V. Kumar, Rajkumar Venkatesan, & Werner Reinartz

Performance Implications of Adopting a Customer-Focused Sales Campaign

Through field experiments conducted in two business-to-business firms, the authors evaluate the financial and relational consequences of adopting a customer focus in sales campaigns. In both the experiments, salespeople adopting the customer-focused sales campaign coordinated their sales calls with the objective of selling all the products that a customer was predicted to purchase only at the time the customer was expected to purchase. The authors compare this strategy with the current practice in the organization in which salespeople for each product category independently contacted the customers who were expected to purchase in that category without any guidance on the expected timing of customer purchase. The experiments show that adopting a customer-focused sales campaign can significantly increase firm profits and return on investment. The total incremental profits obtained from implementing the customer-focused sales campaign was more than $1 million. High-revenue customers were the source of improvements in the efficiency of marketing contacts, whereas low-revenue customers were the source of improvements in the effectiveness of the marketing contacts. A customer-focused sales campaign also improved the relationship quality between the customer and the firm. This research provides empirical evidence for theoretical expectations of the benefits provided by a customer-focused sales campaign. Organizations can use the field experiments illustrated in this study as a template for implementing the first step in migrating to a customer-centric organization.

Keywords: customer focus, field experiment, cross-selling, performance metrics, sales force coordination

According to a 2003 Gartner Report (Shah et al. 2006, p. 1), "By 2007, fewer than 20 percent of marketing organizations among Global 1000 enterprises will have evolved enough to successfully leverage customer centric, value added processes and capabilities." The report also states (p. 1) that "by 2007, marketers that devote at least 50 percent of their time to advanced, customer centric marketing processes and capabilities will achieve marketing ROI [return on investment] that is at least 30 percent greater than their peers, who lack such emphasis." Our research reveals that many *Fortune* 100 firms, such as Citigroup, General Electric (GE), United Technologies Corporation, and PepsiCo, have organized their marketing and sales activities around the products they offer rather than the customers they serve.

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Anecdotal evidence finds that customer centricity is often misinterpreted by organizations as selling a bundle of products to all customers. For example, Gulati (2007) indicates that GE medical systems faced major setbacks when equipment salespeople also began selling consulting services for all GE's customers. By marketing the unit's consulting services with its product portfolio, GE generated solutions for customers whose problems could be solved using GE's equipment, but these services were less compelling for those whose needs were linked only loosely to the imaging products. In another context, because of Hewlett-Packard's failure to realize benefits from customer-focused sales campaigns and because of competition from more focused competitors, Mark Hurd scaled back Hewlett-Packard's customer-centric initiatives. Whereas the earlier objective of Hewlett-Packard's sales force was to sell product bundles to all customers, it was reorganized to be more product-focused, with the belief that it would reduce selling costs because less central coordination would be required (Burrows 2005).

The academic literature suggests that the strategic advantage of a customer-centric organization is to create value for the customer and, in the process, to create value for the firm—that is, a focus on dual value creation (Boulding et al. 2005). A successful migration from a product-centric to a customer-centric organization is expected to proceed through a multistage process of aligning the organization's structure, performance metrics, processes (espe-

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cially customer-facing activities, such as sales calls), and culture to be externally focused with the objective of satisfying customers' needs (Shah et al. 2006). The first step in this migration is proposed as the informal coordination of customer-connecting activities, such as sales calls across product silos (Day 2006)—that is, implementing a customer-focused sales campaign. Although customer-focused sales campaigns are theoretically expected to increase profits and improve ROI, firms' adoption of customer-focused sales campaigns has been low (Day 2006). Major reasons identified in the literature (Day 2006; Gulati 2007; Shah et al. 2006) for the failure of the migration toward a customer focus include (1) poor implementation of the coordination of customer-facing activities across product silos, (2) the failure to understand customer requirements across product categories, and (3) the failure to customize firm offers to customer requirements.

Our goal in this study is to provide an assessment of the consequences of implementing a customer-focused sales campaign through field experiments. Following the dual value creation objective of customer centricity, we assess the performance of customer-focused sales campaigns using both relational and financial metrics. The relational metrics provide an evaluation of customer perceptions of the value provided by a customer-focused sales campaign. The financial metrics enable us to evaluate whether a customer-focused sales campaign provides value to the firms. In the field experiments, we control for the accuracy of customer knowledge available to salespeople and evaluate the consequences of aligning a sales force along customers or products. Objective evidence regarding the benefits obtained from adopting a customer-focused sales campaign can serve as an aid for top management to gain support for initiatives that would help develop a customer-centric organization (Gulati and Oldroyd 2005). The field experiments can provide organizations with a template for implementing the first step in migrating toward a customer-centric organization.

Through the field experiments, we also intend to contribute to the theoretical understanding of customer-focused organizations by generating insights into the process of ROI improvement. In other words, if profit consequences can be demonstrated, we attempt to understand the source of these benefits. Higher profits can be obtained from cost reduction (greater efficiency), revenue growth (greater effectiveness), or both. Improved efficiency of targeting implies that the organization is able to reduce the campaign cost while maintaining overall revenue levels. For example, by understanding each customer's total needs, a firm can design a single, consistent message, leading to a lower number of sales calls required to complete a sale. An improved effectiveness of targeting implies a match between customer needs and either the type of message or the timing of the message. For example, predicting when a customer is likely to purchase and timing the sales call to coincide with the customer's expected purchase time would enable a firm to achieve better customer penetration, thus leading to higher revenue. We propose that a customer-focused sales campaign can provide efficiency and effectiveness gains relative to a product-focused sales campaign.

To summarize, in this study, we present two case studies in which we (1) conduct a field experiment that explicitly compares the proposed customer-focused sales campaign with a more traditional product-focused sales campaign and (2) assess the efficiency and effectiveness of the customer-focused sales campaign by documenting relationship quality, cost, revenue, and ROI implications.

The empirical context of the first field experiment is an organization that markets a range of high-technology products and services to other firms. In each planning period (quarters), the company allocates sales campaign resources (or marketing investments) to contact its customers for three principal product categories: A1, A2, and A3.[1] The first field experiment shows that the firm can obtain impressive financial returns from adopting a customer-focused sales campaign. For an average investment of $5,000, which was required by both the test- and the control-group customers, the test-group customers provided $13,253 in profits, whereas the control group provided only $9,584 in profits. The test-group customers, who were exposed to a customer-focused sales campaign, provided more than $1 million in total incremental profits compared with the control-group customers, who were exposed to a product-focused sales campaign. The total profits from the test-group customers were more than $3.7 million.

The results from the second field experiment, which was conducted in another multinational organization in the telecommunications industry, validate the results from the first field experiment and improve the generalizability of our findings. This telecommunications firm provided four different services in the business-to-business (B2B) environment. We observed in the second field experiment that for an average investment of approximately $4,000, customers in the test group provided $10,082 in profits, whereas the control group provided only $7,938 in profits. The test-group customers provided more than $500,000 in incremental profits compared with the control-group customers and $2.4 million in total profits.

In the next section, we provide the conceptual background and develop hypotheses regarding the benefits from adopting a customer-focused sales campaign. We then provide the context of the first field experiment, illustrate the model used to develop predictions of the customer requirements used in the experiment, and provide the results of the model estimation and details of the results observed. Following this, we contrast the second field experiment with the first to highlight the generalizability of our findings. Next, we provide a discussion of the results and highlight their managerial implications. Finally, we provide the limitations of our study and provide suggestions for further research.

Conceptual Background and Hypotheses

The concept of customer focus or customer centricity has been discussed widely in the marketing literature. For

[1]We are unable to reveal the product category because of confidentiality reasons.

example, Deshpandé, Farley, and Webster (1993, p. 27) define a customer orientation (which has also been referred to as customer focus) as the "set of beliefs that puts the customer's interest first, while not excluding those of all other stakeholders such as owners, managers, and employees in order to develop a long-term profitable enterprise." Furthermore, Shah and colleagues (2006, p. 115) suggest that "the true essence of the customer-centricity paradigm lies not in how to sell products but rather on creating value for the customer and, in the process, creating value for the firm." Although most of the early literature concentrated on the performance benefits of an organizationwide focus on customers, there is a dearth of research on implementation of various steps required in the migration to a customer-focused organization. Therefore, our experiment takes a narrower view and tests the benefits from a customer-focused sales campaign. This activity is considered the first step in the migration toward a customer-centric organization (Day 2006). The customer-focused sales campaigns can be considered an organizational process that needs to be implemented for an organization to be customer centric (Shah et al. 2006).

In a customer-focused sales campaign, the entire set of product or service needs for each customer or customer segment and the consumption rate (i.e., purchase frequency) of the customer are first identified. The firm's sales calls would then focus only on each customer's needs and would target the customer only when the need is expected to arise. A customer-focused sales campaign would entail coordinating sales calls across product silos to address each customer's expected needs. In other words, salespeople from different product specializations would coordinate their sales calls to provide a coherent and consistent message to a customer who has a need for multiple products.

In contrast, under a product-focused sales campaign, a firm would identify the customers who are likely to purchase a product. The sales force of that product division would then target all the customers who are likely to purchase that product. Within a product-focused sales campaign, the same customer is likely to be targeted by different salespeople (each with a specialization in a particular product) separately and multiple times from the same firm. As Shah and colleagues (2006) indicate, the goal of a product-focused sales campaign is to maximize the number of customers to whom a product can be sold. Conversely, the goal of a customer-focused sales campaign is to maximize the extent to which the firm's products address customers' needs. The salespeople in a product-focused sales campaign do not aim to contact customers only when they expect customers to need the product. Therefore, a customer focus in a sales campaign calls for both coordinating sales calls across product silos and restricting the timing of sales calls to coincide with the expected customer purchase rate.

Customer-focused sales campaigns are different from customer-oriented selling. In customer-oriented selling, a salesperson assists customers in making purchase decisions that aim to satisfy their underlying needs (Siguaw, Brown, and Widing 1994), and it refers to the behavior of a single salesperson. However, we are interested in the orientation of the entire sales campaign across salespeople, product categories, and time. Salespeople could individually practice customer-oriented selling for their respective product category, but the resultant sales campaign is still product focused if there is no coordination among salespeople from different product category groups. Furthermore, salespeople would need to know the timing of customer purchases to coordinate their sales calls.

Impact of Customer-Focused Sales Campaigns

Consistent with theoretical expectations, previous empirical research has found that the collection and integration of customer information needs to coexist for improved performance (Jayachandran et al. 2005). In addition to sharing customer information, the benefits of a customer focus can be obtained only if the acquired customer information is deployed in customer-facing activities (i.e., sales calls) in a manner consistent with the philosophy of customer centricity. However, the benefits obtained from an effective and consistent deployment (in customer-facing activities) of the information obtained from customer data have not been explored.

Recall that we defined a customer-focused sales campaign as one in which salespeople coordinate their contact strategy across product categories, salespeople, and time to address customers' underlying, dynamically changing needs. We propose that such an approach has a positive association with customer-level revenues, a negative association with customer-level costs to serve, and a positive association with relationship quality compared with a product-focused sales approach.

The positive association with revenue generation (i.e., improved effectiveness of marketing actions) is likely to come from the following factors: First, there is a greater likelihood of sales conversion because of a better alignment with customers' needs as a result of possible complementary cross-category effects and better incorporation of purchase-timing information. Second, there is upside volume potential because of the various possible category combinations now coming from the same firm (as opposed to sales potentially lost to competitors for individual products).

The negative association with costs of serving customers (i.e., improved efficiency of marketing actions) is likely to come from the following effect: Because of the incorporation of the purchase-timing component, there will be a better alignment of actual sales interventions and occasions of high purchase propensities. For example, salespeople might consciously spend more time with established personal contacts, even though they have little additional sales potential, rather than targeting potentially interesting but personally unknown customers. However, a model-based approach will help the salesperson use the scarce resource time as effectively as possible (Gensch 1984).

Finally, we propose that there is a positive association between a customer-focused sales campaign and customer relationship quality, which is likely to come from the improved ability to address true customer needs. This improvement will be derived from the better matching of sales propositions with actually needed product requirements, the better matching of sales propositions with actual timing of requirements, and the possible second-order synergistic effects due to better product compatibility across categories and/or better internal functional coordination in the customer's organization. These effects should drive customer perceived value and satisfaction, which in turn should lead to improved loyalty and recommendation likelihood (Gupta and Zeithaml 2006). Formally, we hypothesize the following:

> H_1: A customer-focused sales campaign is associated with (a) higher revenues (i.e., improved effectiveness), (b) lower costs (i.e., improved efficiency), and (c) more improved relationship quality than a product-focused sales campaign.

Sources of Performance Improvement

Conceptual models propose that, all else being equal, improved productivity can come from (1) more efficiently creating value—achieving equal response as before but with less input—and (2) efficiently creating more value—achieving greater resource-produced value than before (Hunt and Morgan 1997). We further refine H_{1a} and H_{1b} by proposing different sources of these effectiveness and efficiency improvements.

In particular, we argue that effectiveness and efficiency gains also depend on the historical level of sales calls or the level of marketing investment. Customers who receive a higher number of sales calls are likely to be those the firm expects to generate higher current volume (or higher potential). Similarly, customers who receive fewer sales calls are likely to be those the firm expects to generate lower current volume (or lower potential). This is the well-known endogeneity phenomenon that has been well documented in direct-marketing contexts (Shugan 2004). Note that this endogeneity issue does not create any statistical problems in our context, because we are comparing two experimental groups at the same point in time. It can be hypothesized that the benefits flowing to the firm (efficiency and effectiveness creation) are distributed unequally among these two customer groups. Figure 1 illustrates our rationale for expecting different gains from these groups.

Specifically, we hypothesize that the current high-sales-call customers are those who disproportionately contribute to the cost savings, whereas the low-sales-call customers disproportionately contribute to the revenue gains. This is because there is a ceiling effect among high-sales-call customers, who already spend a lot with the firm, and therefore they have little upside potential. Thus, we would expect that the gain, if any, would come from the cost-savings side (i.e., using fewer but more calculated sales calls). The low-sales-call customers have more of an upside potential, though they have a ceiling effect as well. Here, the ceiling effect is more likely due to an overall smaller wallet size or an overall lower utility for the firm's offering. Therefore, although growth potential is likely, low-sales-call customers would never be expected to grow to the same size as high-sales-call customers. In addition, the possibility of savings gains from low-sales-call customers is low because they already receive few sales calls. Thus, there is a floor effect with respect to marketing touches. Formally, we hypothesize the following:

> H_2: The improvement in the efficiency of customer-focused sales campaigns is greater (a) for customers with a higher level of marketing investment and (b) for customers with a lower level of marketing investment.

Field Experiment 1

Method

We conducted the first field experiment with a multinational firm that provides three product categories in the information technology industry to business customers. The firm that participated in this experiment is similar to a *Fortune* 1000 firm in terms of annual sales, sales growth, net income, and number of customers. Through its strategic alliances, the firm provides products and services in three related major categories, which is typical of several high-tech firms, such as Microsoft, Dell, IBM, Hewlett-Packard, and Cisco. External storage devices, antivirus software, network servers, personal computers, and workplace productivity software are examples of products that are analogous to those provided by the firm. The sales transactions for customers in the field experiment range from \$5,000 to approximately \$25,000. In this field experiment, customers are proposed a combination of three product categories: A1, A2, and A3. The sales force of the organization is also structured along this categorization strategy. Therefore, our product categorization allows for easy execution of the field experiment.

FIGURE 1
Effectiveness and Efficiency Gains Across Customer Segments

	Past Behavior						
	Customer		**Firm**		**Current State**		**Expected Behavior**
Segment 1	Higher utility for offering, thus higher revenue	→	Allocation of *higher* level of sales calls	→	Customer has little upside potential	→	Gains, if any, are derived from cost savings (efficiency)
	Customer		**Firm**				
Segment 2	Lower utility for offering, thus lower revenue	→	Allocation of *lower* level of sales calls	→	Customer has moderate upside potential	→	Gains, if any, are derived from revenue growth (effectiveness)

We use a sample of 566 customers, who are currently served by 850 salespeople. For a particular product category, more than one customer is assigned to a single salesperson. However, one customer can also be assigned many salespeople, such that each salesperson is responsible for a different product category. In other words, a customer can be contacted by a maximum of three salespeople given that there are three product categories. Thus, there are more salespeople than customers involved in this experiment. The customers are assigned to the test (n_1 = 283) and control (n_2 = 283) groups on the basis of matched-pair comparisons. We compare the customers across several customer characteristics, such as establishment sales, number of employees, distribution of industry category, and behavioral factors (e.g., purchase frequency, total revenue, past customer value). The customer assignments to the test and control groups are carried out such that the distribution of the previously mentioned factors is similar in both the test and the control groups. For example, we ensure that if the test group had 20% of the customers with between 100 and 1000 employees, approximately 20% of the customers in the control group also had between 100 and 1000 employees. We chose the factors used for the matched-pair comparisons on the basis of our discussions with the organization that provided the data. The firm uses these factors to segment customers for sales and marketing purposes.[2] When we obtained the matched pairs, we randomly assigned the customers to the test and control groups. Depending on the customer assignment, we also assigned the corresponding salespeople to the test and control groups. We conducted the experiment for one year between the first quarter of 2006 and the end of the last quarter of 2006.

Customer-focused sales campaign. We use the predictions from a joint-timing and product category choice model to prioritize sales calls for customers in the test group. During the experiment, the customers in the test group are contacted only in the quarter when they are expected to make a purchase. The salespeople from the product categories that the customer is expected to purchase from work as a team to make coordinated sales calls. For example, if a customer is expected to purchase from product category A1, the salesperson responsible for A1 calls that customer. If a customer is expected to purchase from multiple product categories, salespeople from the respective product categories form a team to make coordinated or joint sales calls. For example, if a customer is expected to purchase from product categories A1 and A3, both the salesperson responsible for A1 and the salesperson responsible for A3 call this customer together.

Product-focused sales campaign. The salespeople for a product category are proactive in proposing only their respective product categories on their sales calls to the control-group customers. The joint-timing and product category choice model also provides inputs for the control group. Unlike the test group, the salespeople remain aligned with their product category in the control group. We use the outputs from the joint-timing and product category choice model to identify customers who are likely to buy a particular product category—for example, A1—in the experimental period. The salespeople responsible for category A1 are provided the list of customers expected to purchase A1 and are instructed to contact these customers in the upcoming year. A similar approach is implemented for product categories A2 and A3.

The timing of sales calls within the year is typically at the discretion of the sales force; in general, customers with a higher predicted purchase probability were contacted before others. Under a product-focused strategy, multiple salespeople (corresponding to the different product categories) from the firm might contact a customer at the same time to propose their respective products. In addition, ignoring the timing of customer purchases could lead to salespeople from the firm proposing the right product to a customer at the wrong time, which could result in lost sales. Figure 2 illustrates the implementation of our field experiment.

Salesperson compliance with the field experiment. Fully controlled laboratory experiments allow for random allocation of participants to treatments in a between-subjects design to ensure that all other relevant factors do not vary systematically across treatments. In contrast, our data are generated in a field experiment that does not allow for a similar level of controlled comparison. An issue that is important to monitor is whether the experimental condition generates a potential demand effect, which then might affect the participant's (salesperson's) behavior (Orne 1962). In our case, it could be argued that participants know that their behavior is being observed and that this would generate potential deviations from their usual behavior. However, in our case, we had several conditions that would help minimize any potential demand effects.

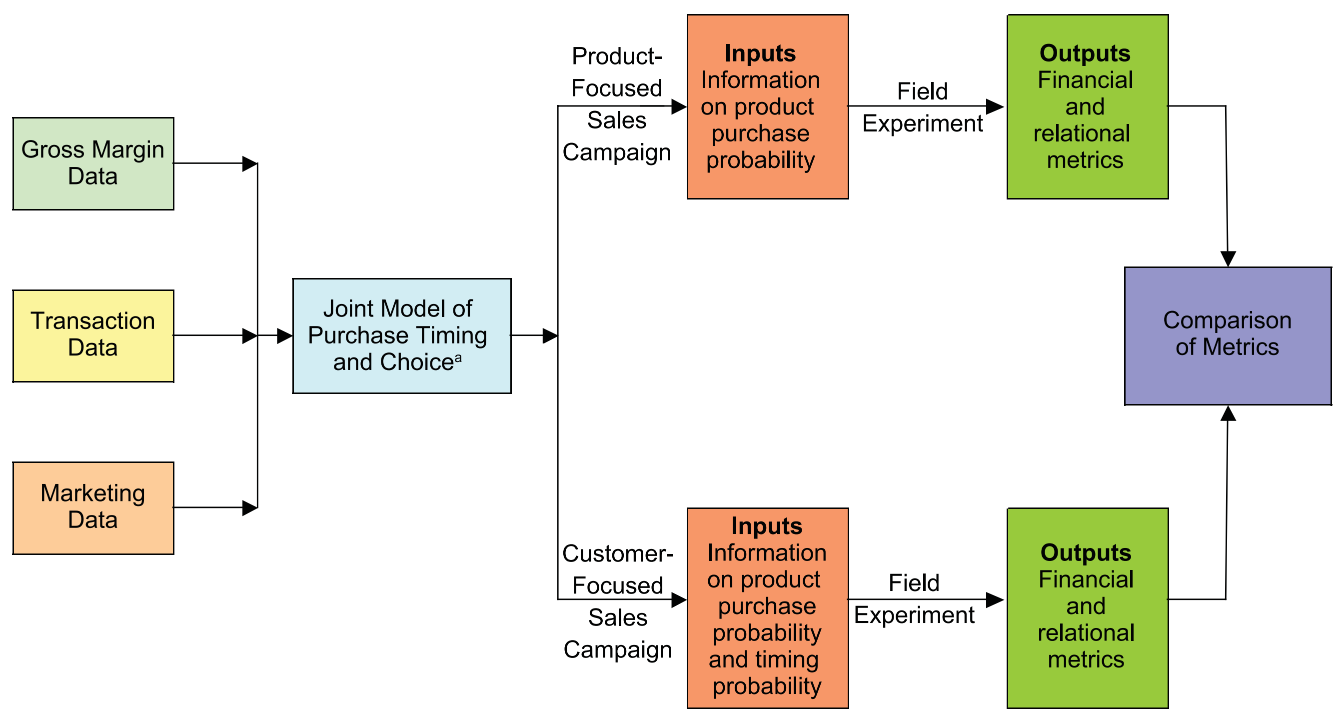
First, salespeople are not involved in the customer scoring process. The analysis and scoring of customers is conducted by a specialized market intelligence group, which then delivers the results to the sales function. Therefore, although participants were fully aware that a field experiment was being conducted, they were not aware of the kinds of models that were being employed.

Second, both groups (test and control) were involved in the experiment. Thus, both groups were normalized insofar as they knew that an experiment was being conducted; this should minimize demand-effect impacts between the two groups. Furthermore, the ability to compare pre- and post-experiment behavior of the control group enabled us to determine that there was no significant behavior change with respect to our dependent measures.

Third, the organization that we worked with has strong organizational processes in place. Indeed, this organization is well known among its peers for its thoroughly developed internal processes. Thus, compliance with existing sales processes and scripts is high, which helps minimize any potential demand effects. Another advantage of the strong

[2]We did not match the test and control customers on sales or sales growth (e.g., Lodish and Pekelman 1978), because all the customers selected in this experiment have similar sales.

FIGURE 2
Customer-Focused Versus Product-Focused Sales Campaign



[a]The best-performing model is chosen after a detailed comparison with other benchmark models presented in the Appendix.

process orientation was that we did not need to revert to using incentives to motivate salespeople to engage in the test group. Rather, we found that incentives would potentially aggravate the demand-effect problem and therefore would be counterproductive.

Predicting Purchase Timing and Customer Category Choice

One aspect of a customer-focused sales campaign involves the ability to predict a customer's category needs reliably. We accomplish this through a joint-timing and choice model because it addresses the main idea of a customer-focused sales campaign—that is, providing customers with all the products they need at the time they need them. We control for bias due to level of customer profitability by targeting only highly profitable customers as the sample for the field experiment.

Figure 3 shows the conceptual objective of our model. Our joint approach to investigating purchase timing and category choice is based on the dynamic McFadden model formulation (for an application, see Chintagunta and Prasad 1998). Although it is possible to implement our experiment using a simpler model structure, the proposed model structure will enable us to minimize loss of revenue due to inaccurate predictions of customer behavior. In turn, this will enable us to assess and identify the potential gains of a customer-focused sales strategy. Therefore, we incorporate the recent developments in the literature to create a sophisticated model of purchase timing and category choice for the experiment.

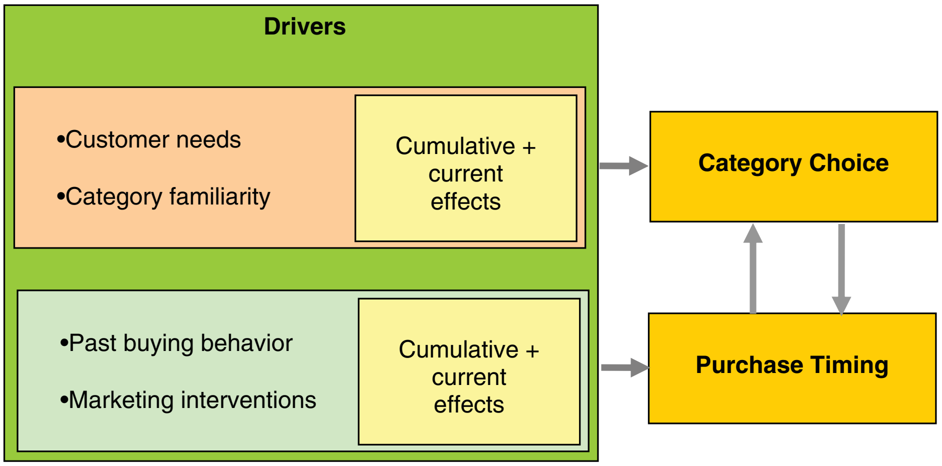
Let $P_i(t)$ denote the probability that customer i will purchase from the firm at time t, and let $P_i(j|t)$ denote the probability that customer i will purchase in product category j, given that the purchase time is equal to t. Then, the joint probability of customer i purchasing in product category j in time t, $P_i(t, j)$, is given by the following:

$$P_i(t, j) = P_i(t) \times P_i(j|t). \quad (1)$$

We assume that a customer has a specific interpurchase time for each of the products purchased from the firm. The interpurchase times in each product category will result in an overall interpurchase time for the customer with the firm. We model this interpurchase time using a statistical distribution, which answers the question, When is the customer likely to purchase next [$P_i(t)$]? Knowledge about a customer's history of interpurchase times, the product categories from which he or she purchased at each purchase instance, and the timing of the current purchase occasion will enable us to deduce consumption patterns in each product category and thus satisfactorily predict the category in which a customer is most likely to purchase [$P_i(j|t)$]. We first develop our model formulation for each of the components, $P_i(t)$ and $P_i(j|t)$, and then we provide the joint likelihood function. As we explained previously, the joint probability of purchase timing and category choice is the product of the marginal probability of purchase timing and the conditional probability of category choice, given purchase timing.

Purchase timing [$P_i(t)$]. We use a log-logistic distribution to model customer interpurchase times because the dis-

FIGURE 3
Conceptual Model Specification



tribution accommodates a variety of forms and is suitable to model consumption patterns (Chintagunta and Prasad 1998).[3] The purchase times are measured from the same time origin to reflect the natural sequence of events; that is, the time for the first purchase, T_1, is less than the time for the second purchase, T_2, and so forth. If we assume a log-logistic distribution for interpurchase time, the probability that the kth purchase for customer i will occur at time t, given the timing of the customer's previous purchases, is given by the following:

$$(2) \qquad \lambda_i(t_k) = \frac{\gamma_{0i}\gamma_{1ik}^{\gamma_{0i}} t_k^{\gamma_{0i}-1}}{1+\gamma_{1ik}^{\gamma_{0i}} t_k^{\gamma_{0i}}},$$

where the two parameters of the log-logistic model are γ_{0i} and γ_{1ik}, both of which are greater than zero. The parameter γ_{1ik} is expressed as $\gamma_{1ik} = \exp(Z_{ik}\zeta_i)$, where ζ_i are a set of response coefficients of customer i and Z_{ik} denotes the vector of variables for each customer i in purchase occasion k. We use a random-effects formulation to estimate customer-specific response coefficients, ζ_i.

Category choice [p(j|t)]. At each purchase occasion t, customer i makes purchase decisions (Y_{it}) across J product categories. We model the observed binary (buy/not buy) decision for each product category j, in terms of latent utilities for the categories. The latent utilities for the jth category can be represented as follows:

$$(3) \qquad u_{ijt} = x_{ijt} \times \beta_j + t^*_{ij} \times \alpha_{ij} + \varepsilon_{ijt},$$

where X_{ijt} represents the covariates affecting the utility (u_{ijt}) for product category j at time t for customer i, β_j represents the response coefficient for product category j,[4] and ε_{ijt} is a random error obtained from a multivariate normal distribution. We capture coincidence in purchases across product categories by allowing the covariance terms in the variance–covariance matrix of the multivariate normal error distribution to be nonzero.

A customer is expected to make a purchase in a particular product category if his or her latent utility in a product category is higher than a threshold that is set to zero in our model formulation. Therefore, we can represent the link between the observed behavior and the latent utility for product category j as follows:

$$(4) \qquad y_{ijt} = \begin{cases} 1 \text{ if } u_{ijt} > 0 \\ 0 \text{ if } u_{ijt} \le 0 \end{cases}.$$

This formulation of the category choice model represents the multivariate probit model (Chib and Greenberg 1998; Manchanda, Ansari, and Gupta 1999). We follow the procedure that Edwards and Allenby (2003) recommend to ensure that the model parameters are identified in the multivariate probit formulation. Unlike previous applications of the multivariate probit model, we include only observations in which a purchase was made because we model the conditional probability of category choice given expectations about when a purchase is expected to occur rather than the probability of purchase in a product category in any time interval, such as weeks or months.

Relationship between purchase timing and category choice. It can reasonably be assumed that a customer has an inherent purchase pattern for each product category. Therefore, we include the time elapsed since a customer purchased in product category j, t^*_{ij}, in the utility function for product j. We measure the covariate t^*_{ij} as the difference

[3]On the basis of the Andersen-Darling tests, we found that a log-logistic distribution would represent the data best. In other words, we failed to reject the null hypothesis that the data belong to a log-logistic distribution at a significance level of α = .01. We rejected the null hypothesis for other distributions, such as log-normal, exponential, and Weibull.

[4]Because customers do not purchase in all categories in our sample, allowing the coefficient to vary across customers also does not provide reliable estimates.

between the period of the current purchase occasion and the period when product j was last purchased. This enables us to model explicitly the relationship between purchase timing and product category choice. For example, a customer may be expected to purchase A1 every six months and A2 every three months. At the current purchase time t, if the time since the last purchase of A1 ($t^*_{ij = P1}$) is six months and the time since the last purchase of A2 ($t^*_{ij = P2}$) is one month, the customer is more likely to purchase A1 at time t. Finally, α_{ij} is the response coefficient that measures the influence of t^*_{ij} on the utility for product j.

Joint likelihood of purchase timing and product category choice. The joint likelihood function for customer i is given by the following:

$$(5) \qquad L_i = \prod_{k=1}^{r_i} \left\{ \prod_{j=1}^{J} \left[f_i(t_k, j_k)^{d_{ijk}} \right]^{c_{i,k}} \right\} s_i(t_k)^{(1 - c_{i,k})},$$

where

r_i = the number of purchase occasions (spells) for customer i,
$c_{i,k}$ = 1 if the kth spell for customer i ends in a purchase and 0 if otherwise,
$d_{i,j,k}$ = 1 if customer i chooses product category j in spell k and 0 if otherwise,
$f_i(t_k, j_k)$ = the joint probability of purchasing in product category j at time t (Equation 1), and
$s(\cdot)$ = the survivor function of the log-logistic distribution in the purchase-timing model.

When an observation is censored (i.e., $c_{ik} = 0 \ \forall\ j$), the likelihood function is not affected by the product category choice factor, d_{ijk}, and therefore depends only on the survivor function $s(\cdot)$ of the log-logistic distribution. We estimate the model in Equation 5 using Markov chain Monte Carlo methods. We simultaneously estimate both purchase timing and category choice so that the variance in the interpurchase time probabilities is accommodated in the estimation of the category choice probabilities. The Appendix provides further details on the model framework; it compares our proposed framework with other benchmark models in which choice and timing models are estimated either independently or jointly and determines whether these models account for customer heterogeneity.

Data

Longitudinal information on each customer's purchase dates, the corresponding purchase category, and amount spent is available to the managers for decision making. Drawing from existing literature in cross-category purchases and customer lifetime value (Knott, Hayes, and Neslin 2002; Reinartz and Kumar 2003; Rust, Zeithaml, and Kumar 2004), we obtain drivers of (variables that influence) product category choice and purchase timing. The description, the operationalization of the variables, and the expected effects appear in Table 1. We include variables that are specific to a particular product category in the category choice model and variables that are common across all categories (e.g., relationship benefits) in the purchase-timing model. Our expectation is that customers' needs for certain product types and their familiarity with the focal categories are the key drivers of product category choice. In contrast to the choice of product categories, timing of purchases is a function not only of the customer's buying behavior and patterns but also of managerial interventions. This specification reflects the finding that in the context of capital goods, it is easier to influence when a customer purchases than whether a customer purchases (Anderson and Narus 1999).

We can classify the variables used in the models as cumulative or current effects. We calculate the current-effects variables in terms of the activities of the customer or the supplier (in case of channel communications) between the previous observed purchase (t – 1) and the current observed purchase (t). We calculate the cumulative-effects variables in terms of the activities of the customer or the supplier from the first purchase occasion until the current observed purchase (t).

Table 2, Panel A, provides the descriptive statistics for the drivers of category choice, and Table 2, Panel B, provides the distribution of category purchases. Table 2, Panel A, shows that the customers tend to split their purchases across product categories evenly. On average, 32% of their purchases are within a single category (the mean proportion of same-category purchases is equal to .32). This implies that customers in our data exhibit a fair level of cross-category purchases, which provides face validity for the use of a product category choice model. The distribution of product category purchases (Table 2, Panel B) indicates that only the purchase of A3 is the most prevalent in the sample (48%) and that A1 and A3 are purchased together more often (20%) than any other product category combination. Finally, the least prevalent product category combinations are A1 and A2 (2%) and A2 and A3 (2%). On average, there are approximately ten product types within each product category, and Table 2, Panel A, shows that the mean level of cross-buying within a product category is approximately equal to 2.

Table 3 provides the descriptive statistics for the drivers of purchase timing. The average interpurchase time for the customers in our sample is 4.2 months. Customers in the analysis sample make an average of at least one upgrade and have bought across two product types within each product category (A1, A2, or A3). The customers make frequent contacts with the organization through the Web sites (on average, once every two months). The number of customer-initiated contacts through online channels is less frequent than the number of standardized contacts made by the organization (on average, 1.6 contacts every month) but more frequent than the number of contacts made by the organization through rich modes (on average, once every quarter). The customers also make transactions across two channels and seem to prefer using direct modes of transaction. Finally, we evaluate the correlation matrix of the independent variables for both the product category choice and purchase-timing models and found that multicollinearity is not an issue in our analyses.

To address potential endogeneity in the model covariates that could be caused by time-varying missing variables,

TABLE 1
Variables and Operationalization

Driver Category	Variable	Operationalization	Type	Expected Effect	Rationale
Category Choice Model					
Category familiarity	Proportion of same-category purchases	The ratio of number of past purchases in the focal product category to the total number of purchases. For example, P1 purchases are purchases in the focal product category for predicting P1 category choice (indicator of category dominance)	Cumulative	+	The more a customer purchases in a particular product category, the higher is the propensity of the customer to purchase in the same category in the future.
	Size of same-category purchases	Total number of items bought in the focal product category (indicator of size of wallet in focal category)	Cumulative	+	Customers who spend more in a product category have a higher size of wallet and also recurrent needs. This leads to higher expected propensity to purchase again in the category.
	Cross-buying within a category	Total number of unique product types bought in the focal product category (indicator of within-category knowledge)	Cumulative	+	If a customer purchases several different products within a category, it increases switching costs in the category, leading to higher propensity to shop in the category in the future.
Customer needs	Recency of same-category purchase	The time interval between the most recent focal category purchase and the current purchase occasion (indicator of buying needs)	Current	+	Contrary to consumer packaged goods, for high-tech products, the customers typically use the product before repurchasing it. Therefore, the longer the time since last purchase in a product category, the more likely the customer is to purchase in that category.
Purchase-Timing Model					
Past buying behavior	Upgrading	Number of upgrades until the current purchase (indicator of need to buy)	Cumulative	–	Customers who upgrade have higher switching costs with each upgrade, leading to lower propensity to churn (Bolton, Lemon, and Verhoef 2004).
	Cross-buying	Number of different product types that a customer has purchased (indicator of affinity to the firm)	Cumulative	–	Customers who purchase across several product categories have higher switching costs and recurrent needs (Reinartz and Kumar 2003).
	Returns	Total number of products returned by the customer (indicator of satisfaction)	Cumulative	U	Returns provide an opportunity for firms to satisfy customers (Reinartz and Kumar 2003). Too many returns can be detrimental to the relationship and can indicate that the firm has not used the return opportunities appropriately.
	Relationship benefit	Indicator variables of whether a customer is a premium service member (indicator of commitment to the firm)	Current	–	Acknowledgment of customers with relationship benefits reduces the propensity of customers to quit (Morgan and Hunt 1994).

TABLE 1
Continued

Driver Category	Variable	Operationalization	Type	Expected Effect	Rationale
	Number of distinct channels of transaction	Cumulative number of distinct channels used for a transaction. The available channels include salesperson, telesales, Web site, catalog, distributor, reseller, and retail (indicator of client sophistication and relationship quality)	Cumulative	–	Customers who shop in multiple channels are expected to transact frequently with the firm and also have deeper relationships with the firm (Venkatesan, Kumar, and Ravishanker 2007).
	Number of direct transactions	Cumulative number of transactions through the direct channel. The available channels include salesperson, telesales, Web site, and catalog (indicator of client size)	Cumulative	–	Customers who use the direct transaction channels value efficiency and trust the firm (Morgan and Hunt 1994).
	Lagged interpurchase time	The duration between the previous two purchase occasions (indicator of past purchase frequency)	Current	+	Control variable used to account for missing variables and past customer characteristics (Venkatesan and Kumar 2004).
Marketing Interventions	Bidirectional communication	The ratio of total number of customer-initiated contacts to the total contacts between the supplier and the customer (indicator of relationship strength and customer involvement)	Current	–	Two-way communication between parties strengthens the relationship and leads to frequent transactions (Morgan and Hunt 1994).
	Frequency of Web-based contacts	Number of times the customer contacts the supplier through the Internet per month (indicator of marketing intensity)	Current	–	Customers who use online communication want transaction efficiencies, and customers who want to create efficiencies are highly relational and transact frequently (Venkatesan and Kumar 2004).
	Frequency of rich modes of communication	Number of contacts made to the customer by the supplier firm per month through sales personnel (indicator of marketing intensity)	Current	U	
	Frequency of standardized modes of communication	Number of contacts made by the supplier firm to the customer in a month through telephone or direct mail (indicator of marketing intensity)	Current	U	Timely communication between parties reduces the propensity of a customer to quit a relationship (Morgan and Hunt 1994), but too much communication can be detrimental to the relationship (Fournier, Dobscha, and Mick 1997).
	Intercontact time	Average time between two contacts made to the customer by the supplier across all channels of communication (indicator of marketing intensity)	Current	U	

Notes: U = U-shaped relationship.

TABLE 2
Descriptive Statistics for Category Choice

A: Drivers of Category Choice

Variable	M	SD
Proportion of same-category purchases	.32	.26
Size of same-category purchases	2.65	2.45
Cross-buying within a category	2.41	2.20

B: Distribution of Category Purchases

		A2	
A3 = No Buy		N	Y
A1	N	0%	4%
	Y	21%	2%

		A2	
A3 = Buy		N	Y
A1	N	48%	2%
	Y	20%	3%

TABLE 3
Descriptive Statistics for Drivers of Purchase Timing

Variable	M	SD
Interpurchase time	4.23	5.32
Upgrading	1.15	.60
Cross-buying	2.42	1.19
Bidirectional communication	.65	2.09
Returns	.96	2.58
Web-based contacts[a]	.50	3.17
Relationship benefit	.2	.86
Rich modes[a]	.3	.16
Standard modes[a]	1.56	7.87
Intercontact time	.25	3.3
Distinct channels of transaction	2.12	.85
Transactions using direct channels	1.94	1.80

[a]Web-based contacts, rich modes, and standard modes represent the frequency of contacts in each channel respectively.

we use lagged variables in our analysis (Venkatesan and Kumar 2004; Villas-Boas and Winer 1999).[5] Specifically, for observed purchase j, the cumulative-effects variables represent activity of the customer since birth until observed purchase t – 1. Similarly, for observed purchase t, the current-effects variables represent activity of the customer (or supplier) between observed purchases t – 2 and t – 1.

Model Estimation Results

We have a sample of 6350 observations that belonged to the 566 customers in the test group and control group. We estimate the choice and purchase-timing models simultaneously (from the likelihood function in Equation 5) in a Bayesian framework using Markov chain Monte Carlo algorithms. The Appendix provides the in-sample fit capability and the predictive capability of the proposed joint model of category choice and purchase timing along with other benchmark models. The in-sample fit (Table A1) and predictive accuracy (Table A2) results provide support for the full model specification outlined in Equation 5. The coefficient estimates of the drivers of category choice and timing appear in Table 4. The estimation results confirmed a majority of the expected effects (Table 1). Because the estimated effects of the drivers of category choice and purchase timing are similar to the previous literature, we do not discuss them here. Subsequently, we discuss the findings from the category choice model that are unique to this research.

The estimation results indicate that recency of product purchase is significant and positive for the A1 and A2 product categories. However, we do not find a significant influence for recency of purchase in the A3 category. We speculate that this may be because the customers in our sample purchase A3 regularly. The average interpurchase time for A3 purchases in our sample is approximately 1.5 months. Therefore, it is reasonable to expect a high probability for the purchase of A3 at every purchase occasion. The significant influence of recency for A1 and A2 emphasizes the need to model the dependence between purchase timing and category choice. The significance of the recency measure also translates into better predictive accuracy for the joint model than for the independent model.

Field Experiment Results

Recall that in the field experiment, 283 customers were assigned to the test group, and another 283 customers were assigned to the control group on the basis of matched-pair comparisons. A customer-focused sales campaign was adopted to contact customers in the test group from the first quarter of 2006 to the end of the last quarter of 2006 (for one year). The customers in the control group were contacted using a product-focused sales campaign. Both groups obtained inputs from the proposed joint-timing and product category choice framework. Thus, we control for model accuracy in the experiment. Figure 2 highlights the difference in inputs for the test and control groups. The product-focused strategy used in the control group is the null model for comparison of the results in the test group. The results from the field experiment appear in Table 5, Panels A and B. We evaluate the performance of the field experiment using both financial and relational metrics. We capture the value the customers provide to the firm with financial metrics, including revenue, marketing investment, number of contacts per purchase,[6] profits, and ROI for each customer. The relational metrics capture the value the firm provides and the relationship quality the customer perceives. The

[5]Lagged covariate values have been identified as suitable instruments to control for any time-varying factor that is not included in the model (i.e., missing variable) but is correlated with both the independent variables and the dependent variable. The lagged covariate values are expected to be correlated with the current covariate value but uncorrelated with the missing variable (Villas-Boas and Winer 1999).

[6]Marketing contacts refer to sales calls in the field experiment.

TABLE 4
Results from Model Estimation

Variable	Coefficient Estimate
Product Category Choice: A1	
Intercept	.51**
Proportion of A1 purchases	.39**
Size of A1 purchases	.31**
Cross-buying within A1	.37**
Recency of A1 purchase	.12**
Product Category Choice: A2	
Intercept	.31**
Proportion of A2 purchases	.17**
Size of A2 purchases	.22**
Cross-buying within A2	.22**
Recency of A2 purchase	.09**
Product Category Choice: A3	
Intercept	.61**
Proportion of A3 purchases	.57**
Size of A3 purchases	.23**
Cross-buying within A3	.48**
Recency of A3 purchase	.003
Purchase Timing	
Intercept	.22**
Upgrading	–.11*
Cross-buying	–.07**
Bidirectional communication	–.52**
Returns	–.25**
Square of returns	.07**
Frequency of Web-based contacts	–1.5**
Relationship benefits	–.06**
Frequency of rich modes of contact	–.82**
Square of frequency of rich modes of contact	.51**
Frequency of standard modes of contact	–.23**
Square of frequency of standard modes of contact	.09**
Intercontact time	–.37**
Number of distinct channels of transaction	–.16**
Number of transactions in direct channels	–.08**
Log of lagged interpurchase time	.45**

*Significant at $\alpha = .05$.
**Significant at $\alpha = .01$.
Notes: Aggregate log–conditional predictive ordinate (aggregate log-CPO) = –5,641.

various relational metrics measure (1) whether the firm understands the customer's needs, (2) whether the firm provides value to the customer, (3) whether the customer is likely to repurchase from the firm, and (4) whether the customer is likely to recommend the firm. These metrics were measured with a ten-point interval scale, anchored by "strongly agree" (10) and "strongly disagree" (1). Prior research has indicated that these financial and relational measures are critical indicators of the profitability and sustainability of the customer firm relationship (Kumar, Petersen, and Leone 2007; Rust, Zeithaml, and Lemon 2004; Venkatesan and Kumar 2004).

Overall benefits from a customer-focused sales campaign. Table 5, Panel A, provides a comparison of both the financial and the relational metrics within the test and control groups during the experimental period (first quarter in 2006 to last quarter in 2006) and during the corresponding preexperimental period (first quarter of 2005 through fourth quarter of 2005). The mean values for the test and control groups appear in Table 5, Panel A; they represent the increase or decrease in the experimental period from the preexperimental period.

We first evaluated whether the test and control groups were different from each other in the five financial metrics during the preexperimental period using Hotelling's T-square test. The test revealed that customers in the test and control groups did not significantly differ in any of the five financial metrics in the year before the experiment was conducted. This indicates that there were no sources of bias between the test and the control groups before the experiment. Hotelling's T-square test indicated that the means of at least one of the metrics were significantly different between the experimental and the preexperimental periods for both the test and the control groups. We then tested the difference in means for each metric using a T-test with Bonferroni adjustment (Table 5, Panel A) for both the test and the control groups.

We find that the revenues ($\alpha < .10$, \$898) and, thus, profits ($\alpha < .10$, \$890) increased between the preexperimental and experimental periods for the control group. The improvement in revenues and profits for the control group is attributable to the better performance of the proposed model in identifying the customers who are expected to purchase in each product category. For the test group, we observe a significant improvement in the performance between the preexperimental and the experimental periods along all the metrics: revenues ($\alpha < .01$, \$1,828), marketing investment ($\alpha < .05$, –\$1,906), profits ($\alpha < .01$, \$3,734), and ROI ($\alpha < .01$, 2). The better performance observed in the test group is attributable to both the better performance of the model and the customer-focused alignment of the sales force. The difference between the financial metrics for the test and control groups in the experimental period provides a measure of improvement in performance attributable to a customer-focused alignment of the sales force in the test group (Table 5, Panel B).

Similar to the within-group analysis, we used Hotelling's T-square test and a t-test with Bonferroni adjustment to evaluate the significance of the differences between the test and the control groups. We used the average values in the control groups as the base levels in these tests. After we accounted for better model performance in the experimental period (for both the test and the control groups), our field experiment results indicate that a customer-focused sales campaign leads to a significant (at $\alpha < .01$) improvement in revenues (\$1,376) (i.e., an improvement in effectiveness), reduction in marketing investment (–\$2,247) and level of contacts required to induce a purchase ($12 - 7 = 5$) (i.e., an improvement in efficiency), and improvement in profits (\$3,630) and ROI (1.9).

TABLE 5
Field Experiment Results

A: Comparison Within Test and Control Groups (High-Tech)[a]

	Test Group: Customer-Focused Sales Campaign		Control Group: Product-Focused Sales Campaign	
Financial Metrics				
Revenue ($)	1,828***	(15,710)[b]	898*	(15,263)
Marketing investment ($)	–1,906**	(6,191)	10	(6,570)
Number of contacts before purchase	–4**	(11)	1	(11)
Profits ($)	3,734***	(9,519)	890*	(8,694)
ROI	2***	(1.5)	.13	(1.3)
Relational Metrics[c]				
Firm understands my needs	3.32***	(5.17)	–.10	(5.12)
Firm provides good value	2.32**	(5.77)	.10	(5.32)
Likely to repurchase from the firm	3.64***	(5.25)	.63	(5.30)
Likely to recommend the firm	3.10***	(5.09)	.27	(5.61)

B: Difference Between Test and Control Groups for Each Purchase Possibility (High-Tech)

	Financial Metrics[d]			
Purchase Possibility	**Revenue ($)**	**Cost ($)**	**Profits ($)**	**ROI**
Product 1	1,186	–1,872	3,810	2.1
Product 2	1,332	–2,023	3,636	2.2
Product 3	1,280	–2,475	3,522	1.9
Products 1 and 2	1,167	–2,137	3,885	1.8
Products 1 and 3	1,500	–2,405	3,530	1.5
Products 2 and 3	1,540	–2,505	3,501	1.9
Products 1, 2, and 3	1,629	–2,310	3,525	1.9
Average	1,376	–2,247	3,630	1.9
	Relational Metrics			
	Firm Understands Needs	**Firm Provides Good Value**	**Likely to Repurchase from the Firm**	**Likely to Recommend the Firm**
Product 1	3.48	2.05	2.49	3.17
Product 2	3.15	2.01	2.82	2.36
Product 3	2.89	2.02	3.24	2.46
Products 1 and 2	3.64	2.03	3.90	3.51
Products 1 and 3	4.43	2.15	3.08	2.45
Products 2 and 3	3.15	2.32	2.48	2.82
Products 1, 2, and 3	3.16	3.02	3.10	3.06
Average	3.41	2.23	3.01	2.83

*Significant at $\alpha = .10$.
**Significant at $\alpha = .05$.
***Significant at $\alpha = .01$.
[a]The reported values have been scaled by an arbitrary constant for confidentiality reasons. The reported values are increases or decreases in the year of the experiment compared with the previous year per customer and are cell means.
[b]Values in parentheses represent the levels in the preexperimental period.
[c]The relational metrics are measured on a ten-point interval scale, where 10 represents "completely agree" and 1 represents "completely disagree."
[d]The reported values are unit values per customer during the experiment year and are cell medians and have been scaled by an arbitrary constant for confidentiality reasons. All the reported values are significant at $\alpha = .01$ unless otherwise specified.

We assess the impact of contacting customers only when they are expected to purchase (i.e., using the predicted purchase-timing information) on the ROI of the sales campaign from the difference between the test and the control groups when there are purchases from only one product category (purchase possibility of Product 1, 2, or 3 in Table 5, Panel B). Under these scenarios, the additional revenue per customer in the test group is approximately $1,264, and the marketing investment per customer is lower by approximately $2,123 in the test group than in the control group. Compared with the overall average across purchase scenarios, our results indicate that predicting purchase timing has a greater impact on reducing marketing investment than increasing revenue. Improvement in all the four relational metrics is lower when there are purchases from only one product category compared with the average across all purchase possibilities. This is possible because customers who purchased more than one product category have had a chance to experience the better value the firm provides through customizing the product offering to their requirements and also the better timing of its messages. Customers who purchased from only one product category experienced only partial value from a customer-focused sales campaign (i.e., the better timing of their messages).

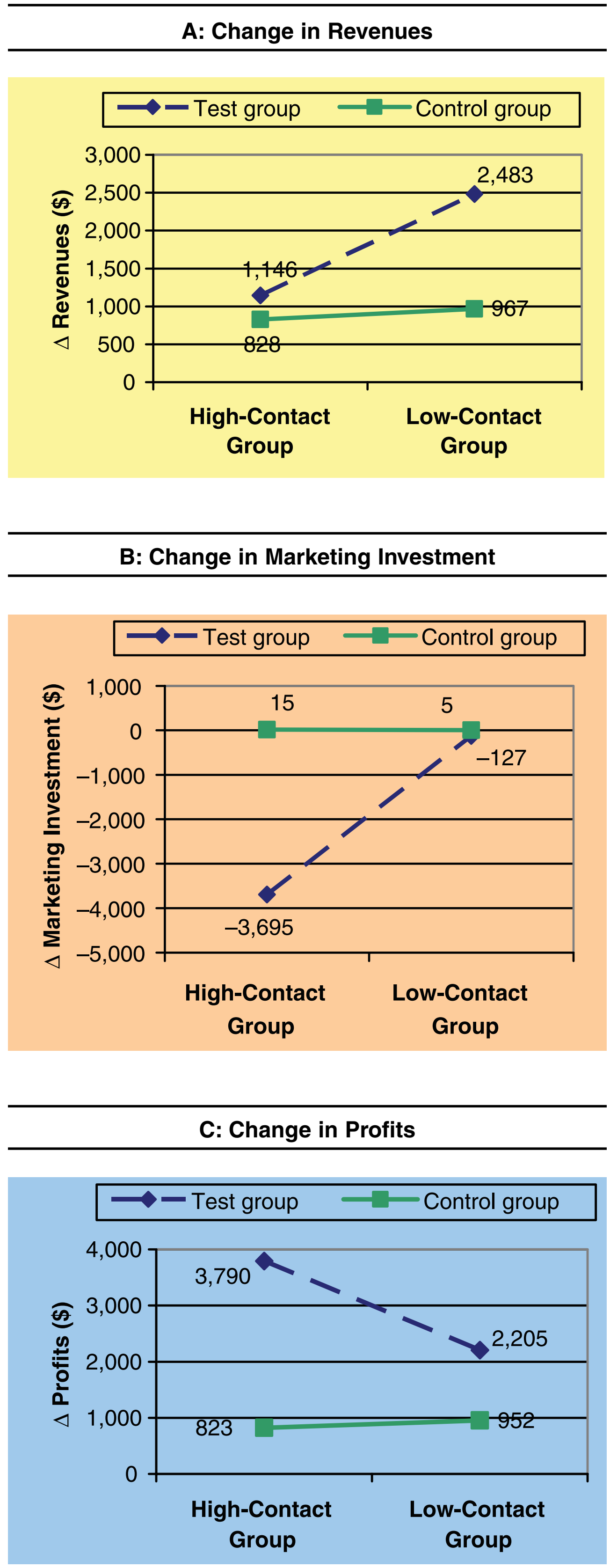
We acknowledge that in the scenarios in which customers purchased more of the one product, the better performance of the test group is due to the coordination of sales across product silos and the better timing of the sales calls. However, the coordination of sales calls across products and the better timing of sales calls result from an overarching customer focus. Thus far, the results from the field experiment indicate that customer-focused sales campaigns are more effective and efficient than product-focused sales campaigns, in support of H_{1a} and H_{1b}.

We adopt the same procedure used for the financial metrics to assess the impact of a customer-focused sales campaign on the relational metrics. Hotelling's T-square test revealed that the test and control groups were not significantly different from each other in the preexperimental period. However, the test and control groups were significantly different from each other in the experimental period. A t-test with Bonferroni adjusted revealed that in the experimental period, customers in the test group perceived an improvement in all the relational metrics from the preexperimental period. Specifically, the customers in the test group believed that the firm better understood their needs (3.32, $\alpha < .001$) and provided better value (2.32, $\alpha < .01$) in the experimental period than in the preexperimental period. Furthermore, the customers in the test group indicated that they were more likely to repurchase from the firm (3.64, $\alpha < .01$) and more likely to recommend the firm (3.10, $\alpha < .01$) in the experimental period than in the preexperimental period.

As a result of the nature of our experimental design, any improvement in the relational metrics from the preexperimental period for the test group is attributable to both better model performance and a customer-focused alignment of the sales force. Similar to the financial metrics, we compare the difference in the relational metrics between the test and the control groups in the experimental period (see Table 5, Panel B) to obtain a measure of the improvement in relationship quality that is attributable solely to the customer-focused alignment of the sales force. The results in Table 5, Panel B, indicate that a substantial portion of the improvement in all the four relational metrics for the test group is attributable to a customer-focused alignment of the sales force, in support of H_{1c}.

Source of ROI improvement effectiveness and efficiency gains. The main effects not only demonstrate the general superiority of the proposed customer-focused model but also show that, on average, there are both sales gains and cost-reduction gains. To test H_{2a} and H_{2b}, we conducted a split-sample analysis. We median-split the entire sample on the basis of the number of past customer contacts (from 2000 until the end of 2005). The dependent variable is the dollar change in the respective variables, not the absolute values. The results of this subgroup analysis appear in Figure 4, Panels A–C.

FIGURE 4
Changes in the Experimental Versus Preexperimental Period



Notes: All figures are in dollars per customer.

With respect to revenues (Figure 4, Panel A), there is a significant, positive change for the low-contact group but not for the high-contact group. Thus, the model improves the effectiveness of targeting—in particular, for customers with upside potential. Recall that the absolute revenues for the high-contact group are much higher than those for the low-contact group. Still, the absolute change in revenues is much higher for the low-contact group.

With respect to marketing investment (Figure 4, Panel B), the savings for the high-contact group are substantial, whereas there is virtually the same expenditure for the low-contact group. Thus, the model improves efficiency of targeting—in particular, for the customers with little upside potential (i.e., the current high-contact customers). Thus, an approximately similar absolute value of revenues is generated at a much lower level of investment (for the high-contact group, on average, –$3,695 per customer; Figure 4, Panel B). For the low-contact group, significantly higher revenue (on average, +$2,483 per customer; Figure 4, Panel A) is generated at investments that are similar to the previous levels.

With respect to profits (Figure 4, Panel C), the ensuing outcome is that the test group results in positive profit changes for both high- and low-contact customers. However, we find that beneath this positive aggregate-level outcome, the subgroup analysis provides further relevant diagnostic insight into the high-contact and low-contact groups. As we already stated, a potential conclusion from this analysis could be that the high-contact group is exploited in terms of revenues. Thus, the greatest benefit for the organization lies in optimizing its spending and investments to enable this level of revenue extraction. In contrast, through the optimization of type and timing of contacts, the low-contact group provides the firm further revenue growth with a similar level of contact resource spending. Thus, this type of analysis provides direct process insight, which can be used at the managerial decision-making level. For example, ceteris paribus, it gives greater confidence to sales managers to decrease their marketing investment, which they intuitively have a difficult time accomplishing.

Marginal revenue and marginal cost can be measured as annual change in revenues and cost, respectively. Based on this definition, our analysis of effectiveness and efficiency improvements from customer-focused sales campaigns also provides insight into the alignment of marginal revenues and marginal cost in the sales campaign. From Figure 4, Panels A and B, we observe that in the test group, customers with low historic marketing investments have higher marginal cost than customers with high historic marketing investments. Similar to the distribution of marginal costs, customers with low historic marketing investments also have higher marginal revenues than customers with high historic marketing investments. However, for the product-focused sales campaigns, customers with low historic marketing investments have lower marginal cost than customers with high historic marketing investments. However, the marginal revenues are higher for customers with low historic marketing investments than for customers with high historic marketing investments. Therefore, we observe that the customer-focused sales campaigns lead to a better alignment of marginal revenues and marginal cost than product-focused sales campaigns.

Field Experiment 2: Generalizing the Findings

We conducted the second field experiment in the telecommunications industry. Here, the firm markets its services to both B2B and business-to-consumer (B2C) segments. We conducted the experiment for the B2B segment in the following manner: We selected B2B customers that belonged to the midmarket category for the study. These midmarket customers have annual revenues of more than $50 million and have between 100 and 999 employees. The telecommunications firm markets the following services: (S1) local telephone service, domestic long distance, and international long distance; (S2) wireless; (S3) Internet; and (S4) satellite communication services. The B2B customers were in the market at some intervals for each of these services. The firm has a sales force that contacts these customers to sell the services. We used the product/service purchase and attitudinal data for a period of three years—January 2002 to December 2004—to estimate the choice and timing models. Then, we validated the model accuracy by comparing it with the actual data from 2005. We used a sample of 480 customers for this study. Compared with the other models we discussed previously, our proposed model produced the lowest aggregate log–conditional predictive ordinate (aggregate log-CPO) of –4965. Furthermore, the predictive accuracy for each purchase of services was as follows: S1 (77%), S2 (80%), S3 (72%), and S4 (74%).[7] The variables that predicted the choice and the timing were similar to those of the high-tech product category.

For this field study, we split the sample into test and control groups on the basis of matched-pair comparisons. We contacted the test-group customers (n = 240) using a customer-focused sales campaign, and we contacted the control-group customers (n = 240) using a product-focused sales campaign. These 480 customers were served by 436 salespeople. For a particular service category, more than one customer was assigned to a salesperson. Customers could also have many salespeople assigned to them, such that each salesperson was responsible for a service category. We conducted this field experiment in 2006. The results appear in Table 6.

In the preexperimental period, the customers in the test and control groups did not show any significant differences in terms of the metrics used in this study. Similar to the previous findings, the revenue and profits increased by approximately $670 between the preexperimental and the experimental periods for the control group. However, the revenue increased more than 2.5 times ($1,702), and profits increased more than 4 times ($2,681) for the test group. Consequently, the ROI for the test group doubled from the preexperimental period, but there was no significant improvement in the ROI for the control group. Similar to the previous findings, both the financial and the relational

[7]The results of the model estimation for this service category are available on request.

TABLE 6
Comparison Within Test and Control Groups (Telecommunications)[a]

	Test Group: Customer-Focused Sales Campaign		Control Group: Product-Focused Sales Campaign	
Financial Metrics				
Revenue ($)	1,702***	(13,181)[b]	671*	(13,252)
Marketing investment ($)	–2,190**	(5,288)	30	(5,206)
Number of contacts before purchase	–6**	(17)	2	(18)
Profits ($)	2,681***	(7,401)	654*	(7,284)
ROI	1.9***	(1.4)	.11	(1.4)
Relational Metrics[c]				
Firm understands my needs	3.58***	(4.92)	–.09	(4.96)
Firm provides good value	2.74**	(5.34)	.12	(5.40)
Likely to repurchase from the firm	3.52***	(5.42)	.38	(5.36)
Likely to recommend the firm	3.23***	(5.21)	.42	(5.47)

*Significant at α = .10.
**Significant at α = .05.
***Significant at α = .01.
[a]The reported values have been scaled by an arbitrary constant for confidentiality reasons. The reported values are increases or decreases in the year of the experiment compared with the previous year per customer and are cell means.
[b]Values in parentheses represent the levels in the preexperimental period.
[c]The relational metrics are measured on a ten-point interval scale, where 10 represents "completely agree" and 1 represents "completely disagree."

metrics showed a significant gain. The relational metrics increased by an average of approximately 3.3 points (on a ten-point scale), or by more than 63%, compared with the preexperimental period. The differences between the test- and the control-group customers on likelihood to repurchase (3.14) and likelihood to recommend (2.81) were higher in this experiment than in the high-tech product category. As testimony to this, the telecommunications firm has implemented a referral program to take advantage of this recommendation effect.

Discussion and Implications

Our study shows that the promise of a customer focus, at least in customer-facing activities, such as sales calls, can be realized by (1) understanding each customer's needs, (2) customizing the firm's offerings to customer needs, and (3) coordinating sales calls across product silos to deliver a consistent and single message to the customer. A joint-timing and category choice model can enable firms to obtain a better understanding of a customer's needs across the product portfolio. Our results add to the literature that provides empirical evidence that marketing decision support models, especially choice models, can improve the ROI of marketing actions (e.g., Gensch 1984).

However, a better understanding of customer needs alone does not guarantee financial returns or develop relationship quality. The success of a customer-focused sales campaign depends on the firm translating the better understanding of customer needs into coordinated sales calls that deliver a consistent and single message to the consumers.

The two field experiments in the high-technology and the telecommunications industries show that impressive financial returns can be obtained from adopting a customer-focused sales campaign. For example, in the high-technology industry, the average investment per customer (including both the test- and the control-group customers) in the postexperimental period was $5,000. For this investment, the test-group customers provided $13,253 in profits, whereas the control group provided only $9,584 in profits. The test-group customers who were exposed to a customer-focused sales campaign provided more than $1 million in total incremental profits compared with the control-group customers who were exposed to a product-focused sales campaign. When projected to the entire customer base of approximately 10,000 customers, adoption of the customer-focused sales campaign is expected to provide incremental profits of more than $36 million and total profits of more than $132 million.

For a restricted set of scenarios (i.e., when customers purchase only one product category), our results imply that in addition to the firm, customers gain from a customer-focused sales campaign by avoiding the plethora of marketing communication and sales calls. This is one of the potential causes for a significant improvement in the relationship quality between customers and the firm when a customer-focused sales campaign is implemented. From the field experiments, we find that customers who were exposed to the customer-focused sales campaign believed that the firm understood their needs better and provided better value than the customers who were exposed to a product-focused sales campaign. Compared with customers exposed to a product-focused sales campaign, customers exposed to a customer-focused sales campaign were also more likely to repurchase from the firm and to recommend the firm.

However, improvements in effectiveness and efficiency of sales calls are not distributed uniformly across customers. The customer-focused sales campaign resulted in a higher increase in revenues; in other words, it increased the effectiveness of sales calls among customers who were contacted infrequently under a product-focused sales campaign. However, the cost of marketing decreased without any decrease in revenues; that is, we observed an improvement in the efficiency of sales calls among customers who were contacted frequently under a product-focused sales campaign. This implies that adopting a customer-focused sales campaign enables firms to uncover ineffective marketing resource allocations and thus helps firms reduce their required marketing input without sacrificing the top-line results.

This research contributes to business practice by providing academic case studies (through the model and the field experiments) in the area of customer relationship management implementation. The modeling framework and the sales coordination based on the model's outputs used in this study can form a template for organizations that adopt a customer-focused sales campaign. The returns observed from the field experiment can support other top management initiatives that are intended to help develop a customer-centric organization, such as changing an organization's structure and culture. Thus, we provide the following generalizations that firms can take from our study:

- Among large B2B firms that offer products in multiple categories, a customer-focused sales campaign can improve the relationship quality between firms and customers and can increase a firm's ROI.
- Improvement in the effectiveness and efficiency of sales calls from adopting a customer-focused sales campaign does not need to be distributed equally across customers.

Limitations and Further Research

Our proposed model framework is best applied to firms that sell multiple products and/or services and to firms that can allocate their sales force resources at the individual customer level. This is typically the case in most B2B settings but not necessarily in many B2C situations. The generalizability of the findings from our study is restricted to medium-sized and large multinational firms in the B2B settings. Because most sales campaigns are implemented in B2B environments, our experiments provide a fair assessment of our research objective. Further research should explore the potential for customer-focused sales campaigns in smaller companies and the potential for customer-focused direct marketing in B2C settings. Although in principle the model is still applicable to mass marketing, its degree of insight diminishes. The methodological and computational effort that is necessary is not small. Likewise, the analytical and modeling capabilities of the organization need to be firmly established or procured externally.

In our model framework, we chose not to accommodate quantity purchased for two reasons. First, the way the focal firm makes the sales force allocation decision for the group of customers in the study is based on who is likely to buy and not on how much they are going to buy. This is because all the customers that participated in the experiment are large in terms of number of employees. The variation in revenue among these customers arises from the number of different product categories they buy from the firm and the frequency at which they buy. The customers do not vary much with regard to their order size per product category. This is evident from the empirical distribution of the quantity of purchases of these customers. Specifically, in the pre-experimental periods, for a given purchase occasion, the average quantity of purchases across firms is 2.3 with a standard deviation of .2. However, we acknowledge that our model framework needs to be suitably modified to model purchase quantity in scenarios in which purchase quantity is an important determinant of customer profitability.

It is reasonable to expect that customer responsiveness may vary across salespeople who are responsible for the different products. However, a restriction of the customer database this firm uses is that the number of sales calls directed toward each customer is recorded, but the description of each sales call (e.g., the identity of the salesperson, the product category that is targeted in the sales call) is not identified. Therefore, we cannot disaggregate the number of sales calls for a customer at the product level. Although model performance would improve from including the level of sales calls for each product category, we believe that the substantive results from the field experiment would not change, because customers in both the test and the control groups were targeted on the basis of model predictions that did not include product-level sales-call information.

The model framework we used in this study does not account for possible correlations between the level of marketing touches directed toward a customer and the customer's response to them (Manchanda, Rossi, and Chintagunta 2004). However, we do not expect the substantive results of our field experiment to change, because customers in both the test group and the control group were targeted on the basis of models that did not allow for the correlation between the level of marketing touches and customer responsiveness. However, we expect that the model structure would change if we were to accommodate the correlation between the level of marketing touches and customer responsiveness. The manipulation of timing of sales calls in our field experiments is also a manipulation of team versus individual selling. Thus, we cannot assess the pure effects of team selling and of timing sales calls to coincide with customer needs on customer profits. Further research that evaluates the consequence of team selling would provide a worthwhile contribution to the literature.

Appendix
Model Comparison

In-Sample Fit

We use the aggregate log-CPO to evaluate the in-sample fit (Gelfand and Dey 1994) of Models 1–4.[8] Similar to the log-likelihood, a higher value of the aggregate log-CPO is interpreted as a better model fit. Table A1 provides the descriptions of Model 1–4. Model 1 is similar to the "next-product-to-buy" model that Knott, Hayes, and Neslin

[8]We obtained the log-likelihood contribution of product category choice, which is necessary for calculating the aggregate log-CPO, from the proportion of times the repeated random samples of the latent utility, U_{ijt}, from Equation 4 agreed with the constraints imposed by the observed choice, y_{ijt}, from Equation 3. Such a method provided similar results to other simulation-based integration techniques used to calculate the log-likelihood contribution in multivariate probit models (Chib and Greenberg 1998).

(2002) propose, Model 2 is similar to the model that Kumar, Venkatesan, and Reinartz (2006) propose, Model 3 is similar to several models in the scanner panel literature (Seetharaman et al. 2005), and Model 4 is the proposed model. Table A1 shows that Model 4 provides the best in-sample fit to the data (aggregate log-CPO = –5641), followed by Model 3 (aggregate log-CPO = –6105), Model 2 (aggregate log-CPO = –6307), and Model 1 (aggregate log-CPO = –8792). The aggregate log-CPO measures indicate support for incorporating customer heterogeneity (the aggregate log-CPO for Model 1 is higher than the aggregate log-CPO for Model 3) and for a joint model of purchase timing and product category choice (the aggregate log-CPO for Model 3 is higher than the aggregate log-CPO for Model 4).

Predictive Accuracy

We use the posterior distribution of the parameters obtained from the calibration sample to simulate the predictive distribution of hazard rates for the customers in the holdout sample. We obtained the first purchase time for a customer from the inverse cumulative distribution function derived on the basis of the hazard function in Equation 2. We use the predicted purchase time in the utility function for product category choice (Equation 3) to obtain the predicted choice probabilities for each product category. We then augment the predicted purchase time and choice probability to the data and predict the customer's second purchase time and the corresponding product category choice. We repeat this process until a customer's predicted purchase time for the next purchase is beyond one year in the holdout sample (i.e., the predicted purchase time exceeds December 31, 2004). We use a one-year interval because the field experiment is also intended to be conducted over one year. For each customer, we then classify the predicted purchase-timing and category choice probabilities into 12 months.

A customer is predicted to purchase product category j in a particular quarter—for example, Month 1—if the customer is predicted to purchase product category j at least once in that month. We then calculate a classification matrix of the predicted versus the observed product choices in each quarter for the various models. We calculate the predictive accuracy of the models in this way because it integrates the predictions of both purchase timing and category choice. Furthermore, this measure of predictive accuracy closely reflects how the model is intended to be used in the field experiment.

In Table A2, we present the ratio of predicted purchasers to the observed number of purchasers in each quarter in the first quarter of the holdout period. Table A2 shows that the better in-sample fit also translates into better predictive accuracy for Model 4. The percentage of correct predictions of buyers for Model 4 ranges from 83% to 76% for products A1–A3, and in the majority of the scenarios, it is more accurate than the other models. Model 2 provides more accurate predictions than Model 1 for all the product categories. This implies that the joint estimation of purchase timing and product choice improves model predictions for all the product categories.

TABLE A1
Model Comparison

Model Description	Aggregate Log-CPO
Model 1: Independent model with homogeneous parameters	–8792
Model 2: Joint model with homogeneous parameters	–6307
Model 3: Independent model with heterogeneous parameters	–6105
Model 4: Joint model with heterogeneous parameters (proposed model)	–5641

TABLE A2
Comparison of Predictive Accuracy

	Quarter 1[a]		
Product Category	A1	A2	A3
Model 4: Joint model with heterogeneous coefficients (proposed model)	79%	76%	83%
Model 3: Independent model with heterogeneous coefficients	77%	67%	73%
Model 2: Joint model with homogeneous coefficients	72%	66%	69%
Model 1: Independent model with homogeneous coefficients	56%	55%	62%

[a]Predictive accuracy of the models were similar in Quarters 2–4.

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