioral traits are likely to carry over to the consumption of additional products/services of the firm, thereby resulting in an increase in customer loss despite increase in cross-buy. In contrast, the reverse would hold true for an unprofitable customer with nonpersistent adverse behavioral traits. Such a customer is likely to augment revenue and profit by cross-buying additional products over time.

It is important to understand that unprofitable cross-buy is conceptually different from unprofitable cross-sell. A firm’s cross-selling efforts will have no impact on a customer’s revenue unless that customer responds to the cross-selling efforts by cross-buying. Consequently, unprofitable cross-sell can be an outcome of ineffective cross-selling efforts of a firm that fails to generate the intended cross-buy from the respective customers. Ineffective cross-selling may be mitigated by adopting one of the several cross-selling frameworks suggested in extant research (e.g., Bodapati 2008; Kamakura, Kosar, and Wedel 2004; Kamakura, Ramaswami, and Srivastava 1991; Knott, Hayes, and Neslin 2002; Kumar, Venkatesan, and Reinartz 2006, 2008). Whereas these studies are valuable contributions to the literature in terms of enabling managers to determine which customer is likely to buy what product at what time, the focus of researching unprofitable cross-buy (as we do in this study) is to evaluate whether customers who eventually respond favorably to a firm’s cross-selling efforts (by cross-buying) prove to be unprofitable for the firm and, if so, why.

In the following sections, we seek empirical support to validate the theoretical arguments presented in this section. A potential challenge with such an investigation is the lack
of availability of longitudinal data sets containing customer-level transaction history recorded over several years. Even if such a data set were available for a particular company, a related issue is generalization of the findings to other industries and/or business settings. For example, would our arguments for unprofitable cross-buy hold for firms that cater to industrial/business markets, in which relationships are primarily driven and nurtured by sales force personnel or an account manager? Would it hold for businesses that are characterized by a contractual relationship that results in a continuous stream of revenue from the customer versus firms with noncontractual business? To ensure generalizability of unprofitable cross-buy phenomenon in general and our findings in particular, we selected customer data sets of firms representing a broad spectrum of industries and business settings, as described in the following section.

Data

The first data set comes from a Fortune 500 financial services firm and is composed of a representative sample of 1025 small, medium, and large business organizations. The company has a sales presence across several states in the United States, where it offers 15 financial products such as investment management, institutional brokerage, and financial risk management. The observation period for the data set extends over four years, during which the purchase transaction history of each customer (including cross-buying and customer service requests) and the firm-initiated marketing history (primarily composed of face-to-face sales calls and direct mail) are recorded on a monthly basis.

The second data set comes from a Fortune 500 information technology (IT) firm that sells hardware, software, and services to a representative sample of 360,819 businesses and government and educational institutions located across the United States. The observation period of the data set extends over four years, during which every customer’s order history as well as various firm-initiated marketing communications are recorded on a monthly basis. The IT firm uses multiple channels composed primarily of e-mail, personal selling, web meeting, outbound telemarketing, and direct mail for its marketing communication and cross-selling campaigns.

The third data set comes from a multinational retail bank with operations in 27 countries. The customer data set spans four years and comprises a representative sample of 147,901 retail customers from a specific Asian country where the bank’s second-largest operation in terms of annual revenue is located. The bank has a national presence and spans a period of five years. The firm employs direct marketing communication primarily through e-mail and direct mail corresponding to 18 product categories sold on its website as well as the brick-and-mortar factory and retail stores. Table 1 provides a descriptive summary of the data sets, including the cross-buy statistics corresponding to the observation period of the five firms.

The data sets of all five firms represent rich customer data sets containing information on customer characteristics (e.g., age, income, gender), firm characteristics (e.g., type of industry, annual revenue, number of employees), exchange characteristics (e.g., purchase frequency, customer service requests), product characteristics (e.g., type of product purchased, product margin), and firm-initiated marketing efforts (e.g., marketing communications, cross-sell campaigns). All five firms employ sophisticated cross-selling models developed along the lines of Knott, Hayes, and Neslin (2002) and/or Kamakura et al. (2003) that provide guidance in terms of which product to offer to what customer in a given time frame. A key characteristic of the five customer data sets is that they represent customer cohorts acquired by the respective firms in the first year of the observation period. Thus, customer transactions are not left censored.

The five firms collectively offer a fair representation of different industries, serving both business and consumer markets and characterizing both contractual/stream revenue and noncontractual/nonstream revenue business settings. For

<table>
<thead>
<tr>
<th>Number</th>
<th>Firm</th>
<th>Time Horizon</th>
<th>Number of Customers</th>
<th>Min</th>
<th>Max</th>
<th>M</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>B2B financial services firm</td>
<td>2001–2004</td>
<td>1025</td>
<td>1</td>
<td>7</td>
<td>3.6</td>
</tr>
<tr>
<td>3</td>
<td>B2C retail bank</td>
<td>2002–2005</td>
<td>147,901</td>
<td>1</td>
<td>7</td>
<td>1.7</td>
</tr>
<tr>
<td>4</td>
<td>B2C catalog retailer</td>
<td>1997–2003</td>
<td>92,155</td>
<td>1</td>
<td>9</td>
<td>3.4</td>
</tr>
<tr>
<td>5</td>
<td>B2C fashion retailer</td>
<td>1999–2003</td>
<td>32,389</td>
<td>1</td>
<td>15</td>
<td>2.2</td>
</tr>
</tbody>
</table>

Unprofitable Cross-Buying / 81
example, the financial services and IT firms cater to business customers and thus represent a business-to-business (B2B) setting. In contrast, the remaining three firms (catalog retailer, fashion retailer, and retail bank) service individual consumers and thus represent a business-to-consumer (B2C) setting. Furthermore, the financial services firm and the retail bank represent a business setting that is often characterized by a contractual agreement and/or results in a continuous stream of revenue. For example, banking products such as checking accounts and credit cards are characterized by a continuous revenue stream from the customer. Similarly, loan-based products (e.g., home loans) are characterized by a contractual agreement between the bank and the customer and also result in a continuous revenue stream from the customer in the form of monthly payments. In contrast, the IT firm and two retailers represent business settings characterized by discrete purchase incidences (and an absence of any binding contract), which result in a discontinuous revenue stream from the customer. Table 2 categorizes the distinctions among the five firms on the basis of the type of customers served and nature of business/revenue stream.

Another fundamental distinction lies in terms of the geographical differences. Four of the firms serve customers in the United States, and the retail bank serves customers of an Asian country. Given the fundamental differences across firms in terms of industry, type of customers served, geographic location, and nature of revenue stream, it is worthwhile to determine whether the phenomenon of unprofitable cross-buying and the underlying factors (i.e., the adverse behavioral traits) can be empirically generalized across the broad spectrum of scenarios.

For analyses, we include only those customers in our data set who were targeted for cross-selling by the respective firms during the observation period.2 Given the relatively long time span of the data sets, virtually all customers were subject to two or more cross-selling efforts by the respective firms within the observation period. We split our empirical analyses into two parts. In the first part, we conduct simple descriptive analyses to evaluate the extent to which customers exhibit unprofitable cross-buy across the five firms and its potential impact on firm performance. In the second part, we focus on quantifying the underlying customer-specific factors associated with unprofitable cross-buy and its potential relationship and implications for firm-level marketing practices and policies.

**Evaluating the Existence of Unprofitable Cross-Buy**

The available data sets represent a cohort of customers who initiated a relationship with the firm at the same time (i.e., in the first year of the observation period). Given the relative newness of the relationship, customer profitability may be initially constrained. Therefore, we compute the customer profitability over a relatively long period (i.e., over the entire observation period for which the data are available and the customer is deemed to be active) to ensure that the respective firms and the customers have had sufficient time to forge a relationship. Therefore, the average monthly profit \( P \) for customer \( i \) corresponding to a product \( n \) is as follows:

\[
P_i = \frac{(GCM_{in} - A_{in} - M_{in})/t_n}{tn},
\]

where \( GCM \) is the gross contribution margin, \( A \) is the acquisition cost, and \( M \) is the marketing cost (comprising communication costs, customer service costs, and so on) corresponding to customer \( i \) and product \( n \). Time \( t \) represents the length of the contract (in the case of contractual or stream revenue product/service) or the number of months in the observation period since the corresponding product \( n \) was first purchased (in the case of noncontractual or non-stream revenue product/service). The computation of average profit helps remove the time bias due to late versus early adoption of a product category due to cross-buy (in the observation period). The acquisition cost corresponding to each customer is amortized by the respective firms over the expected lifetime of the customer. The GCM for every customer is calculated as gross customer returns (in dollars), after deducting the cost of corresponding products/services sold. Following Equation 1, the total average profit of the customer \( i \) across \( N \) products purchased during the observation period is

\[
\text{Profit}_i = \sum_{n=1}^{N} P_{in}.
\]

Consistent with the previous marketing literature (e.g., Kamakura, Ramaswami, and Srivastava 1991; Knott, Hayes, and Neslin 2002), the level of cross-buy is computed as the number of different product categories from which a customer makes a purchase during the observation period. We divide the customers of each firm into three segments according to the level of cross-buy:3 (1) no cross-buy, (2) low-medium cross-buy, and (3) high cross-buy. The no-cross-buy

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2 This includes customers that initiated the relationship with the firm with multiple products.

3Note that we create the low-medium and high-cross-buy segments to present the results in a concise manner. The basic interpretation of the results remains the same even if we were to disaggregate the cross-buy segments.

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**TABLE 2**

Classification of Firms

<table>
<thead>
<tr>
<th>Contractual and/or stream revenue</th>
<th>Financial services firm</th>
<th>Retail bank</th>
</tr>
</thead>
<tbody>
<tr>
<td>Noncontractual and/or nonstream revenue</td>
<td>IT firm</td>
<td>Catalog retailer and fashion retailer</td>
</tr>
</tbody>
</table>

| B2B | B2C |

82 / Journal of Marketing, May 2012
segment comprises customers who have purchased only from a single product category during the observation window. We determined the criterion to define the cutoff between low-medium and high cross-buy in consultation with the firms involved. For example, the B2C bank regards customers with two to three product purchases as low-medium cross-buy and customers with four or more product purchases as high cross-buy. Consequently, we apply the profitability and cross-buy segment computation to all customers of the firm. Our results indicate that, on average, during the observation window, customer profitability increases with the increase in level of cross-buy, as shown in Figure 1.

These results are consistent with the marketing literature to date. Indeed, the average profit of a high-cross-buy customer is at least five times greater than the average profit of a no-cross-buy customer. These results underscore the importance of cross-buying as the means to increase customer profitability across firms. However, the focus of our investigation is whether this necessarily holds true for all customers of the firm. Availability of longitudinal customer-level data facilitates a more detailed view of customer profits. Consequently, we now shift our level of analyses from the aggregate to the individual customer level and from all customers of the firm to the unprofitable customers of the firm. Given our basic understanding of the profitable consequences of cross-buying, we expect to find a negligible proportion of unprofitable customers who cross-buy. However, our investigation of the five data sets reveals that approximately 10%–35% of the firms’ customers who cross-buy are unprofitable during the observation period. Furthermore, these customers account for a disproportionately large influence on the performance of the firm: They account for 39%–88% of the respective firms’ total loss from its customers during the observation period. In addition, we report the dollar value of the losses corresponding to the sample of customers used in the analyses, as shown in Table 3, Panel A. If we extrapolate these results to all customers of the respective firms, unprofitable cross-buy has the potential to generate $33 million–$1.2 billion in customer losses for the five firms.

Notably, across all five firms, customers exhibiting unprofitable cross-buy have significantly higher losses corresponding to higher levels of cross-buy, as illustrated in Table 3, Panel B. The loss disparity is extremely high for the two B2B firms, for which the average customer loss for a high-cross-buy customer is approximately 40–50 times as much as a no-cross-buy customer. For the B2C retail bank and the catalog retailer, the average customer loss for a high-cross-buy customer is twice as much as a no-cross-buy customer. For the B2C fashion retailer, the average customer loss for a high-cross-buy customer is 22 times as much as a no-cross-buy customer.

To test the sensitivity of these results, we recalculate the relationship between customer profitability and cross-buy for different time horizons of the observation period, ranging from the first two years to the maximum time period for which the data are available for each firm.4 The results are

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**FIGURE 1**

Relationship Between Customer Cross-Buying and Profitability (Across All Customers of the Firm)

<table>
<thead>
<tr>
<th></th>
<th>No cross-buy</th>
<th>Low-medium cross-buy</th>
<th>High cross-buy</th>
</tr>
</thead>
<tbody>
<tr>
<td>B2B Financial Service Firm</td>
<td>$1,189,549</td>
<td>$559,686</td>
<td>$262,981</td>
</tr>
<tr>
<td>B2B IT Firm</td>
<td>$53,135</td>
<td>$48,883</td>
<td>$12,185</td>
</tr>
<tr>
<td>B2C Retail Bank</td>
<td>$12,185</td>
<td>$510</td>
<td>$1200</td>
</tr>
<tr>
<td>B2C Catalog Retailer</td>
<td>$10</td>
<td>$74</td>
<td>$331</td>
</tr>
<tr>
<td>B2C Fashion Retailer</td>
<td>$135</td>
<td>$702</td>
<td>$990</td>
</tr>
</tbody>
</table>

Notes: All values represent average customer profit. To preserve data confidentiality, we rescaled all values by a constant term.

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4We held the minimum time horizon for analysis at two years to allow sufficient time for the cohort of new customers to cross-buy and strengthen their relationship with the firm.
fundamentally similar for every time horizon (computed in one-year increments beginning from the first two years). In other words, for every time horizon, we find a proportion of customers who exhibit unprofitable cross-buy, account for a disproportionately high level of total losses from its customers, and have a higher amount of losses corresponding to higher levels of cross-buy. What changes (for the different time horizons) is the relative number of customers who cross-buy, the magnitude of the losses, and the average levels of cross-buy corresponding to the different time horizons.

The results in this section indicate that unprofitable cross-buying is widespread across firms (in both consumer and business markets with stream and nonstream revenue), and its adverse impact on firm performance is significant enough to warrant managerial action. To enable firms to take the necessary action, managers would first need to quantify what adverse habits are prevalent in which customers to evaluate what marketing actions to take in the form of customer-level marketing interventions and/or firm-level policy changes. We address this topic in the second part of our empirical analyses.

Quantifying Factors Related to Unprofitable Cross-Buying

Consistent with our previous theoretical discussion, a firm may be able to distinguish customers who are likely to result in unprofitable and profitable outcome on the basis of persistence of adverse behavioral traits (by virtue of habit). To establish a statistical validation of this relationship, we specify a random coefficient logistic model with the dependent variable \(y_i\) specified as a binary outcome with 1 and 0 indicating that the customer \(i\) exhibits unprofitable and profitable cross-buying, respectively. Therefore, the propensity of a customer to exhibit unprofitable cross-buying is specified as follows:

\[
P\{y_i = 1 \mid \beta_i, x_i, \sigma_{\beta_i}, \sigma_{\epsilon_i}\} = \frac{\exp(x_i\beta_i + \epsilon_i)}{1 + \exp(x_i\beta_i + \epsilon_i)}.
\]

where \(\beta_i\) represents the vector of response parameters corresponding to the vector of covariates \(x_i\) comprising the habit strength measures of the adverse customer behavioral traits and relevant control variables; \(\epsilon_i\) is the error term that is assumed to follow a normal distribution with zero mean and standard deviation of \(\sigma_{\epsilon_i}\) (i.e., \(\epsilon_i \sim N(0, \sigma_{\epsilon_i}^2)\)). The response parameter \(\beta_i\) can be decomposed as follows:

\[
\beta_i = \bar{\beta} + \tau_i.
\]

where \(\bar{\beta}\) represents the average effect of the respective covariate (across customers) and \(\tau_i\) represents the customer-specific random deviation of the response from the mean. Consequently, we assume each \(\beta_i\) to be a random draw from a distribution with mean \(\bar{\beta}\) and variance \(\sigma_{\beta_i}^2\). To enable the response parameter to have any sign, we assume \(\tau_i\) to be normally distributed: \(\tau_i \sim N(0, \sigma_{\tau_i}^2)\). The random customer-specific variation of the response parameter (as shown in Equation 4) helps in accounting for unobserved customer heterogeneity. We estimate the model by employing the Bayesian GENMOD procedure of SAS. We chose diffused or noninformative priors with uniform distribution to obtain the posterior. The Bayesian approach offers the added

<table>
<thead>
<tr>
<th>Number</th>
<th>Firm</th>
<th>Proportion of Cross-Buy Customers Who Are Unprofitable</th>
<th>Proportion of Total Loss from Unprofitable Cross-Buying</th>
<th>Total Loss (in Millions of US$) from Unprofitable Cross-Buying</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>B2B financial service firm</td>
<td>9.57%</td>
<td>80.09%</td>
<td>3.8</td>
</tr>
<tr>
<td>2</td>
<td>B2B IT firm</td>
<td>18.50%</td>
<td>87.54%</td>
<td>325</td>
</tr>
<tr>
<td>3</td>
<td>B2C retail bank</td>
<td>19.13%</td>
<td>38.65%</td>
<td>.3</td>
</tr>
<tr>
<td>4</td>
<td>B2C catalog retailer</td>
<td>35.10%</td>
<td>51.52%</td>
<td>.25</td>
</tr>
<tr>
<td>5</td>
<td>B2C fashion retailer</td>
<td>31.61%</td>
<td>76.91%</td>
<td>1.2</td>
</tr>
</tbody>
</table>

Notes: We rescaled all values by multiplying and/or dividing the original values by a constant to preserve the confidentiality of the data.
advantage of accounting for the inherent uncertainty associated with the parameter estimates.

**Variable Operationalization**

Measuring adverse behavioral traits. We operationalize the four behavioral traits of the customers that could potentially be adverse for the firms as service request, revenue reversal, (low) revenue growth, and promotion purchase. One way to operationalize them would be to treat them as event occurrences (e.g., the number of times a customer made revenue reversals in a year by returning previously purchased products, the number of times a person purchased products on promotion). However, such an approach to measurement would not indicate the true intensity of the behavior. For example, a customer may return previously purchased products ten times a year, but the products returned during each occurrence may be just 2% of the total products the customer purchased. In comparison, a customer may return just once in a year, but the products returned during that single occurrence may be 100% of the products the customer purchased. Therefore, we operationalize the four adverse behavioral traits as the total dollar amount of the spend/cost/revenue associated with the respective behavioral trait per customer per year. Table 4 summarizes how each behavioral trait is measured along with a brief rationale for its selection and potentially adverse impact on the firm.

To account for customer-level differences, we normalize the annual measure of each adverse behavioral trait of a customer by the customer’s revenue in the given year to yield a relative measure of the adverse behavioral trait. Therefore, we compute the mean normalized measure (MNM) of each adverse behavioral trait (ABT) over an observation period of N years as follows:

$$MNM_{ABT} = \frac{\sum_{i=1}^{N} \frac{\text{Value of ABT}_{Ai}}{\text{Revenue of Customer}_{iT}}}{N}$$

Note that the measure represented in Equation 5 is a continuous variable, and the extent to which it proves to be adverse for the firm can be expressed only in relative terms. That is, the higher the MNM of ABT such as service request, revenue reversal, and promotion purchase and the lower the MNM of ABT such as revenue growth, the greater is the extent to which these behavioral traits are deemed adverse for the firm.

Measuring the habit strength of adverse behavioral traits. The main covariates of interest are the persistence of adverse behavioral traits. Although a relatively large (or low) value of the MNM of ABT (as computed in Equation 5) can prove to be adverse for the firm, the objective of the study is to relate them to unprofitable cross-buy outcome.

<table>
<thead>
<tr>
<th>Variable Operationalization</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Variable</strong></td>
</tr>
<tr>
<td>Adverse Behavioral Traits</td>
</tr>
<tr>
<td>Service request</td>
</tr>
<tr>
<td>Revenue reversal</td>
</tr>
<tr>
<td>Low revenue growth</td>
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<tr>
<td>Promotion purchase</td>
</tr>
<tr>
<td>Control Variables</td>
</tr>
<tr>
<td>Marketing inefficiency ratio (MIR)</td>
</tr>
<tr>
<td>Age, income, zip code, and gender</td>
</tr>
<tr>
<td>Industry type, number of employees, and annual sales revenue</td>
</tr>
<tr>
<td>Product category indicators</td>
</tr>
</tbody>
</table>
As we discussed previously, this could happen when customers exhibit the adverse behavioral traits persistently or by virtue of habit. Customer behavior driven by habit is characterized by repetitive behavior that is temporally consistent (e.g., Wood and Neal 2009). Consequently, the greater the temporal consistency of a particular behavior, the stronger is the habit associated with that behavior, as prior literature (e.g., Ronis, Yates, and Kirscht 1989; Triandis 1977, 1980) has suggested. Therefore, to capture the habit strength of the adverse behavioral traits, we need to measure the extent to which each of the adverse behavioral traits is temporally consistent.

To quantify the temporal consistency (over the observation period), we calculate the standard deviation ($\sigma_A$) for each MNN of ABT A corresponding to customer $i$ over the observation period of $N$ years. Consequently, we define temporal consistency as $1/(1 + \sigma_A)$. The greater the temporal consistency, the closer to 1 is its value, and the lesser the temporal consistency, the closer to 0 is its value.

Consequently, we operationalize the habit strength of each adverse behavioral trait $A$ corresponding to each customer $i$ over an observation period of $N$ years as the MNN of the ABT multiplied by $1/(1 + \sigma_A)$ (for the mathematical notation, see Equation 6):

$$\text{(6) Habit Strength of ABT}_i = \frac{\text{MNN of ABT}_i}{1 + \sigma_A}.$$ 

With such an operationalization, the habit strength of a customer with greater temporal consistency of an adverse behavioral trait (over the observation period) will be higher than that of a customer with lower temporal consistency of the adverse behavioral trait (assuming the same mean normalized measure of the adverse behavioral trait). To understand the intuition behind this approach, consider this simple example. A customer exhibiting an adverse behavioral trend of returning products worth $100, $100, $100$, and $100$ over four years will have a higher habit strength than a customer exhibiting an adverse behavioral trend of returning products worth $200, $200, 0, and 0$ over the same four years (assuming the same annual customer revenue and thus the same value of MNN of the ABT). The habit strength operationalized in this manner enters our logit model (i.e., Equation 3) as the following key covariates to help determine the probability of a customer to engage in unprofitable cross-buying: revenue growth habit (RGH), service request habit (SRH), revenue reversal habit (RRH), and promotion purchase habit (PPH). In essence, the greater the value of SRH, RRH, and PPH and the lower the value of RGH, the greater is the probability of a customer to engage in unprofitable cross-buying.

Measuring the time trend of adverse behavioral traits. It is possible that customers gain adverse behavioral traits over time. For example, a customer may exhibit a product return trend of $100, $200, $300, and $400 over four years, while another customer may exhibit a product return trend of $400, $300, $200, and $100. To account for the possible time effect of the customer’s adverse behavioral traits during the observation period of $N$ years, we compute the mean annual growth (MAG) of the normalized measure of the ABT of each customer as follows:

$$\text{(7) MAG of ABT}_i = \frac{\sum_{T=1}^{N} \frac{\$ Value of ABT}_{iT}}{\$ Value of ABT}_{iT-1} - \frac{\$ Revenue of Customer}_{iT}}{\$ Revenue of Customer}_{iT-1}}.$$ 

In the final model, we include this growth measure as a main effect as well as an interaction term with the habit measure of ABT (as computed in Equation 6).

Control variables. We include the following set of control variables in the model: (1) product category dummies to control for potential differences in profit margins as a driver of cross-buy profitability, (2) firm-initiated marketing costs (including customer acquisition and retention costs such as cross-sell campaigns and other customer communication costs) relative to the revenue realized from the respective customer, and (3) customer- and firm-level characteristics to account for observed heterogeneity as summarized in Table 4.

To facilitate prediction, the dependent variable and the corresponding covariates are spaced apart in time. That is, the dependent variable is operationalized as a binary variable indicating unprofitable or profitable cross-buying status of a customer in year $T$. The corresponding covariates included in the model correspond to their values as of year $T-1$. For example, a firm with observation data of five years will have a dependent variable equal to 1 or 0 according to whether the customer exhibits profitable or unprofitable cross-buying in the fifth year, while the corresponding covariates will represent a measure of the behavioral traits (and controls) corresponding to the first four years of the observation period. Such an operationalization of the variables and model specification can help establish whether persistence (or lack thereof) of adverse behavioral traits (of every customer) in the past can relate to an unprofitable (or profitable) cross-buy outcome for the firm in the future.

The final set of covariates included in the logit model corresponding to each firm is conditional on the relevancy and availability of the data in the respective data sets. For example, the covariate pertaining to the dollar amount of items purchased on promotion (PPH) is not relevant for service-based products sold by the B2C retail bank and the B2B financial services bank. For model estimation, consistent with the recommendation of Kohavi (1995), we randomly split the data sets of all five firms into a calibration sample comprising 70% of the customers and a holdout sample comprising 30% of the customers. The model estimation is carried out for the calibration sample.

Model Results

The parameter estimates for models corresponding to each of the five firms are obtained with 1000 burn-in and 20,000 iterations. The models indicate a good overall fit on the basis of visual inspection of the posterior distribution plots. The autocorrelation in the posterior draws of the model results is within the recommended limit of 10


86 / Journal of Marketing, May 2012
lags (p < .3 for lag > 10). Furthermore, the Geweke (1992) diagnostic test indicates good model convergence by virtue of the Z-values of all parameters, which are nonsignificant at the .05 level. Table 5 lists the parameter estimates (computed from the calibration sample of the five firms) for the key covariates of interest.

Overall, the results render empirical support for the influence of persistent (or nonpersistent) adverse behavioral traits on unprofitable (or profitable) cross-buy outcome. More specifically, we observe that for all firms, the habit of customer-initiated revenue reversals (RRH) in the form of persistent account defaults (for the financial services firm and the retail bank) or product returns (for the IT firm and the two retailers) has a positive impact on the propensity of a customer to engage in unprofitable cross-buy. Likewise, the habit of customer-initiated service requests (SRH) has a positive impact on the propensity of unprofitable cross-buy. This implies that across all five firms, high-maintenance customers who persistently demand excessive customer service from the firm are likely to be unprofitable with an increase in the number of products purchased from the firm. Furthermore, across all five firms, we find that the lower the habit of revenue growth per product purchased (RGH), the higher is the propensity of a customer to exhibit unprofitable cross-buy in the future. This is because customers with low RGH tend to redistribute their expenditure with the firm over a greater number of products, thereby failing to offset the incremental marketing and other expenditures the firm incurs in selling additional products. For the two retailers (i.e., the B2C fashion retailer and B2C catalog retailer) and the B2B IT firm, opportunistic customers who tend to habitually purchase a large number of items on price promotion (PPH) tend to exhibit a higher propensity of unprofitable cross-buy behavior. In contrast, PPH is not relevant for the two financial services firms. The parameter estimates corresponding to the main and interaction effects of the mean annual growth of adverse behavioral traits are not statistically significant, thereby implying that the effect of a behavioral trend (if any) in the observation period is not significantly strong enough to explain unprofitable cross-buy after accounting for the persistence of the adverse behavioral traits over time.

The control variable, marketing inefficiency ratio (MIR), has a positive impact on the propensity of a customer to exhibit unprofitable cross-buy across all five firms. For the B2B IT firm, we find that the size of the firm in terms of number of employees and the annual sales revenue have a negative relationship with the propensity of a customer to exhibit unprofitable cross-buy, implying that large firms tend to exhibit profitable cross-buy. However, customers from three industry classification codes (actual names of industries withheld as requested by the IT firm providing the data set for this study) have a positive impact on the propensity of unprofitable cross-buy. We find none of the firm-level characteristics for the B2B financial services firm to be statistically significant. One possible reason is that data pertaining to firm-level characteristics are missing for several customers of the B2B financial services firm. For the three B2C firms, we find a negative relation-

ship associated with the annual income of the customer, while the remaining demographic variables (primarily age, gender, and marital status) fail to have any significant relationship with the propensity of unprofitable cross-buy. We do not report the parameter estimates of the different control variables pertaining to the demographics and firm-level characteristics in Table 5 as they are not uniformly available for the different data sets of the firms.

We find the effect of all product category dummies (employed across five firms) to be nonsignificant and thus do not report them in Table 5. This implies that the type of a product purchased by a customer does not really matter in terms of driving unprofitable cross-buy after accounting for the persistence (or habit strength) of the adverse behavioral traits of the respective customer.

Model Performance Checks

To evaluate model performance, we apply the parameter estimates of the calibration model to predict the probability of each customer in the holdout sample. If the predicted probability of a customer in the holdout sample is greater than the cutoff threshold .5, we classify the customer as 1, or someone who is likely to exhibit unprofitable cross-buy. Otherwise, we classify the customer as 0, or someone who is likely to exhibit profitable cross-buy. The model is able to correctly classify 85%–90% of the customers in the holdout sample of the five firms (see Table 6).

In general, the proportion of customers with profitable cross-buy is higher than unprofitable cross-buy in the holdout sample of all five firms. Given the disparity in the relative proportion of the customers in the holdout samples, we evaluate the model performance (as indicated by the hit ratios in Table 6) with the proportional chance criterion Morrison (1969) suggests. The proportional chance criterion represents the conditional probability of classifying a person correctly, given the relative size of each of the groups. Upon comparison, we find that the ability of the model to correctly classify the two groups of customers (hit ratios range from 85% to 90%) is significantly higher than the proportional chance criterion benchmark value (which ranges from 59%–68%) across the five firms.

To assess the robustness of the model performance, we conduct a series of sensitivity analyses. First, we randomly and repeatedly resample the calibration and holdout sample and evaluate the parameter estimates corresponding to the calibration sample and the predictive performance of the holdout sample. The results obtained are similar with respect to the parameter estimates and model performance. The hit ratio values across multiple samples vary within a maximum deviation range of 7%–11% from the values reported in Table 6 for the five firms. Next, we vary the time horizon of the calibration and the holdout sample beginning from the maximum time available (i.e., the observation period reported in Table 1) and then steadily decreasing by one year (up to an observation period of two years) to evaluate whether the model results hold for shorter time frames. The results indicate that the parameter estimates do not change significantly for the five firms. The hit ratio values (corresponding to the five firms) drop margin-
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<tbody>
<tr>
<td></td>
<td>Estimate</td>
<td>SD</td>
<td>Estimate</td>
<td>SD</td>
<td>Estimate</td>
</tr>
<tr>
<td>Intercept</td>
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<td>-3.94</td>
<td>.08</td>
<td>-2.99</td>
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<tr>
<td>RRH</td>
<td>4.18</td>
<td>.29</td>
<td>15.54</td>
<td>.33</td>
<td>53.79</td>
</tr>
<tr>
<td>SRH</td>
<td>.08</td>
<td>.01</td>
<td>.09</td>
<td>&lt; .001</td>
<td>5.31</td>
</tr>
<tr>
<td>GGH</td>
<td>-.01</td>
<td>&lt; .001</td>
<td>-.03</td>
<td>&lt; .01</td>
<td>-.45</td>
</tr>
<tr>
<td>PPH</td>
<td>N.A.</td>
<td>N.A.</td>
<td>2.5</td>
<td>.05</td>
<td>N.A.</td>
</tr>
<tr>
<td>MIR</td>
<td>.91</td>
<td>.07</td>
<td>10.87</td>
<td>.19</td>
<td>15.50</td>
</tr>
</tbody>
</table>

Notes: RGH = revenue growth habit, SRH = service request habit, RRH = revenue reversal habit, PPH = promotion purchase habit, and MIR = marketing inefficiency ratio. N.A. = not applicable.
ally by approximately 5%-9% from the values reported in Table 6.

**Tracking the Impact of Persistent Adverse Behavioral Traits over Time**

To demonstrate the relative importance of the model to managers, we evaluate the implications of early (or timely) identification of potentially unprofitable cross-buy customers due to persistent adverse behavioral traits. We apply the parameter estimates of the model (obtained from a randomly drawn calibration sample with two-year observation data) to a holdout sample of each of the five firms to identify customers that are likely to exhibit unprofitable cross-buy in year 3. We then track and report the observed average cumulative loss of these customers for year 3 and beyond (up to the number of calendar years for which the observation data are available) along with their level of cross-buy. The objective is to evaluate whether customers that exhibit persistent adverse behavioral in the first two years of their relationship with the firm give more, less, or no losses in the future with increase in cross-buy over time. The results indicate (see Table 7) that across all five firms, the average cumulative loss per customer per year increases substantially despite the increase in the level of cross-buy per customer. For example, for the two B2B firms, the cumulative loss per customer more than doubles in four years compared with the first two years.

It is noteworthy that not all customers who were correctly classified as likely to exhibit unprofitable cross-buy in year 3 were necessarily unprofitable in the first two years. Similarly, not all customers who were correctly classified as likely to exhibit profitable cross-buy in year 3 were necessarily profitable in the first two years of the observation period.

The results from the empirical analyses imply that the history of persistent adverse behavioral traits can serve as a reliable basis for identifying customers that are likely to result in unprofitable cross-buy in the future. Furthermore, the need for timely detection of customers that are likely to exhibit unprofitable cross-buy is underscored by the finding that the cumulative customer losses for such customers are likely to increase with the level of cross-buy over time. This is because the inherent adverse behavioral traits of the customers (e.g., demanding excessive customer service, excessive product returns) stay persistent over time and thus transfer to additional product categories. In addition, incremental marketing expenses incurred by the respective firms to encourage customers (with persistent adverse behavioral traits) to cross-buy will further contribute to increase in customer losses. Another significant insight derived from the longitudinal analyses is that persistence (of adverse behavioral traits) trumps history of customer losses in predicting future cross-buy profitability of the customer. As stated previously, upon investigation of the holdout sample, we observe incidences of (historically) profitable customers resulting in unprofitable cross-buy and vice-versa across each of the five firms.

To establish the robustness of the aforementioned empirical analyses, we repeated the procedure several times across each of the five firms with a different mix of a randomly drawn holdout sample. We obtained similar results and substantive insights.

**Influence of Marketing Practices and Policies on Persistent Adverse Behavioral Traits**

A related issue of research significance is to understand whether there is any heterogeneity in the relative importance of different customer-specific factors (associated with unprofitable cross-buy) across different firms. Likewise, of managerial importance is to evaluate whether each firm’s marketing policies and/or practices can possibly relate to the relative importance of the adverse behavioral traits of the respective firm’s customers.

The relative importance of the different adverse behavioral traits of the customers within each firm (based on the results obtained in Table 5) can be empirically determined by multiplying the regular coefficient ($\beta$) by the sample standard deviation of the corresponding covariate (Carpio, Sydorovych, and Marra 2007). However, this method is unreliable when covariates are not perfectly orthogonal. (Covariates are likely to be partially correlated in most practical cases.) Tonidandel and LeBreton (2009) suggest a more sophisticated approach that entails the computation of the relative contribution (or weight) of each predictor variable to the overall predictable variance while accounting for potential correlation of the predictor variables. The basic intuition underlying this methodology is to first transform the predictor variables ($X$) into a set of orthogonal factors ($Z$) and then calculate the relative weight according to the regression between dependent variable ($Y$) and $Z$ as well as the regression between $X$ and $Z$ (for details related to the computation algorithm, see Tonidandel and LeBreton 2009). We apply this method for computing the relative importance of the adverse behavioral traits and obtain the rank order in terms of their relative importance as summarized in Table 8. Note that we only provide the relative rank ordering of the four adverse behavioral traits (within each firm), given the focus of our study. The results indicate that there is considerable heterogeneity in the relative rank ordering of the four adverse customer behavioral traits across the five firms.

Next, we requested the senior marketing managers of the five firms to list the distinguishing features of their marketing practice and/or business policy. The managers at the four U.S.-based firms distinguished their marketing practice and/or policy vis-à-vis their close competitors. The manager at the Asia-based B2C retail bank distinguished its practices and policies from firms in other (developed) markets. We summarize the qualitative responses in Table 8.
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<tbody>
<tr>
<td></td>
<td>Cumulative Loss per Customer ($)</td>
<td>Level of Cross-Buy per Customer</td>
<td>Cumulative Loss per Customer ($)</td>
<td>Level of Cross-Buy per Customer</td>
<td>Cumulative Loss per Customer ($)</td>
</tr>
<tr>
<td>2</td>
<td>-84,176</td>
<td>3.73</td>
<td>-10,627</td>
<td>3.64</td>
<td>-575</td>
</tr>
<tr>
<td>3</td>
<td>-147,449</td>
<td>3.95</td>
<td>-15,928</td>
<td>4.20</td>
<td>-630</td>
</tr>
<tr>
<td>4</td>
<td>-174,180</td>
<td>4.51</td>
<td>-22,300</td>
<td>4.67</td>
<td>-823</td>
</tr>
<tr>
<td>5</td>
<td>N.A.</td>
<td>N.A.</td>
<td>N.A.</td>
<td>N.A.</td>
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</tr>
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</table>

Notes: N.A. = not applicable.
TABLE 8
Influence of Firms’ Marketing Policies/Practices on the Persistence of Adverse Behavioral Traits of Firms’ Customers

<table>
<thead>
<tr>
<th>Number</th>
<th>Firm</th>
<th>Distinguishing Features of the Firm’s Marketing Practices and/or Policies (as Reported by the Marketing Manager of Each Firm)</th>
<th>Relative Importance of Adverse Behavioral Traits</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>B2B financial service firm</td>
<td>Stringent credit lending policies; aggressive cross-selling marketing programs with relatively high sales force commission based on the number of products sold</td>
<td>RGH 2  SR 1  RRH 3 PPH N.A.</td>
</tr>
<tr>
<td>2</td>
<td>B2B IT firm</td>
<td>Relatively high emphasis on preserving customer relationships over time; company provides easy access to relationship managers through dedicated phone lines</td>
<td>RGH 4  SR 1  RRH 3  PPH 2</td>
</tr>
<tr>
<td>3</td>
<td>B2C retail bank</td>
<td>Standardized consumer credit score monitoring system not available in the country (Asia-based bank) to prequalify customers for loan-based products</td>
<td>RGH 3  SR 2  RRH 1 PPH N.A.</td>
</tr>
<tr>
<td>4</td>
<td>B2C catalog retailer</td>
<td>Company has an extremely liberal product-return policy</td>
<td>RGH 2  SR 4  RRH 1  PPH 3</td>
</tr>
<tr>
<td>5</td>
<td>B2C fashion retailer</td>
<td>Heavy emphasis on cross-sell campaigns; new cross-sell campaigns rolled out each month</td>
<td>RGH 1  SR 4  RRH 2  PPH 3</td>
</tr>
</tbody>
</table>

Notes: The relative importance is indicated by the rank order, with 1 indicating the most important. RGH = revenue growth habit, SRH = service request habit, RRH = revenue reversal habit, and PPH = promotion purchase habit. N.A. = not applicable.

Notably, the differences in the marketing practices/policies of the five firms seem to explain the differences in the relative rank ordering of the persistent adverse behavioral traits. For example, for the B2B financial services firm, RGH emerges as the most important and RRH emerges as the least important adverse behavioral trait. These results are consistent with the firm’s stringent credit lending policies, which ensure minimal delinquent customers, thereby reducing the importance of RRH in driving unprofitable cross-buy. However, the firm’s sales force is compensated according to the number of different products sold to the customer (i.e., level of cross-buy) rather than the overall profitability of the customer. This has led the sales team to focus more on selling additional products to customers through aggressive cross-selling rather than increasing customer profitability. Given the high importance of RGH in driving unprofitable cross-buy, the firm might consider revisiting its sales compensation structure.

In contrast, the relative importance of adverse behavioral traits for the B2C retail bank follows a reverse rank order compared with the B2B financial services bank. The B2C retail bank data set comes from a country in Asia where standardized consumer credit scores (as available in the United States) are nonexistent. The loans or credit cards issued by the bank’s employees are based on proxy measures such as a pay stub, tax returns, value of home owned, and/or history of the savings/checking account with the bank. These measures may not be as effective as the credit score system employed in the United States, thereby increasing the occurrences of delinquent accounts and raising the importance of RRH relative to SRH and RGH.

In B2B firms, the emphasis is generally on managing individual customer relationships (Bowman and Narayandas 2004). Likewise, the B2B IT firm included in the analyses has an extensive customer relationship management program that gives a high level of importance to preserving customer relationships. Customers have easy access to relationship managers through dedicated phone lines. Consequently, there is scope for some customers of the firm to demand excessive customer service, thereby raising the relative importance of SRH to the top position for the firm. For the two B2C retailers, the rank ordering is somewhat similar except for the top two factors. The B2C catalog retailer has one of the most liberal return policies in the retail industry, which indirectly encourages certain consumers to abuse the system through excessive returns. This could explain why RRH ranks as the most important factor for the catalog retailer. For the B2C fashion retailer, the high importance of RGH underscores the need to consider up-selling to certain customers and/or revisiting its cross-sell campaigns to avoid targeting customers with small share/size of wallet.

The results of Table 8 indicate the role of firms’ marketing policies/practices in influencing habitual proneness of adverse customer behavioral traits. Our findings are also consistent with literature on habit formation that has explored the dependence of consumer habits on environmental cues (Verplanken and Woods 2006). In such a scenario, disruption of the environmental cues may offer an opportunity to change consumer habits (Wood, Tam, and Wit 2005). In the context of our study, changing marketing practices and policies (e.g., making product return policy more restrictive, charging customers for excessive customer service, limiting deep discounted product sales to select customers) may serve as the required environmental cue to deter the persistence of the adverse behavioral traits of the firms’ customers.

Implications

For Marketing Literature

Our findings call for two important refinements to the marketing literature. First, researchers need to refine the basic understanding that not all cross-buying is profitable. The proportion of customers engaging in unprofitable cross-
buying is relatively small. However, these customers account for a disproportionately high level of total losses from customers by virtue of habitual proneness of adverse behavior. Second, conventional cross-buy models that focus on the propensity of a customer to cross-buy fail to account for persistence of adverse customer behavioral traits and thus fail to detect customers who are likely to result in an unprofitable outcome. In the light of these findings, cross-buy models should make cross-sell recommendations to firms conditional on the propensity of the customer to generate more profits (after cross-buy). We further elaborate on this through Figure 2 and the related discussion in the following subsection.

For Marketing Practice

The findings from this study imply that it is not prudent to cross-sell a product to every customer who is likely to buy an additional product. This is a significant shift from conventional marketing practices that emphasize cross-selling to all customers. A substantial proportion of the firm’s total losses from customers can be minimized if firms can identify and dissuade customers (exhibiting persistent adverse behavioral traits) from cross-buying in a timely manner. This is imperative, as the results from the empirical analyses (of all five firms) show that the level of losses associated with unprofitable customers with persistent adverse behavioral traits tends to increase with the level of cross-buy. A direct implication for marketing managers is implementation of a two-stage framework, as we illustrate in Figure 2.

The adoption of the framework is straightforward and can be readily operationalized in conjunction with the conventional cross-selling models firms presently use. Stage 1 entails application of the random coefficient logit model (as discussed previously) to partition the firm’s customer database into two segments: customers likely to result in unprofitable and profitable cross-buy. For the segment likely to exhibit profitable cross-buy, firms should apply their existing cross-sell model to determine the right product to offer to the right customer. For the segment likely to exhibit unprofitable cross-buy, firms should desist from any cross-sell initiatives and instead make a no-sell or up-sell decision according to the type of adverse behavioral traits associated with each customer. For example, if a customer demonstrates a dominant adverse behavioral trait of excessive product returns, the firm may discourage any further cross-buy by suspending all cross-sell initiatives targeted toward that customer. If poor revenue growth is predominantly associated with unprofitable cross-buy of a customer, the solution may lie in extending up-sell offers to the relevant customer, provided that the size of wallet (of the customer) is inferred to be large enough. For example, a B2C bank customer who has a perennially low balance in the checking account and a dormant credit card may be a good candidate for up-sell if his or her demographic indicators (e.g., annual income) suggest a large size of wallet. In either case, the application of the model (including the parameter estimate associated with the adverse behavioral trait) can provide guidance to the manager in terms of the extent to which a

FIGURE 2

A Two-Stage Framework for Profitable Cross-Selling
particular adverse behavioral trait of a customer needs to change for the customer’s overall propensity of unprofitable cross-buy to become less than .5.

Rethinking marketing policies and practices. The relative importance of adverse behavioral traits in each of the five firms (as discussed in Table 8) seems to be affected by the marketing practices and policies of the respective firms. In such a scenario, should the firm change its marketing practices (tactical actions) or policies (strategic actions) to break the habitual adverse behavior of its customers? The answer is not trivial. Regarding marketing policies, imposing a restrictive return policy, for example, could certainly deter any customer of the firm from abusing the return policy. However, it may also result in discouraging profitable customers from shopping for additional products from the firm. Likewise, a universal change in sales compensation policy (e.g., aligning sales incentives to overall customer profitability rather than cross-buy ratio) may deter the sales force from reaching out to certain customer accounts (e.g., government institutions, large prestigious firms) that may be less profitable but strategically more important for the firm’s business and/or reputation. Given that the existing marketing policies of the respective firms may have more upside benefits (i.e., contributing to positive returns from a majority of the firm’s customers), it may not be in the best interest of the firm to alter it. However, every firm can have customized marketing practices (e.g., Kumar and Shah 2009; Ramani and Kumar 2008) to influence the specific behavior of select customers. This is particularly relevant for firms serving business markets (e.g., Bowman and Narayandas 2004). Therefore, our recommendation is to selectively change marketing practices corresponding to each customer (e.g., for selectively discouraging high-maintenance customers by migrating them to lower-cost customer service channels such as the Internet) rather than imposing a uniform change in marketing policy across all the firm’s customers.

Proactive relationship termination. Not all customer cross-buying may necessarily occur in response to the cross-selling efforts of the firm. In other words, customers exhibiting persistent adverse behavioral traits may purchase additional products from the firm of their own accord. In such cases, it may be prudent for firms not only to suspend all cross-selling initiatives but also to proactively discourage such customers from having any further relationship with the firm. Is this possible? Would firms be willing to proactively terminate a relationship with their customers? Mittal, Sarkees, and Murshed (2008) maintain that as many as 85% of executives (across different firms and industries) they interviewed had undertaken proactive termination of customer relationships. Their claim is supported by anecdotal evidence of firms restricting or terminating their relationship with select customers. For example, Best Buy banned a section of its unprofitable customers from entering its store (Mc-Williams 2004), Sprint “fired” 1000 customers for demanding unreasonably high levels of customer service (Reardon 2007), and Comcast restricted the bandwidth for 1% of its heavy Internet users (Borland 2003). In the context of this research, if a firm chooses to follow the path of proactively terminating relationship with select customers, the proposed two-stage framework can help firms identify problem customers according to the persistence of adverse behavioral traits.

Revisiting cross-buy as a performance metric. A critical factor driving the practice of cross-selling in firms is the metric used to measure its success. The most commonly used metric for evaluating the success of cross-selling campaigns is the cross-buy ratio (i.e., the number of different products [or product categories] sold to a customer). For example, Wells Fargo routinely publishes the average cross-buy ratio of its customer base in its annual report. Furthermore, it cites its target cross-buy ratio (for the future) as one of the key strategic goals. The cross-buy ratio is also commonly employed in companies as a basis for incentivizing sales employees (Herbert-Kuehner 2010). Such practices can contribute to indiscriminate cross-selling. Given that not all cross-buying leads to profitable outcomes, a better measure of cross-buy success could be a metric that measures the growth in customer profitability per additional product sold. In other words, a salesperson should be incentivized on the basis of increase in customer profitability as a consequence of cross-buy rather than the cross-buy ratio alone.

Limitations and Future Directions

Limitations of this study present opportunities for further research. For example, the observation period of the five data sets included in our study is limited to a time horizon of four to seven years. Further research could consider analyzing data over longer time horizons to evaluate whether there are any changes in habit strength over time and its impact (if any) on the phenomenon of unprofitable cross-buying. Further validation of these results could be obtained by replicating the research in the context of different industries not included in this study. Furthermore, while this research took multiple years to collect data and conduct rigorous analyses of multiple data sets, it stops short of conducting a field experiment to validate the effectiveness of the two-stage framework. This presents an opportunity for future studies.

The measurement approach we employed to analyze the persistency of adverse behavioral traits requires the observation data to be available for at least two years. Future studies could develop alternative approaches for detecting the prevalence of persistent adverse behavioral traits over a shorter time span. A possible approach entails employing richer customer data sets that contain more demographic variables or relevant psychographic variables (e.g., personality traits of customers) and thus operationalizing the adverse behavioral traits as endogenous in the model specification.

The concept of unprofitable cross-buying also offers some exciting avenues for research extensions. For example, it would be worthwhile to explore this problem from the perspective of cross-selling rather than cross-buying, thus taking the firm’s perspective rather than the customer’s perspective. For example, Schweidel, Fader, and Bradlow (2011) show how cross-selling to certain dormant customers can actually accelerate the process of customer attri-
REFERENCES


