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Relatively few retailers include metrics such as product returns in their customer selection and optimal resource allocation algorithms when measuring and maximizing customer value. Even when they do include this metric, increases in product return behavior are usually considered merely an economic cost that must be managed by decreasing the marketing resource allocations toward the customers making the returns. However, recent research has suggested that satisfactory product return experiences can actually benefit firms by lowering the customer's perceived risk of current and future purchases. To better understand the role of this perceived risk in the firm–customer exchange process, the authors conduct a large-scale customer selection and optimal resource allocation field experiment with 26,000 customers from an online retailer over six months. They find that the firm is able to increase both its short- and long-term profits when accounting for the perceived risk related to product returns in addition to managing product return costs. Furthermore, the authors find that by including this risk, rather than simply implementing traditional customer lifetime value–based models generically, the firm can target more profitable customers.

Keywords: customer perceived risk, product returns, field experiment, optimal resource allocation, customer lifetime value

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Perceived Risk, Product Returns, and Optimal Resource Allocation: Evidence from a Field Experiment

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When managers make decisions on customer selection and marketing resource allocation, the main objective is often profit maximization. These decisions are based on the premise that the profit objective function that firms try to maximize accurately represents the firm–customer exchange process. However, it is often the case that the objective functions that firms use for customer selection and optimal resource allocation only consider the dynamics between marketing efforts and customer purchase behavior, frequently ignoring customer product return behavior or treating it only as a cost that must be managed. This notion is supported by the qualitative evidence we gathered from a survey of 56 retailers that suggested that less than half of them (44.5%) include metrics such as product returns in their customer selection and optimal resource allocation algorithms when measuring and maximizing customer

value. We provide a summary of the survey results in Table 1 and full details of the survey in Web Appendix A.

Furthermore, we find that even when firms do include product returns as a metric that drives customer selection and optimal resource allocation decisions, the increases in a customer's product return behavior often result in subsequent decreases in the allocation of future marketing resources to that customer. In other words, firms seem to be taking the view that product returns are merely an economic cost to be managed and avoided rather than the view that customer product return behaviors have the potential to provide value by lowering the customer's perceived risk of purchase.

Product returns are no small part of the firm–customer exchange process: indeed, they currently cost firms approximately \$100 billion annually in reverse logistics, an average drain of roughly 3.8% for every retailer (Blanchard 2007). Moreover, this figure is likely conservative because the cost of reverse logistics often does not include the value of lost profits from returned items, which can be substantial, even when partially mitigated by reselling durable products at a lower cost through a secondary channel (Shulman and Coughlan 2007).

Customers might return products because of low product quality, in which case, more investments should be focused on improving product quality to reduce product returns. However, a recent survey has shown that the top two reasons customers cited for returning products were “No trouble found” and “Buyer's remorse,” which accounted for approximately 95% of the responses (Lawton 2008). This finding suggests that product returns are a necessary part of the exchange process because they do not frequently result from product quality issues. Instead, product returns seem to be primarily driven by a lack of fit, which the consumer realizes only after purchase. However, is it truly necessary to manage customers on the basis of their individual product return behavior?

One solution to this problem is that managers could choose to write off their losses from product returns and continue to manage customers on the basis of only their purchase behavior and responsiveness to marketing initiatives, as a traditional customer profitability framework would suggest (e.g., Venkatesan and Kumar 2004). However, it is not clear that this solution is ideal to increase firm profitability. Although product returns do have a direct negative impact on firm profitability through an increase in logistics costs and losses in margins, research has suggested that they can create long-term value through increases in future purchase behavior (Petersen and Kumar 2009). Ignoring product

return behavior would only limit a firm's ability to manage customers to maximize profitability.

Another solution to this problem could be to introduce disincentives to make it less desirable for customers to return products. However, research has found that strict product return policies tend to increase customer purchase risk and decrease the willingness of customers to purchase in the first place (Bechwati and Siegal 2005). This is not necessarily a significant problem if only a small percentage of customers return the majority of products. However, we found that in many instances, a high percentage of customers across multiple firms return products, indicating that this issue must be addressed across all customers. We surveyed managers from three firms operating in different industries and found that the percentage of customers who returned a product during their relationship with the firm at the time of the survey was relatively high. For a catalog apparel retailer, 70% of customers returned a product; for a high-tech business-to-business firm, 64% of customers returned a product; and for a general merchandise retailer, 75% of customers returned a product. This means that approximately two out of every three customers (or more) are likely to return a product in their lifetime with the firm (for details, see Web Appendix A). Thus, offering disincentives to all customers to return products is likely to affect the short- and long-term purchase behavior and profitability of a significant proportion of the entire customer base.

To better understand the role of the customer's product return–related perceived risk in the firm–customer exchange process, we develop and empirically test a conceptual framework that represents the entire process, comprising firm-initiated marketing communications, customer buying behavior, and customer product return behavior. The theoretical framework that guides our conceptual model is grounded in the literature on the role of perceived risk in consumer decision making. This customer perceived risk related to product returns can influence pre- and postpurchase decisions (Bechwati and Siegal 2005), customer willingness to purchase at a given price (Anderson, Hansen, and Simester 2009), perceptions of return policy leniency (Wood 2001), and consumer responsiveness to marketing efforts (Petersen and Kumar 2009). Thus, we expect that treating product returns as merely an economic cost limits the firm's ability to understand both the differences in ongoing customer behavior (both future purchase and product return behavior) and responsiveness to marketing efforts, resulting in a significant decrease in a firm's ability to maximize its profitability.

Table 1
NUMBER OF RETAILERS WHO USE A GIVEN CUSTOMER SELECTION AND OPTIMAL RESOURCE ALLOCATION STRATEGY

<i>Customer Value Measure</i>	<i>Resource Allocation Strategy</i>			
	<i>No Formal Allocation Model</i>	<i>Based on Rank Order</i>	<i>Use an Optimal Resource Allocation Algorithm</i>	
No formal measure	2	0	0	2 (3.5%)
RFM/past customer value	11	12	0	23 (41%)
CLV without product returns	5	5	1	11 (20%)
CLV with net buying	10	7	1	18 (32%)
CLV with product returns	0	0	2	2 (3.5%)
	28 (50%)	24 (43%)	4 (7%)	56

To determine the extent to which product returns can provide value to the firm, we conducted a large-scale customer selection and optimal resource allocation field experiment with 26,000 customers from an online retailer over six months, a key contribution of this study. Few other studies have actually used field experiments to conduct customer selection and optimal resource allocation; both were with business-to-business high-tech firms (Kumar et al. 2008; Kumar, Venkatesan, and Reinartz 2008). The goal of this field experiment was to determine whether improvements in understanding the ongoing relationships between firms and customers can yield profits in the future. After the field experiment, we found that the firm was able to increase profit in both the short run (six-month profit increased by more than 45% per customer on average) and the long run (actual profit over three years increased by more than 29% per customer on average) when accounting for product return costs and a customer's perceived risk (proposed model). These findings suggest that the firm's current strategy of ignoring a customer's perceived risk (i.e., a recency, frequency, and monetary value [RFM]–based strategy, with product returns managed as a cost), as well as the strategies of the several other firms from our qualitative study (as Table 1 summarizes), is suboptimal (represented by two benchmark models).

Furthermore, when we used the proposed model to determine how resources “should” have been allocated for the other groups of customers in our study, we found that accounting for a customer's perceived risk of purchasing by including product returns led to significantly different patterns of customer selection and marketing resource allocation; that is, the correlations between the customer selection strategies were weak at best. This finding suggests that understanding how product returns change a customer's perceived risk should play a significant role in customer selection and optimal resource allocation decisions. Thus, ignoring a customer's perceived risk changes not only the optimal amount of marketing resources that each customer should receive to maximize profitability but also which customers the firm should target with marketing efforts.

CUSTOMER PERCEIVED RISK AND PRODUCT RETURNS

The concept of perceived risk is often defined in terms of the consumer's perceptions of the uncertainty and adverse consequences of buying a product or service (Dowling and Staelin 1994). Furthermore, when consumers make decisions to purchase a good or service, their perceived risk is a function of both the immediate situational factors (e.g., price, service level) and the longer-term implications of purchase, including the potential benefits and sacrifices (Sweeney, Soutar, and Johnson 1999). In the short run, a key risk the customer faces is whether the product provides a sufficient level of postpurchase utility so that a decision can be made to keep, rather than return, the product (Anderson, Hansen, and Simester 2009). In the longer run, a key risk the customer faces is whether future purchases will have a high enough postpurchase utility and, if not, whether those future purchases can be returned to reduce purchase risk. Thus, a customer's perceived risk can have an impact on that customer's behavior during prepurchase, purchase,

and postpurchase, requiring firms to manage customer perceptions throughout the firm–customer exchange process (Petersen and Anderson 2013).

Prepurchase

Before a purchase decision is even made, consumers often use prior interactions and information provided by the firm (e.g., product return policies) to inform their decision to make a purchase. For example, research has shown that customers often perceive a strict product return policy as a potential sign of lower product quality because the firm wants to increase the burden of the return cost to the customer with the intent of influencing the customer not to return the product (Wood 2001). Thus, although it is the case that increasing product return policy leniency often leads to an increase in product returns (Davis, Gerstner, and Hagerty 1995), customers may choose not to purchase in the first place if they perceive the risk of purchase as too high.

Purchase

Research has shown that perceived risk is a key factor when a customer makes a decision to purchase. Sweeney, Soutar, and Johnson (1999) find that lowering the perceived financial risk increases the customer's perception of value for money, which increases the customer's willingness to buy. Indeed, the authors find that lowering the perceived financial risk has the highest impact on increasing perceived value for the money. Furthermore, Anderson, Hansen, and Simester (2009) find that when faced with a purchase decision, customers assign a certain value to the ability to return a product, which is embedded in the price they are willing to pay. In this case, the lower the customer's perceived risks of purchase due to a more lenient product return policy, the more likely he or she is to decide to purchase the product.

Postpurchase

Even after purchase occurs, customers are often faced with information that affects their level of perceived risk. For example, customers may receive disconfirming information postpurchase that may cause them to want to return the product (Bechwati and Siegal 2005). Moreover, research has shown that the customers who are forced to pay for their own product return (i.e., fee-based return) tend to decrease their postreturn spending by approximately 75%–100%, whereas the customers who have free-based product returns tend to increase their postreturn spending by approximately 158%–457% (Bower and Maxham 2012). However, we note that this increase in postreturn purchases includes the purchase of replacement products, suggesting that the gains from free-based returns are still significant, albeit slightly more conservative. Furthermore, increasing the hassle to return products also has been shown to affect other customer behaviors beyond purchase, including customer referrals (Petersen and Kumar 2010).

Although it is the case that product returns provide a direct cost to firms through reverse logistics costs and losses in profit, the current research suggests that both the ability to return products and experience returning products lower customers' perceived risk, leading to an increase in their commitment and trust with a firm (Selnes 1998) and increasing the probability of future purchase.

A FIELD EXPERIMENT

Purpose

The goals of this field experiment are to (1) understand the role that a customer's perceived risk and product return behavior play in the firm–customer exchange process and (2) quantify the value firms can derive by integrating perceived risk and customer product return behavior into their customer selection and optimal resource allocation decisions. We do so by creating several objective functions for customer selection and optimal resource allocation, which are built on the foundational customer lifetime value (CLV) frameworks from the marketing literature. Furthermore, we run a six-month field experiment with an actual firm to quantify the impact of integrating a customer's perceived risk and product return behavior into a CLV framework relative to a control group and several benchmark models. At the end of the field experiment, we observe which resource allocation algorithm is able to maximize profit over a six-month time period (i.e., the short run).

Design

This field experiment uses a classical experimental design with a random set of 26,000 customers from the focal firm of the study. First, the 26,000 customers were randomly segmented into one of the following five groups¹ (with 5,200 customers per group). The groups were selected to represent the common ways retailers measure customer value (see Table 1).

1. Control group: Receives no marketing effort (no formal measure),
2. Firm strategy group: Targeted using the focal firm's RFM-based strategy (RFM),
3. Benchmark Model 1 group: Targeted using a CLV-based² objective function without considering product returns (CLV without product returns),
4. Benchmark Model 2 group: Targeted using a CLV-based objective function with consideration of the cost of product returns (CLV with net buying), and
5. Proposed model group: Targeted using a CLV-based objective function with a consideration of perceived risk and the cost of product returns (CLV with product returns).

Table 2 depicts the design of this field experiment using the notation demonstrated by Shadish, Cook, and Campbell (2002), where O represents a point of measurement and X represents when a treatment was applied. Here, the measurement refers to the value of a customer and the treatment refers to the marketing resources spent on that customer from a given group. Each of the customers from the four noncontrol groups were allocated marketing resources—in this case, e-mails and catalogs—over a period of three months (from May to July 2009). The amount of marketing

¹We acknowledge that there are many alternative benchmark models that we could have used to compare with the proposed model. For example, we could have tested an option in which all customers in a group received all mailings. However, this option, as well as many other benchmark model options, was not palatable to the firm's managers. Thus, we only focus on the results of the five groups described in the field experiment.

²The CLV-based objective function measures the profit (revenue – transaction costs) from purchases as well as when applicable profit is lost from product returns (revenue lost + transaction costs).

Table 2
EXPERIMENTAL DESIGN OF FIELD EXPERIMENT

Measurement 1 (May 2009)	Treatment (May–July 2009)	Observation (August– October 2009)	Measurement 2 (October 2009)
O _{1a}			O _{1b}
O _{2a}	x ₂		O _{2b}
O _{3a}	x ₃		O _{3b}
O _{4a}	x ₄		O _{4b}
O _{5a}	x ₅		O _{5b}

Notes: O_{ia} represents the value of a customer *i*, and x_{*i*} represents the type of treatment that was applied to customer *i*.

resources allocated depended on the group in which the customer was randomly segmented. Then, we observed all the groups for an additional three months (from August to October 2009), during which no marketing resources were allocated; afterward, we took a second measurement. Note that we only optimized marketing communications to customers for three months and observed behavior for another three months (six months total) to allow for the marketing communication effects on purchases (and potentially returns) to wear out and to allow for time to observe customer product return behavior after purchases occur. Although we did not optimize the marketing communications across the entire six-month time period, we do not expect the wear-out of the marketing efforts to vary across segments in the second three months.

At the end of October 2009, we tabulated the purchase behavior, product return behavior, and marketing efforts to evaluate the impact of the five treatment conditions and quantify the short-term effects of resource allocation using each of the objective functions. In addition, we recomputed each customer's CLV at the end of October 2009 to determine whether long-term impact also resulted from the different resource allocations. Furthermore, we compared the CLV computed at the end of the field experiment with the actual profit provided by the customers from the end of October 2009 to the end of October 2012 (three years) to learn whether our prediction of CLV at the end of the experiment is close to the actual profit the customers provided.

Measurement

In this section, our goal is to describe the measurement of the objective functions that we optimize for each of the five groups in the field experiment. Because the control group receives no marketing effort from the firm, no objective function is required. For reasons of confidentiality, we cannot provide the actual objective function used by the focal firm for the firm strategy group. However, we can say that the firm strategy is based on an RFM score that also manages the cost of product returns by reducing the marketing resource allocations to customers who return products. Thus, our focus in this section is on the measurement of the two benchmark models and the proposed model.

Benchmark Model 1. Benchmark Model 1 is the foundational CLV model derived from the marketing literature (Kumar et al. 2008). A customer's CLV to a given firm is generally defined as the expected discounted future profit from a customer. This discounted future profit is constructed using three pieces of information: (1) the expected

stream of profit from purchases, (2) the expected costs incurred by the firm (often only marketing costs), and (3) the discount rate (or cost of capital). This model does not account for the customer's perceived risk related to product returns or the cost of product returns.

Here, the objective function captures the three pieces of information for the CLV objective function in the following way. First, $\pi_1(\text{Purchases}_{it})$ represents the expected stream of profit from purchases over time. This objective function represents both the probability of purchase and the amount conditional on purchase for a given customer i in a given time period t . Second, Marketing_{it} represents the expected marketing costs incurred by the firm. Third, r represents the discount rate.

Our only addition to this objective function for CLV from the original objective function is the prediction of the probability that a customer is active at the beginning of the field experiment window (i.e., the relationship indicator³). This will not directly affect the estimation of $\pi_1(\text{Purchases}_{it})$ or Marketing_{it} ; it only serves to account for the probability that the customer is still engaged in a relationship with the focal firm, which will directly affect the customer's short- and long-term profitability. The result is an equation with three dependent variables that need to be estimated: for $\pi_1(\text{Purchases}_{it})$, for Marketing_{it} , and for $P(\text{Relationship}_{i,t=1})$. Thus, the following equation for Benchmark Model 1 results:

$$(1) \quad \text{CLV}_{i,t=0} = P(\text{Relationship}_{i,t=1}) \times \sum_{t=1}^T \frac{\pi_1(\text{Purchases}_{it}) - \text{Marketing}_{it}}{(1+r)^t},$$

where

- $\text{CLV}_{i,t=0}$ = CLV for customer i at time $t = 0$;
- $\pi_1(\text{Purchases}_{it})$ = Expected profit from purchases by customer i in time t ;
- Marketing_{it} = Expected marketing costs spent on customer i in time t ;
- r = Discount rate (approximately 3.56% by quarter, or 15% annually);
- n = All customers in the sample for Benchmark Model 1;
- T = Number of time periods in the prediction horizon; and
- $P(\text{Relationship}_{i,t=1})$ = The probability that customer i is active in the relationship at $t = 1$.

Benchmark Model 2. The second benchmark model that we use in the field experiment is similar to the first benchmark model. The only difference is that Benchmark Model 2 explicitly accounts for the cost, but not a customer's perceived risk, of product returns in the objective function. To do so, we substitute the expected net profit from buying behavior $\pi_2(\text{NetPurchases}_{it})$ for the expected profit from purchases variable ($\pi_1[\text{Purchases}_{it}]$). Here, the net profit from buying behavior is the profit from purchases in a given time period minus the profit lost from product returns in a given time period. Without a separate measure for purchases

and returns, the objective function cannot differentiate two customers with the same profitability, even when one customer has returned products and the other has not. In this way, the objective function ignores the customer's perceived risk, which can be lowered after satisfactory product return experiences. However, unlike Benchmark Model 1, Benchmark Model 2 accounts for the costs of product returns directly in the objective function. Thus, the CLV objective function captures the three pieces of information in the following way. First, $\pi_2(\text{NetPurchases}_{it})$ represents the expected stream of profit from purchases minus the profit lost from returns over time.⁴ Second, Marketing_{it} represents the expected marketing costs incurred by the firm. Third, r represents the discount rate. Thus, we have the following equation for Benchmark Model 2:

$$(2) \quad \text{CLV}_{i,t=0} = P(\text{Relationship}_{i,t=1}) \times \sum_{t=1}^T \frac{\pi_2(\text{NetPurchases}_{it}) - \text{Marketing}_{it}}{(1+r)^t},$$

where

- $\text{CLV}_{i,t=0}$ = CLV for customer i at time $t = 0$;
- $\pi_2(\text{NetPurchases}_{it})$ = Expected profit from purchases minus profit lost and costs incurred by product returns by customer i in time t ;
- Marketing_{it} = Expected marketing costs spent on customer i in time t ;
- r = Discount rate (approximately 3.56% by quarter, or 15% annually);
- n = All customers in the sample for Benchmark Model 2;
- T = Number of time periods in the prediction horizon; and
- $P(\text{Relationship}_{i,t=1})$ = The probability that customer i is active in the relationship at $t = 1$.

Proposed model. Our proposed model separates $\pi_2(\text{NetPurchases}_{it})$ into two variables: $\pi_1(\text{Purchases}_{it})$ and $\pi_3(\text{Returns}_{it})$. As a result, the objective function captures the three pieces of information for the CLV objective function in the following way. Similar to Benchmark Model 2, we capture the cost of profits through $\pi_1(\text{Purchases}_{it}) - \pi_3(\text{Returns}_{it})$; in our proposed model we observe and model the two metrics separately. Furthermore, we include customer product return behavior as a driver of future customer purchase behavior. In this way, we capture the cost of managing product returns and the dynamics between a customer's perceived risk, product return behavior, and future purchase behavior. In other words, we can differentiate the two customers described previously who have the same overall profitability but different product return profiles. For example, suppose Customer 1 has \$150 profit from purchases and a \$50 loss in profit from product returns, and Customer 2 has \$100 profit from purchases and no loss in profit from product returns. Both customers have a net profit from purchases of \$100, but they have different return profiles. Unlike the proposed model, which splits purchases and returns, Benchmark Model 2 would not be able to differentiate the two customers in this example. Marketing_{it} represents the expected marketing costs incurred by the firm

³The relationship indicator is different from the probability that a customer will purchase in a given time period. The probability that a customer will purchase in a given time period is contained in the measure for $\pi_1(\text{Purchases}_{it})$ and is time varying. The relationship indicator represents a decision by the customer at the start of the prediction window regarding degree to which he or she wants to continue the entire relationship.

⁴Here, the profit lost from product returns includes both the revenue lost from the money returned to the customer and the cost of the reverse logistics (return shipping and restocking fees).

over time, and r represents the discount rate. Thus, we have the following equation for the proposed model:

$$(3) \quad CLV_{i,t=0} = P(\text{Relationship}_{i,t=1}) \times \sum_{t=1}^T \frac{\pi_1(\text{Purchases}_{it}) - \pi_3(\text{Returns}_{it}) - \text{Marketing}_{it}}{(1+r)^t},$$

where

- $CLV_{i,t=0}$ = CLV for customer i at time $t = 0$;
- $\pi_1(\text{Purchases}_{it})$ = Expected profit from purchases by customer i in time t ;
- $\pi_3(\text{Returns}_{it})$ = Expected profit lost and costs incurred from returns by customer i in time t ;
- Marketing_{it} = Expected marketing costs spent on customer i in time t ;
- r = Discount rate (approximately 3.56% by quarter, or 15% annually);
- n = All customers in the sample;
- T = Number of time periods in the prediction horizon; and
- $P(\text{Relationship}_{i,t=1})$ = The probability that customer i is active in the relationship at $t = 1$.

Model Development

To run the experiment, we need to compute each customer's CLV using the three models (Benchmark Model 1, Benchmark Model 2, and the proposed model). To do so, we estimate a model with the drivers of the key variables in the objective functions and ensure that the model is able to predict each customer's CLV accurately. If it can do so, the differences in the results from the field experiment can be attributed more to the treatment effects than to prediction error. To properly model each part of the three objective functions and predict each customer's CLV more accurately for the field experiment, we must accommodate four challenges common in the customer relationship management literature: (1) observed dependence between purchase and product return behavior; (2) unobserved dependence between marketing, purchases, and product returns; (3) customer relationship duration; and (4) customer heterogeneity. The following subsections elaborate on these challenges and how we overcame them.

Purchase and return decisions. We expect that a given customer wants to purchase a product only when the perceived utility of the product is greater than 0. Moreover, this perceived utility of a product can be initially greater than 0 and can be driven by current interactions with the firm (e.g., firm-initiated marketing communications) or through previous interactions with the firm (e.g., changes in a customer's perceived risk levels resulting from product return behavior). In addition, we expect that a customer is likely to keep the product only when the realized postpurchase utility remains greater than 0. Thus, the firm's expectation is that the marketing effort will increase a customer's perceived utility for a given product. The value of this marketing effort, typically in dollars or number of contacts, is censored at 0 (i.e., a firm can only choose to allocate no resources and not negative resources). A customer decides whether to purchase a product when the perceived utility for that product in a given time period is positive. Although a customer can observe several attributes of the product before purchase

(e.g., price), she does not directly observe "fit" until after the purchase occurs. Thus, when the customer observes the fit of the product postpurchase, the utility is modified either upward or downward to reflect the actual fit. In the cases in which the customer's utility of the product is modified downward to the point that the utility becomes negative, she chooses to return the product. Conversely, if the utility is still positive, she chooses to keep the product.

To accommodate this setup, we use a Type I Tobit model⁵ to estimate the profit obtained from purchases ($\pi_1[\text{Purchases}_{it}]$), the profit lost and costs incurred from product returns ($\pi_3[\text{Returns}_{it}]$), and the marketing efforts allocated toward customers (Marketing_{it}), for which we augment the data in cases in which the value of the dependent variable is either censored or unobserved. The Type I Tobit model enables us to accommodate both the probability of a purchase, return, or marketing effort occurring in a given time period and the amount of the purchase, return, or marketing effort, given that one occurs. For example, in the case of purchases, the model technically estimates the following equation: $\pi_1(\text{Purchases}_{it}) = P(\text{Purchase}_{it}) \times E(\text{Profit}_{it} | \text{Purchase}_{it} = 1)$, or the probability of purchase by customer i in time t multiplied by the profit from the purchase by customer i in time t , given that the purchase occurs (i.e., $\text{Purchase}_{it} = 1$).

Unobserved dependence between marketing, buying, and product returns. In any firm–customer exchange process, the firm's decision to initiate marketing communications, the customer's decision to purchase, and the customer's decision to return a purchased product are likely correlated. To accommodate for any issues of unobserved dependence across marketing costs, profit from purchases, and profit lost and costs incurred from product returns, we use a framework that simultaneously estimates the coefficients of Marketing_{it} , $\pi_1(\text{Purchases}_{it})$, and $\pi_3(\text{Returns}_{it})$.

Relationship duration. No customer has an infinite lifetime with a firm. Thus, it is important for firms to account for the time when a customer is likely to defect from the relationship. In the case of a contractual relationship, we observe when the customer defects from the relationship, and we can predict the time until customer defection by modeling the right-censored failure time data using a conditional hazard model (or another parametric survival model). However, when the relationship with the customer is non-contractual, as it is in this case, the point at which the relationship ends is not observed. Thus, we need to predict the probability that a customer is still in the relationship (i.e., the probability that the customer will make any future purchases) with the firm independent of the customer's decision to purchase at each time period. We accommodate this issue by allowing each customer to have a distinct value of $P(\text{Relationship}_{i,t=1})$, or the probability that a customer is still in the relationship with the firm at the beginning of the CLV prediction window or field experiment time period. The result of this computation is distinct from the probabil-

⁵We choose a Type I (rather than Type II) Tobit model because we expect that the underlying drivers of probability and the conditional expectation for each equation are similar. Using a Type II Tobit model increases the complexity of the estimation and is useful mainly when the researcher expects the different variables to drive probability and the conditional expectation or the same variable to have a different effect.

ity of a purchase, return, or marketing effort in a given time period, which is accommodated by the Type I Tobit model. That probability of a purchase, return, or marketing effort is obtained with the assumption that the relationship between the firm and the customer is always active in the future (i.e., an always-a-share approach).

Customer heterogeneity. Customers have different patterns of behavior, and a customer value framework must accommodate these differences in the form of both unobserved and observed heterogeneity. We follow an approach similar to Rust and Verhoef (2005), in which we use a fully hierarchical modeling design to obtain customer-specific coefficients for each of the models in our customer profitability framework. The benefit of this design is twofold. First, we can maximize the profitability for each customer later, on the basis of that specific customer's behaviors and responsiveness to marketing communications. Second, for customers who are not a part of the current sample, we can always use the mean values of the coefficients across all customers (or just customers that share the same characteristics) in the sample to obtain the "best" available coefficients to maximize customer profitability.

To account for these four main issues and challenges, we obtain the parameter estimates for the three models in two steps. First, to estimate $\pi_1(\text{Purchases}_{it})$, $\pi_2(\text{NetPurchases}_{it})$, $\pi_3(\text{Returns}_{it})$, and Marketing_{it} for the different modeling frameworks, we select a hierarchical Bayesian seemingly unrelated regression (SUR) Tobit model with data augmentation. This model enables us to uncover the drivers of each of the components of the firm-customer exchange process for each customer. Second, for each of the modeling frameworks we compute $P(\text{Relationship}_{i,t} = 1)$ using the customer transaction history to determine the probability that a given customer is still actively in a relationship with the firm. In this case, we use the beta geometric/negative binomial distribution (BG/NBD) model as described by Fader, Hardie, and Lee (2008). We discuss these models in the following two subsections.

A Hierarchical Bayesian SUR Tobit Model with Data Augmentation

The hierarchical Bayesian SUR model with data augmentation allows for the simultaneous estimation of each of the two or three dependent variables of the right side of the objective functions and allows for the parameter estimates of the drivers for each of the models to vary for each customer. In addition, the second level of the model that explains the different set of parameter estimates for each customer allows us to incorporate demographic variables that account for observed heterogeneity. The model takes the following format:

$$(4) \quad y_{it} = X_{it}\beta_i + \varepsilon_{it}, \varepsilon_{it} \sim N(0, \Omega), \text{ and}$$

$$(5) \quad \beta_i = Z_i\delta + \tau_i, \tau_i \sim N(0, \Sigma),$$

where

y_{it} = Benchmark Model 1: $[\pi_1(\text{Purchases}_{it}^*), \text{Marketing}_{it}^*]$,
 Benchmark Model 2: $[\pi_2(\text{NetPurchases}_{it}^*), \text{Marketing}_{it}^*]$,
 Proposed model: $[\pi_1(\text{Purchases}_{it}^*), \pi_3(\text{Returns}_{it}^*), \text{Marketing}_{it}^*]$;
 $\pi_1(\text{Purchases}_{it}^*)$ = The latent value of profit from purchases for customer i in time t ;

$\pi_2(\text{NetPurchases}_{it}^*)$ = The latent value of profit from purchases net profit lost and costs incurred from returns for customer i in time t ;

$\pi_3(\text{Returns}_{it}^*)$ = The latent value of profit lost and costs incurred from product returns for customer i in time t ;

Marketing_{it}^* = The latent value of marketing costs for customer i in time t ;

X_{it} = A matrix of the covariates for each customer i ;

β_i = A matrix of coefficients for each customer i that explain y_{it} ;

Z_i = A matrix of customer specific demographic variables;

δ = A vector of coefficients that explain β_i ;

i = Represents each customer; and

t = Represents each period (in this case, each quarter).

To estimate this model, we observe that this model is just the hierarchical form of Zellner's SUR model (Zellner 1962), where instead of X_i and β , we have the following:

$$X_{it} = \text{diag}(x'_{1t}, \dots, x'_{nt}) = \begin{bmatrix} x_{it}^{\text{Purchases}} & 0 & 0 \\ 0 & x_{it}^{\text{Returns}} & 0 \\ 0 & 0 & x_{it}^{\text{Marketing}} \end{bmatrix};$$

$$\beta_i = \text{diag}(\beta_1, \dots, \beta_n)' = \begin{bmatrix} \beta_{01} & \dots & \beta_{0m} \\ \vdots & \ddots & \vdots \\ \beta_{n1} & \dots & \beta_{nm} \end{bmatrix}.$$

In the case of Benchmark Models 1 and 2, we only have two equations instead of three. For the purposes of this study, we can implement a Gibbs sampler in a series of seven steps that are iterated until convergence. For Benchmark Models 1 and 2, there are six steps (these two benchmark models skip Step 2):

1. Augment $\pi(\text{Purchases})$ using the following algorithm:

$$\pi_1(\text{Purchases}_{it}^*) = \begin{cases} \pi_1(\text{Purchases}_{it}), & \text{if } \pi_1(\text{Purchases}_{it}) > 0 \\ \text{TN}_{[-\infty, 0]}[\mu_i, \pi_1(\text{Purchases}), \sigma_{i, \pi_1(\text{Purchases})}^2], & \text{if } \pi_1(\text{Purchases}_{it}) = 0 \end{cases},$$

where

$$\mu_{i, \pi_1(\text{Purchases})} = x_{it}^{\text{Purchases}} \beta_{\text{Purchases}} + \sigma_{\text{Purchases}, -\text{Purchases}} \sum_{-\text{Purchases}}^{-1} [y_{-\text{Purchases}, it}^* - E(y_{-\text{Purchases}, it}^*)],$$

$$\sigma_{i, \pi_1(\text{Purchases})}^2 = \sigma_{\text{Purchases}}^2 - \sigma_{\text{Purchases}, -\text{Purchases}} \sum_{-\text{Purchases}}^{-1} \sigma_{\text{Purchases}, -\text{Purchases}},$$

$$\sigma_{\text{Purchases}, -\text{Purchases}} = [\sigma_{\text{Purchases}, \text{Returns}}, \sigma_{\text{Purchases}, \text{Marketing}}], \text{ and}$$

$$y_{-\text{Purchases}, it}^* = \begin{bmatrix} \pi_3(\text{Returns}_{it}^*) \\ \text{Marketing}_{it}^* \end{bmatrix};$$

$$\sum_{-\text{Purchases}} = \begin{bmatrix} \sigma_{\text{Returns}}^2 & \sigma_{\text{Returns}, \text{Marketing}} \\ \sigma_{\text{Marketing}, \text{Returns}} & \sigma_{\text{Marketing}}^2 \end{bmatrix}.$$

When we observe a purchase, the latent value of $\pi_1(\text{Purchases}_{it}^*)$ takes the observed value. When we do not observe a purchase, the latent value of $\pi_1(\text{Purchases}_{it}^*)$ is drawn from a truncated normal distribution (Tanner and Wong 1987).

We note that in the case of Benchmark Model 2, we substitute $\pi_2(\text{NetPurchases}_{it})$ for $\pi_1(\text{Purchases}_{it})$.

2. Augment $\pi_3(\text{Returns}_{it}^*)$ using the following algorithm (only for the proposed model):

$$\pi_3(\text{Returns}_{it}^*) = \begin{cases} \pi_3(\text{Returns}_{it}), & \text{if } \pi_3(\text{Returns}_{it}) > 0 \\ \max\{-\text{NetProfit}_{it}, \text{TN}_{[-\infty, 0]}[\mu_{i, \pi_3(\text{Returns})}, \sigma_{i, \pi_3(\text{Returns})}^2]\}, & \text{if } \pi_3(\text{Returns}_{it}) = 0 \text{ and } \text{NetProfit}_{it} > 0 \\ 0, & \text{otherwise} \end{cases}$$

where

$$\text{NetProfit}_{it} = \sum_{j=0}^t \pi_1(\text{Purchase}_{ij}) - \sum_{j=0}^{t-1} \pi_3(\text{Returns}_{ij}),$$

$$\mu_{i, \pi_3(\text{Returns})} = x_{it}^{\text{Returns}} \beta_{\text{Returns}} + \sigma_{\text{Returns}, -\text{Returns}} \sum_{-\text{Returns}}^{-1} [y_{-\text{Returns}, it}^* - E(y_{-\text{Returns}, it}^*)],$$

$$\sigma_{i, \pi_3(\text{Returns})}^2 = \sigma_{\text{Returns}}^2 - \sigma_{\text{Returns}, -\text{Returns}} \sum_{-\text{Returns}}^{-1} \sigma_{\text{Returns}, -\text{Returns}},$$

$$\sigma_{\text{Returns}, -\text{Returns}} = [\sigma_{\text{Returns}, \text{Purchases}}, \sigma_{\text{Returns}, \text{Marketing}}], \text{ and}$$

$$y_{-\text{Returns}, it}^* = \begin{bmatrix} \pi_1(\text{Purchases}_{it}^*) \\ \text{Marketing}_{it}^* \end{bmatrix};$$

$$\sum_{-\text{Returns}} = \begin{bmatrix} \sigma_{\text{Purchases}}^2 & \sigma_{\text{Purchases}, \text{Marketing}} \\ \sigma_{\text{Marketing}, \text{Purchases}} & \sigma_{\text{Marketing}}^2 \end{bmatrix}.$$

In this case, when we observe a product return, the latent value of $\pi_3(\text{Returns}_{it}^*)$ takes the observed value. In the cases in which we do not observe a product return, we do not assume that we should draw the unobserved utility for the product return in the same way as we do for profit from purchases. When a customer has either never purchased a product or returned all purchased products, $\text{NetProfit}_{it} = 0$, where NetProfit_{it} is the total profit from purchases from customer i until time t , minus the total profit lost from customer i for product returns until time $t - 1$. When $\text{NetProfit}_{it} = 0$, we do not augment the value for product returns. When NetProfit_{it} is positive (meaning that the customer can still return products), we draw from a truncated normal distribution (Tanner and Wong 1987) and compare the value of the draw with $-\text{NetProfit}_{it}$. The greater value between $-\text{NetProfit}_{it}$ and the draw from the truncated normal is kept for $\pi_3(\text{Returns}_{it}^*)$ because a draw from the truncated normal that is smaller than $-\text{NetProfit}_{it}$ would mean that the customer is able to return more products than he or she previously purchased.

3. Augment Marketing_{it}^* using the following algorithm:

$$\text{Marketing}_{it}^* = \begin{cases} \text{Marketing}_{it}, & \text{if } \text{Marketing}_{it} > 0 \\ \text{TN}_{[-\infty, 0]}[\mu_{i, \text{Marketing}}, \sigma_{i, \text{Marketing}}^2], & \text{if } \text{Marketing}_{it} = 0 \end{cases},$$

where

$$\mu_{i, \text{Marketing}} = x_{it}^{\text{Marketing}} \beta_{\text{Marketing}} + \sigma_{\text{Marketing}, -\text{Marketing}} \sum_{-\text{Marketing}}^{-1} [y_{-\text{Marketing}, it}^* - E(y_{-\text{Marketing}, it}^*)],$$

$$\sigma_{i, \text{Marketing}}^2 = \sigma_{\text{Marketing}}^2 - \sigma_{\text{Marketing}, -\text{Marketing}} \sum_{-\text{Marketing}}^{-1} \sigma_{\text{Marketing}, -\text{Marketing}},$$

$$\sigma_{\text{Marketing}, -\text{Marketing}} = [\sigma_{\text{Marketing}, \text{Purchases}}, \sigma_{\text{Marketing}, \text{Returns}}], \text{ and}$$

$$y_{-\text{Marketing}, it}^* = \begin{bmatrix} \pi_1(\text{Purchases}_{it}^*) \\ \pi_3(\text{Returns}_{it}^*) \end{bmatrix};$$

$$\sum_{-\text{Marketing}} = \begin{bmatrix} \sigma_{\text{Purchases}}^2 & \sigma_{\text{Purchases}, \text{Returns}} \\ \sigma_{\text{Returns}, \text{Purchases}} & \sigma_{\text{Returns}}^2 \end{bmatrix}.$$

When marketing resources are allocated to a customer, the latent value of Marketing_{it}^* takes the observed value. When the firm allocates no resources, the latent value of Marketing_{it}^* is drawn from a truncated normal distribution (Tanner and Wong 1987).

4. Draw $\Omega^{-1} | y, \beta \sim \text{Wishart}\left\{v_0 + n, \left[R_0^{-1} + (y - X\beta)(y - X\beta)'\right]^{-1}\right\}$, where $n = I \times T$.

5. Draw $\beta | y, \Omega^{-1}, \delta, \Sigma \sim N\left[(\Sigma^{-1} + X'\Omega^{-1}X)^{-1}(\Sigma^{-1}Z\delta + X'\Omega^{-1}y), (\Sigma^{-1} + X'\Omega^{-1}X)^{-1}\right]$.

6. Draw $\delta | \Sigma, \beta \sim N\left[(M_0^{-1} + Z'\Sigma^{-1}Z)^{-1}(M_0^{-1}\delta + Z'\Sigma^{-1}\beta), (M_0^{-1} + Z'\Sigma^{-1}Z)^{-1}\right]$.

7. Draw $\Sigma^{-1} | \beta, \delta \sim \text{Wishart}\left\{\rho_0 + I, \left[D_0^{-1} + (\beta - Z\delta)(\beta - Z\delta)'\right]^{-1}\right\}$.

We use noninformative priors for v_0 , R_0^{-1} , ρ_0 , and D_0^{-1} so that all inferences are driven by the data. We repeat steps 1 through 7 until convergence is reached, whereby the fit and convergence of the model were judged visually and by using the Geweke (1992) test. We iterate 10,000 times, with the first 5,000 iterations considered burn-in and dropped from the results. We observe convergence after approximately 1,000 iterations, so we use 5,000 as a burn-in and 5,000 as posterior. For complete details of the Gibbs sampler procedure followed in steps 4 through 7, see Chib and Greenberg (1995).

A Method to Compute $P(\text{Relationship}_{i,t} = 1)$

In the previous section, we describe a model that helps compute the drivers of $\pi_1(\text{Purchases}_{it})$, $\pi_2(\text{NetPurchases}_{it})$, $\pi_3(\text{Returns}_{it})$, and Marketing_{it} for predicting an individual customer's stream of profit over a given period of time. However, that model does not account for the possibility that a customer will end the relationship with the firm, and customer defection is often treated as independent of the

transaction rate (Fader, Hardie, and Lee 2005). A key assumption is that $P(\text{Relationship}_{i,t=1})$ is independent of purchases, product returns, and marketing efforts. Treating $P(\text{Relationship}_{i,t=1})$ as independent of the expected stream of profit allows us to multiply the two independent processes together and obtain a prediction of CLV for each customer. We do so for several reasons. First, we find the correlation between $P(\text{Relationship}_{i,t=1})$ and the other three dependent variables to be weak at best (see Table 3). We tested the correlations in the following manner by using the data from the empirical study. Because we only have one measure of $P(\text{Relationship}_{i,t=1})$ for each customer, we take the average of the other four dependent variables for each customer and compare them with $P(\text{Relationship}_{i,t=1})$.

There is a very low correlation between $P(\text{Relationship}_{i,t=1})$ and the other three dependent variables, which suggests that treating $P(\text{Relationship}_{i,t=1})$ as independent of the other three processes is likely not an issue. It also suggests that although it is possible to extend the Fader, Hardie, and Lee (2005) approach to include past marketing and return information, using purchases, returns, or marketing as a driver of $P(\text{Relationship}_{i,t=1})$ should not add much value to the prediction of $P(\text{Relationship}_{i,t=1})$. Second, this result supports the assumption generally held regarding the Pareto/NBD and BG/NBD models (Fader, Hardie, and Lee 2005) and the empirical evidence (Abe 2009) that the customer's dropout rate is independent of the customer's transaction rate. As a result, we treat $P(\text{Relationship}_{i,t=1})$ as independent of the purchase process, product return process, and marketing efforts of the firm. We use the BG/NBD model as described by Fader, Hardie, and Lee (2008) to compute the probability that customer i is in a relationship with the firm:

$$(6) \quad P(\text{Relationship}_{i,t=1}) = \frac{1}{1 + \delta_{x>0} \frac{a}{b+x+1} \left(\frac{\alpha+T}{\alpha+t_x} \right)^{r+x}},$$

where

x = The number of transactions for customer i during the time period $(0, T]$,

$\delta_{x>0}$ = This notes that the function is conditional on the number of transactions being greater than zero,⁶

t_x = The time of the last transaction,

T = The end of the observation time window ($t = 0$),

r = The shape parameter from the gamma distribution,

α = The scale parameter from the gamma distribution, and

a, b = Shape parameters of the beta distribution.

⁶When $x = 0$, the $P(\text{Relationship}_{i,t=1}) = 1$, which suggests that consumers with no purchases are actively engaged in a relationship with the firm. Because we only use customers in our sample with $x > 0$, this is not an issue.

This measure of $P(\text{Relationship}_{i,t=1})$ will build the uncertainty of the relationship duration into the prediction of each customer's value at the beginning of the field experiment.⁷ We then multiply this prediction of the probability that a customer is active at time $t = 1$ with the net present value of expected discounted profits over the time horizon for the prediction.

Model Validation

Data. For the purpose of model validation, we estimate the models with a random sample of 935 customers. The data for the model validation and the field experiment come from two samples in two time periods from a business-to-customer company that sells footwear, apparel, and other accessories online and through mail-order catalogs and is aggregated by quarter. This store's return policy is considered very lenient in that it is willing to give 100% of a customer's money back for any reason if, at any time after the purchase, he or she does not want to keep the product. The data for this cohort come from Q2, 2003, to Q1, 2006. To remove any issues with left-censoring of data, we use a cohort of customers who made their first purchase during Q2, 2003. These customers purchased 9,943 products, at an average of 10.6 products⁸ per customer. These purchases generated approximately \$1.94 million in profit, or \$195 in profit per product. This sample of customers also includes a total of 1,741 products returned, at an average of 1.9 products returned per customer. These returned products generated a loss of approximately \$343,000, or \$197 per product return. This means, on average, approximately one in six products purchased was returned for a refund or an exchange (1,741/9,943, or approximately 17.5%), which falls within the expected range (4%–25%) of direct marketers (Fenvesy 1992). In addition, these customers received a total of 41,837 catalogs and e-mails between Q2, 2003, and Q1, 2006, approximately 45 catalogs and e-mails per customer or 15 catalogs and e-mails per customer, per year.

Variable selection and operationalization. The variables selected as predictors in each of the models ($\pi_1[\text{Purchases}_{it}^*]$, $\pi_2[\text{NetPurchases}_{it}^*]$, $\pi_3[\text{Returns}_{it}^*]$, and Marketing_{it}^*) are based on the commitment–trust theory of relationship marketing (Morgan and Hunt 1994). We selected these variables because

⁷We only calculate the value of $P(\text{Relationship}_{i,t=1})$ at the beginning of the field experiment (or at the beginning of any CLV computation) because it measures the probability of obtaining a stream of profits. If the firm wants to compute CLV again in the future, it would calculate $P(\text{Relationship}_{i,t=1})$ at the beginning of expected stream of future profits.

⁸There was an average of 5.4 transactions per customer, or approximately 2 products per transaction. Each customer made at least one transaction because the sample includes customers who made their first purchase during Q2, 2003.

Table 3
CORRELATIONS BETWEEN $P(\text{RELATIONSHIP}_{i,t=1})$, PURCHASES, RETURNS, AND MARKETING

Correlations	$P(\text{Relationship}_{i,t=1})$	$\text{Avg}(\text{Purchases})$	$\text{Avg}(\text{Returns})$	$\text{Avg}(\text{Mktg})$
$P(\text{Relationship}_{i,t=1})$	1			
$\text{Avg}(\text{Purchases})$	.08	1		
$\text{Avg}(\text{Returns})$	.03	.42	1	
$\text{Avg}(\text{Mktg})$	.04	.61	.66	1

research has shown that a customer's perceived risk plays a significant role in that customer's commitment to and trust in a firm. A reduction in a customer's perceived risk acts as a mechanism to build feelings of commitment and trust between the customer and the firm (Selnes 1998). Furthermore, this increase in trust provides value to the customer by increasing his likelihood of purchasing with the firm. In addition, all variables selected for these models are based on variables in previous studies that have been shown to be significant predictors of customer buying behavior, customer product return behavior, and a firm's marketing resource allocation decisions (Petersen and Kumar 2009; Venkatesan and Kumar 2004; Venkatesan, Kumar, and Bohling 2007). We summarize the list of variables selected and how each variable is operationalized for each of the three equations in

Table 4. We note that the intention here was to be inclusive of variables previously used in CLV models and not to introduce new variables.

We also use two independent variables in the second level of the hierarchical model to capture observed heterogeneity in responses by explaining the differences in the coefficients across customers: age (in years) and income (in thousands of dollars) for each customer. Depending on available data, any set of demographic variables can be used as independent variables in the second-level equation. These variables can help significantly increase the model fit, and they can also potentially aid managers in acquisition strategies in which the demographic profiles of the prospects are known and there are no purchase histories on which to rely for prediction. For the purpose of this study, we only use demo-

Table 4
VARIABLE OPERATIONALIZATION

Variable	Operationalization
<i>Model: $\pi_3(\text{Returns}_{it}^*)$</i>	
Average value of past product returns	The average value of profit lost and costs incurred from product returns of customer <i>i</i> up to the current time period
Net value of past product returns	The total profit lost and costs incurred from product returns from customer <i>i</i> up to the current time period
Log marketing costs	The log (marketing costs + 1) from the current time period for customer <i>i</i>
GM from purchasing	The profit from the purchases in the current time period for customer <i>i</i>
Lag of purchase indicator	An indicator of whether customer <i>i</i> purchased a product in the previous time period
Lag of product return indicator	An indicator of whether customer <i>i</i> returned a product in the last time period
Average interreturn time	The average time between product returns for customer <i>i</i> (in months)
Average interreturn time ²	The square of the average time between purchases for customer <i>i</i>
Crossbuying	The number of product categories purchased by customer <i>i</i> from time 0 to <i>t</i>
Multichannel shopping	The number of distribution channels purchased by customer <i>i</i> from time 0 to <i>t</i>
Crossbuying × multichannel shopping	The interaction between crossbuy (number of product categories purchased) and multichannel (the number of distribution channels purchased) for customer <i>i</i>
Holiday indicator	A dummy variable equal to 1 when the time period is quarter 4, 0 otherwise
<i>Model: $\pi_1(\text{Purchases}_{it}^*)$ or $\pi_2(\text{NetPurchases}_{it}^*)$</i>	
Average value of past purchases	The average value of profit from purchases of customer <i>i</i> up to the current time period
Net value of past purchases	The total profit from purchases of customer <i>i</i> up to the current time period
Log marketing costs	The log (marketing costs + 1) from the current time period for customer <i>i</i>
Lag of GM from purchasing	The profit from the purchases in the previous time period for customer <i>i</i>
Lag of GM lost from product returns	The profit lost and costs incurred from product returns in the previous time period for customer <i>i</i>
Average interpurchase time	The average time between purchases for customer <i>i</i> (in months)
Average interpurchase time ²	The square of the average time between purchases for customer <i>i</i> (in months)
Crossbuying	The number of product categories purchased by customer <i>i</i> from time 0 to <i>t</i>
Multichannel shopping	The number of distribution channels purchased by customer <i>i</i> from time 0 to <i>t</i>
Crossbuying × multichannel shopping	The interaction between crossbuy (number of product categories purchased) and multichannel (the number of distribution channels purchased) for customer <i>i</i>
Holiday indicator	A dummy variable equal to 1 when the time period is quarter 4, 0 otherwise
<i>Model: Marketing_{it}^*</i>	
Average value of past purchases	The average value of profit from purchases of customer <i>i</i> up to the current time period
Lag of purchase indicator	An indicator of whether customer <i>i</i> purchased a product in the last time period
Lag of product return indicator	An indicator of whether customer <i>i</i> returned a product in the last time period
Lag of marketing costs	The marketing costs from the previous time period for customer <i>i</i>
Average interpurchase time	The average time between purchases for customer <i>i</i> (in months)
Average interpurchase time ²	The square of the average time between purchases for customer <i>i</i> (in months)
Holiday indicator	A dummy variable equal to 1 when the time period is quarter 4, 0 otherwise
<i>Second-Level Model: Demographic Variables</i>	
Age	Age of customer at the first time period of the analysis
Income	Income of the customer at the first time period of the analysis

graphic variables to aid in model fit, but a future study could leverage these variables for customer acquisition.

Estimation. We estimate the models using the framework as described previously and present a summary of the results of the estimation in Tables 5 and 6. We choose to use the same set of variables for each model (except adding the product return-related variables as needed⁹) to aid in model comparison. To simplify the presentation of the results, we provide the means and standard deviations of each of the coefficients in Table 5. We note that each customer's values for the dependent variables are still predicted using the customer-specific parameter coefficients. However, summarizing the results helps in the interpretation of how each variable typically affects the dependent variables. We find that the results are similar to those in previous studies, offering some external validation. For example, we find in the proposed model that product returns have a negative impact on

future marketing expenditures and a positive impact on future purchase behavior. This finding highlights the article's focus—that is, the exact trade-off between the firm managing the costs of product returns and benefiting from higher future purchase behavior as a result of lowering a customer's perceived risk.

We present the results of the estimation of $P(\text{Relationship}_{i,t} = 1)$ in Table 6. The results show that there is a significant difference between the likelihoods of different customers being active at the beginning of the prediction period ($M = .81$, $\min = .002$, $\max = .95$). Furthermore, we test for the potential presence of endogeneity of marketing efforts using the Wu–Hausman test.¹⁰ The posterior of the parameter estimate on the error from the marketing equation as an independent variable in the purchase equation was not significantly different from 0 ($p > .41$), suggesting that endogeneity bias is not an issue in this study.

Out-of-sample fit. It is necessary to test how well the proposed framework can fit the data and accurately predict the firm's marketing efforts and the customers' purchase and product return behavior compared with the benchmark

⁹We include product returns as an explanatory variable in the marketing equation for Benchmark Model 2 because we want to account for firms that manage costs by considering past product return behavior. We also include product returns as an explanatory variable in the purchase equation for the proposed model because it captures the impact of product return behavior on future purchase behavior.

¹⁰We thank one of the anonymous reviewers for raising this issue.

Table 5
HIERARCHICAL BAYESIAN SUR TOBIT MODEL ESTIMATION RESULTS

Variable	Benchmark Model 1	Benchmark Model 2	Proposed Model
<i>Model: $\pi_3(\text{Returns}_{it}^*)$</i>			
Intercept			−37.10 (7.31)
Average value of past purchases			.63 (.01)
Net value of past product returns			.03 (.004)
Log marketing costs			2.68 (.09)
GM from purchasing			.07 (.02)
Lag of purchase indicator			16.49 (5.44)
Lag of product return indicator			52.94 (3.79)
Average interreturn time			9.52 (1.70)
Average interreturn time ²			−.26 (.43)
Crossbuying			n.s.
Multichannel shopping			n.s.
Crossbuying × multichannel shopping			3.53 (1.25)
Holiday indicator			29.16 (10.03)
<i>Model: $\pi_1(\text{Purchases}_{it}^*)$ or $\pi_2(\text{NetPurchases}_{it}^*)$</i>			
Intercept	15.13 (5.02)	30.01 (9.05)	15.34 (4.93)
Average value of past purchases	.75 (.03)	.58 (.03)	.77 (.03)
Net value of past purchases	.07 (.005)	.014 (.005)	.06 (.004)
Log marketing costs	.53 (.06)	.41 (.04)	.54 (.07)
Lag of GM from purchasing	.12 (.013)	.035 (.01)	.15 (.01)
Lag of GM lost from product returns	— ^a	— ^a	.05 (.001)
Average interpurchase time	22.74 (2.04)	6.23 (1.99)	23.63 (1.99)
Average interpurchase time ²	−.60 (.09)	−.13 (.02)	−.68 (.09)
Crossbuying	n.s.	n.s.	n.s.
Multichannel shopping	n.s.	n.s.	n.s.
Crossbuying × multichannel shopping	17.85 (2.08)	7.06 (2.04)	17.55 (2.08)
Holiday indicator	56.58 (2.22)	31.12 (2.17)	56.44 (2.21)
<i>Model: Marketing_{it}[*]</i>			
Intercept	−.47 (.09)	−.51 (.09)	−.46 (.08)
Average value of past purchases	.01 (.0002)	.008 (.0002)	.008 (.0002)
Lag of purchase indicator	1.62 (.09)	1.57 (.08)	1.61 (.08)
Lag of product return indicator	— ^a	−1.01 (.13)	−.98 (.13)
Lag of marketing costs	.75 (.01)	.74 (.01)	.75 (.01)
Average interpurchase time	.64 (.02)	.64 (.02)	.63 (.02)
Average interpurchase time ²	−.04 (.01)	−.04 (.01)	−.03 (.01)
Holiday indicator	1.15 (.09)	1.14 (.09)	1.15 (.09)

^aDenotes that the variable is not included in the model.

Notes: n.s. = Not significant from 0. Means and standard deviations (in parentheses) are from distributions of parameters estimates across customers.

Table 6
BG/NBD ESTIMATION RESULTS FOR $P(\text{RELATIONSHIP}_{i,t=1})$

Parameter	Estimate
r	4.794
α	6.777
a	17.385
b	294.443
Log-likelihood	-7,515.8
μ of $P(\text{Relationship}_{i,t=1})$	.81
Min of $P(\text{Relationship}_{i,t=1})$	.002
Max of $P(\text{Relationship}_{i,t=1})$	.95

models. To do so, we use the estimates from the model to predict the values of each of the dependent variables in a holdout time period. In this case, our holdout time period is three years of data beginning immediately after the data we used to estimate our model (holdout time period: Q2, 2006, to Q1, 2009). Given the results of the model estimation, we use the posterior distribution of the response parameters to predict the values of the three dependent variables in each time period (for details of the algorithm, see Web Appendix B). In addition, we compute $P(\text{Relationship}_{i,t=1})$ directly from the results of the estimation found in Table 6 and from the historical transaction information from each customer (i.e., x , t_x , and T as of the beginning of the prediction window). We compare the out-of-sample fit for each of the two benchmark models and the proposed model with the actual data (see Table 7).

We observe from the results in Table 7 that each of the models seems able to effectively predict each of the dependent variables in the holdout time period. For Benchmark Model 1, we find that the model has an average deviation of 3.61 for marketing costs (mean absolute percentage error [MAPE]¹¹: 21.1%) and 27.91 for profit from purchases (MAPE: 17.1%). Benchmark Model 2 has an average deviation of 3.60 for marketing costs (MAPE: 21.0%) and 45.82 for net profit from purchases minus product returns (MAPE: 34.3%). Finally, we find that the proposed model has an average deviation of 3.54 for marketing costs (MAPE: 20.7%), 27.35 for profit from purchases (MAPE: 16.8%), and 6.94 for profit lost and costs incurred from product returns (MAPE: 23.8%). These results suggest that the models we use are able to generate accurate estimates of the drivers of each of the three dependent variables. Thus, to run the field experiment with the firm, we reestimate the models for a new and larger sample of customers and use the customer-level parameter estimates from the models to

¹¹The MAPE is computed only conditional on the occurrence of a purchase, product return, or marketing effort.

guide the resource allocation decisions for the focal field experiment.

Assignment of Customers to Different Groups

The sample we use for the field experiment comes from the same retail firm described in the model development and validation sections. These data contain information on all the transactions for a random sample of 26,000 customers. The 26,000 customers were then randomly assigned (5,200 per group) to one of the five previously described groups:

1. Control group (no formal measure),
2. Firm strategy group (RFM),
3. Benchmark Model 1 group (CLV without product returns),
4. Benchmark Model 2 group (CLV with net buying), and
5. Proposed model group (CLV with product returns).

To determine whether the customers were similar in past and predicted behavior across groups, we measured the average total past profit and projected the average long-term profitability over three years (i.e., CLV) for each customer in each group using our proposed model objective function and the general estimation framework as described previously (see Table 8). We provide details on the prediction algorithm for each customer's CLV in Web Appendix C.

The results from Table 8 show that the customers in the five groups were similar in both their past and projected profits. This offers some evidence that the customers were randomly allocated to each group and each algorithm is starting on a level playing field.

Resource Allocation Algorithms

Next, we describe how the resource allocation algorithm was set up for each of the five groups. Because the control group receives no resources, we do not need an objective function to maximize; each customer just receives no marketing efforts during the study. For the firm strategy group,

Table 8
PAST PROFIT AND PREDICTED CLV OF EACH CUSTOMER GROUP

Customer Group	Average Past Profit (SD)	Average CLV (SD)
Control	\$1,226.96 (512.86)	\$1,721.28 (683.88)
Firm's strategy	\$1,206.57 (514.75)	\$1,697.31 (701.23)
CLV without product returns	\$1,201.65 (517.44)	\$1,675.11 (692.57)
CLV with net purchases	\$1,216.80 (503.37)	\$1,680.84 (704.68)
CLV with product returns	\$1,221.62 (521.49)	\$1,719.78 (699.25)

Notes: The values found for average past profit and average CLV are not statistically significantly different from each other for any group.

Table 7
MODEL COMPARISON: MEAN ABSOLUTE DEVIATION/(MAPE) OF OUT-OF-SAMPLE PREDICTION

Model	Marketing ($\mu = 17.11$)	NetPurchases ($\mu = 133.70$)	Purchases ($\mu = 162.81$)	Returns ($\mu = 29.11$)
Benchmark Model 1 (without returns)	3.61 (21.1%)	—	27.91 (17.1%)	—
Benchmark Model 2 (net purchases)	3.60 (21.0%)	45.82 (34.3%)	—	—
Proposed model (with returns)	3.54 (20.7%)	—	27.35 (16.8%)	6.94 (23.8%)

Notes: Numbers in parentheses represent MAPE values. Results are based on the prediction for each customer in each quarter during the holdout time period.

the customer selection and resource allocation algorithm is based on the RFM score, which is common for many direct marketing firms. This score rewards *Recent*, *Frequent*, and *high-spending* (Monetary value) customer purchase behavior. In addition, this firm also had a policy that reduces resources spent on customers who returned products in the past. However, as noted previously, we cannot provide the actual objective function here for reasons of confidentiality. We only show the results of using the firm strategy compared with the other models in the results of the field experiment as a way to compare our CLV-based models with the firm's current model. For Benchmark Model 1, Benchmark Model 2, and the proposed model, we use the equations as detailed previously (see Equations 1, 2, and 3).

For the three models described previously, the customer selection and optimal resource algorithm worked in the following way. First, we fixed the customer-level parameter estimates obtained from the three models and allowed the amount of marketing effort to vary for each customer for the first quarter of the field experiment time period.¹² Similar to Venkatesan and Kumar (2004), we used a genetic algorithm approach to solve for the allocation of resources that lead to the maximum expected profit across all customers. Then, we observed what happened during the six-month field experiment and measured the actual profit during the field experiment time period ($t = 1$ and 2 , where each period is a quarter) discounted to today's value ($t = 0$). For example, for the proposed model we get the following profit function to maximize:

$$(7) \quad \max \left\{ \sum_{i \in n} [P(\text{Relationship}_{i,t=1})] \times \sum_{t=1}^T \left[\frac{\pi_1(\text{Purchases}_{it}) - \pi_3(\text{Returns}_{it}) - \text{OptMktg}_{i,t=1}}{(1+r)^t} \right] \right\},$$

where

$\pi_1(\text{Purchases}_{it})$ = Expected profit from purchases by customer i in time t ,

$\pi_3(\text{Returns}_{it})$ = Expected profit lost and costs incurred from returns by customer i in time t ,

$\text{OptMktg}_{i,t=1}$ = Optimal marketing costs spent on customer i in time $t = 1$ as determined by the resource allocation algorithm,

n = Total sample of customers,

r = Discount rate (Approximately 3.56% by quarter, or 15% annually),

T = Number of time periods to optimize (in this case, $T = \text{one quarter}$), and

$P(\text{Relationship}_{i,t=1})$ = Computed probability a customer is in the relationship with the firm at the beginning of the field experiment ($t = 1$).

We placed two constraints on the optimal marketing spend variable. First, it had to be greater than or equal to 0

for each customer, and the sum of the marketing spend across all customers had to be less than or equal to the marketing budget set by the firm (the budget used for the firm's strategy). At the end of the optimization, each customer who had an optimal marketing effort of 0, as determined by the optimal resource allocation algorithm, was allocated no marketing resources. The customers who had a positive value for marketing effort were allocated resources that were less than or equal to the optimal marketing spend so that we could keep the costs greater than or equal to the budget constraint. For example, if the optimal spend was \$2.55 and the cost of an e-mail is \$1.00,¹³ the customer would receive two e-mails at a total cost of \$2.00 to the firm. Second, we only optimized the allocation of resources to customers for a single time period (one quarter) but observed the continued purchasing and product return behavior of customers for two periods (two quarters). We would expect that the purchase behavior of the customers who received marketing communications during the first time period of the field experiment would regress to the mean. Any incrementally higher purchase behavior is likely a result of the longer-term effect of marketing on purchase behavior. Third, many customers have already chosen whether to receive catalogs, e-mails, or both. In the cases in which the customers choose one or the other, the customers only received the desired marketing effort. When there was no preference or the customers wanted to receive both, an equal number of catalogs and e-mails were sent.

We then ran the study over the six-month time period, in which catalogs were mailed and e-mails were sent during the first three months on the basis of the respective resource allocation algorithms described previously, and purchases and returns were observed throughout the six months. One reason we chose to allow three months to pass with no catalogs is that managers of the focal firm in this field experiment stated that after an e-mail or catalog is mailed, approximately 87% of the purchases occur within 8 weeks (two months) and 95% of the purchases after a catalog or e-mail is sent occur within 12 weeks (three months). Furthermore, managers stated that approximately 90% of product returns occur within 8 weeks after purchase (two months) and 98% of product returns occur within 12 weeks after purchase (three months). Second, recent research has suggested that as time passes, the likelihood of returning a product significantly decreases due to the procrastination effect (Janakiraman and Ordóñez 2012). This suggests that if we wait three months after the last potential catalog or e-mail is sent to each customer, we should observe at least 95% of all of the purchases and more than 90% of the product return behavior that result from sending these catalogs or e-mails to the customers.¹⁴ It is difficult to determine the exact

¹³The firm estimated the cost of an e-mail (\$1.00) and the cost of a catalog (\$3.00). We note that the marginal cost of sending an e-mail is very low (almost nothing), and most of the cost of the e-mail is a fixed cost of setting up the e-mail campaign. However, it is not appropriate to send every e-mail to every customer given the low marginal cost because the cadence of contacting customers (and not overcontacting) is important in maintaining the relationship.

¹⁴We find that the results do not change if we increase or decrease the window of time we wait for the purchase and product return behavior to finish by one month.

¹²For the resource allocation, we do not use the marketing equation because marketing is the decision variable. The marketing model is only relevant in the design of the study to understand the dynamics between marketing efforts, customer purchase behavior, and customer product behavior.

wear-out time of e-mails and catalogs as they pertain to customer purchase behavior. In addition, we can directly compare the results with the control group, which received no catalogs or e-mails during this time same period.

Field Experiment Results

After the six-month time period elapsed, we analyzed the number of e-mails sent, catalogs mailed, purchase behavior, and product return behavior of the firm and customers in each of the groups. We calculated the total profit (profit from purchases minus the profit lost and costs incurred from product returns and the cost of catalogs) as of the end of the field experiment (see Table 9). Using the control group as the benchmark for our comparisons, we find that the 5,200 customers from the control group made purchases totaling \$1.60 million and product returns totaling \$403,200 and received no catalogs or e-mails during this time period. As a result, the profit per customer from the control group is \$235.20.

Under the firm's strategy (RFM-based), 19,760 catalogs and e-mails were sent to the 5,200 customers, resulting in a slight increase in profit from purchases (\$1.62 million) and a decrease in profit lost and costs incurred from product returns (\$373,200) compared with the control group. As a result, we observe an increase in the average profit per customer to \$240.55, or approximately 2%. Although we did observe a small increase in the profit from purchases and a decrease from profit lost and costs incurred from product returns, the increase in cost from e-mails and catalogs caused the profitability to increase only marginally over the control group.

Using the strategy with Benchmark Model 1 (CLV without product returns), 17,199 catalogs and e-mails were sent to the 5,200 customers, resulting in an increase in profit from purchases (\$1.71 million) and a decrease in profit lost and costs incurred from product returns (\$290,160) from the control group. As a result, we find an increase in the average profit per customer to \$273.48, or approximately 16%. When compared with the firm's strategy, we find that Benchmark Model 1 is able to send fewer catalogs and e-mails to the customers to obtain a higher average customer profit through increases in purchases and decreases in returns.

Using the strategy with Benchmark Model 2 (CLV with net buying), 14,664 catalogs and e-mails were sent to the 5,200 customers, resulting in an increase in profit from purchases (\$1.80 million) and a decrease in profit lost and costs incurred from product returns (\$270,210) from the control group. As a result, we observe an increase in the average profit per customer to \$294.21, or approximately 25%. When compared with the firm's original strategy, we find that Benchmark Model 2 also results in sending fewer catalogs and e-mails to the customers to obtain a higher average customer through increases in purchases and decreases in product returns. In addition, when compared with Benchmark Model 1, Benchmark Model 2 provides a higher average profit per customer during the six-month time period, which suggests that accounting for purchases and net product returns (vs. just purchases in Benchmark Model 1) provide a slightly higher profit over the short run.

Using the strategy with the proposed model (CLV with product returns), 12,090 catalogs and e-mails were sent to the 5,200 customers, resulting in an increase in profit from purchases (\$2.02 million) and a decrease in profit lost and costs incurred from product returns (\$201,160) from the control group. As a result, there was an increase in the average profit per customer to \$352.77, or approximately 50%. When compared with the firm's original strategy, the proposed model also results in sending fewer catalogs and e-mails to the customers to obtain a higher CLV through increases in purchases and decreases in returns. In addition, when compared with Benchmark Models 1 and 2, we find that the proposed model is able to provide a significantly higher average customer profit.

Discussion

The results show that the maximum profit during the field experiment time period is achieved only when resources are allocated on the basis of the proposed objective function, which accounts for both the cost of product returns and the role of a customer's perceived risk in his or her purchase and product return behavior. Specifically, if we multiply the average profit in the field experiment time period with the number of customers in the group, we observe significant differences in the profitability of each group. For the control group, the firm obtained \$1.22 million; for the firm strategy group, the firm obtained \$1.25 million; for the Benchmark

Table 9
FIELD EXPERIMENT RESULTS

Customer Group	Total Profit from Purchases in Six Months (in Millions of Dollars)	Total Profit Lost from Product Returns in Six Months (in Thousands of Dollars)	Total Catalogs and E-Mails Sent in the First Three Months	Average Profit per Customer During the Six Months	Average CLV per Customer Poststudy
Control	\$1.60	\$403.20	0	\$235.20	\$1,088.89
Firm's strategy	\$1.62	\$373.20	19,760	\$240.55	\$1,087.03
Benchmark Model 1 (without returns)	\$1.71	\$290.16	17,199	\$273.48	\$1,172.17
Benchmark Model 2 (net purchases)	\$1.80	\$270.21	14,664	\$294.21	\$1,223.16
Proposed model (with returns)	\$2.02	\$201.16	12,090	\$352.77 ^a	\$1,402.96 ^a

^aThe values found for average profit per customer during the six months and average CLV per customer poststudy for the proposed model are statistically significantly larger from each of the other segments.

Notes: The actual CLV per customer in the proposed model group over an extended period of three years after the end of the field experiment was \$1,353.66.

Model 1 Group, the firm obtained \$1.42 million; for the Benchmark Model 2 Group, the firm obtained \$1.53 million; and for the proposed model group, the firm obtained \$1.83 million. By using the proposed model, the firm was able to bring in approximately \$300,000 more than the next-best resource allocation strategy (Benchmark Model 2), or \$58.56 per customer.

First, we believe that these findings are a direct result of a framework that more accurately reflects the complex dynamics of the firm–customer exchange process, which can account for both the costs and a customer's perceived risks of product return behavior. Second, the results in Table 9 illustrate that when firms account for the costs of product returns, they are able to significantly lower the total dollars of products returned, from \$290,160 for Benchmark Model 1 to \$270,210 for Benchmark Model 2. As we expected, when the costs of product returns affect expected profitability, resources are reallocated to minimize the cost of product returns. However, we also find that when a firm accounts for a customer's perceived risk as well as the cost of product returns, the amount of product returns declines further, from \$270,210 for Benchmark Model 2 to \$201,160 for the proposed model. This finding suggests that understanding the dynamics between product return behavior and purchase behavior over time enables firms to distinguish customers who are likely to increase purchase behavior at a faster rate relative to product return behavior rather than focus only on the net profit from purchase behavior—all at a lower marketing cost.

Where do the gains come from? These results raise the question as to the source of the benefits to customer profitability. A firm can realize a higher profit from a given customer using the profit function from the proposed model through the following three ways: (1) an increase in purchases, (2) a decrease in product returns, and (3) a decrease in marketing costs. We found relative gains on each of these metrics from the results we observed from the proposed model group (see Table 10).

With regard to profit from purchases, the proposed model offered increases of 26.3% over the control strategy, 24.7% over the firm's strategy, 18.1% over Benchmark Model 1, and 12.2% over Benchmark Model 2. With regard to profit lost from product returns, the proposed model offered decreases of 50.1% from the control strategy, 46.1% from the firm's strategy, 30.7% from Benchmark Model 1, and 25.6% from Benchmark Model 2. With regard to marketing costs, the proposed model used 38.8% fewer marketing resources than the firm's strategy, 29.7% fewer marketing resources than Benchmark Model 1, and 17.6% fewer marketing resources than Benchmark Model 2.

These findings show that the proposed model is able to provide positive gains over each of the other models in each key category. However, it is also possible to approximate the gains from managing product returns as a cost (i.e., gains from Benchmark Model 1 to Benchmark Model 2) and the gains from accounting for the customer's lower perceived risk (i.e., gains from Benchmark Model 2 to proposed model). If we focus only on the average gains in profit during the six-month time period, we observe that the gains from managing the costs of returns increase profit by approximately 7.6%, and the gains from accounting for a customer's perceived risk increase profit by approximately 19.9%. This finding suggests that managing costs is important, but understanding how customers respond to product return experiences can generate a significantly higher (more than twofold) increase in profit for the firm.

How would the proposed model allocate resources in other groups? These results also raise the question whether the proposed model causes a substantial shift in how marketing resources are allocated. For example, if the proposed model were applied to the other groups, with the exception of the control group, which received no marketing effort, how would the resource allocations differ? To uncover the differences in the resource allocation algorithms, we applied the proposed model algorithm to the firm strategy group, the Benchmark Model 1 Group, and the Benchmark Model 2 Group as of the beginning of the field experiment. Then, we conducted a pairwise correlation in customer-level marketing efforts between the proposed model allocations and the strategy actually used in the field experiment (see Table 11). The goal here is to understand how changing the objective function leads to a change of marketing dollars spent for each customer across the different strategies.

The results suggest that the marketing efforts allocated using the firm's strategy are relatively uncorrelated to the marketing efforts allocated using the proposed strategy. We note that the correlation of .03 is significant from a statistical perspective, but it is more likely due to the sample size of 5,200 than because the two strategies are actually similar in nature. There seem to be two main reasons for this finding. First, there is a difference between using an RFM-based strategy and a CLV-based strategy. Research has shown that there is some correlation between RFM and CLV because recency, frequency, and monetary value are often key drivers of CLV. However, this correlation is not always high. Second, and perhaps more importantly, the firm lowers the resource allocations to customers who return products. The results of the estimation in Table 5 show that past product returns are positively related to future purchase behavior. Thus, many of the customers who received fewer marketing

Table 10
RELATIVE GAINS FOR THE PROPOSED MODEL

Model	Profit from Purchases	Profit Lost from Product Returns	Marketing Costs	Average Profit per Customer	Average CLV per Customer
Control	26.3%	–50.1%	N.A.	51.5%	28.8%
Firm's strategy	24.7%	–46.1%	–38.8%	46.6%	29.1%
Benchmark Model 1 (without returns)	18.1%	–30.7%	–29.7%	28.5%	19.7%
Benchmark Model 2 (net purchases)	12.2%	–25.6%	–17.6%	19.1%	14.7%

Notes: The percentages in each cell represent the benefit the proposed model strategy provides the firm relative to the other strategy. N.A. = not applicable.

Table 11
CORRELATION OF RESOURCE ALLOCATIONS WITH
PROPOSED MODEL

Model	Firm's Strategy	Benchmark Model 1	Benchmark Model 2
Proposed model	.03	.27	.42

Notes: The correlations represent the pairwise correlation between the marketing resources spent on a customer using the strategy from the proposed model (left column) and the strategy used on the field experiment group (top row). All correlations are significant at $p < .01$.

efforts in the firm's strategy group because of their product return behavior received significantly more marketing efforts using the proposed model.

The marketing efforts allocated using Benchmark Model 1 are only weakly correlated (.27, $p < .01$) with the marketing efforts allocated using the proposed strategy. There seems to be one main reason for this finding. Benchmark Model 1 does not include product returns in the profit function. However, more resources are directed at customers who return products: the resource allocation algorithm does not punish customers for excessive returns because the costs of product returns do not affect the allocation decision. Thus, the deviations between the proposed model and Benchmark Model 1 are a result of overspending on customers who return too many products and underspending on customers who are profitable but do not return many products.

The marketing efforts allocated using Benchmark Model 2 are moderately correlated (.42, $p < .01$) with the marketing efforts allocated using the proposed strategy. There seems to be one main reason for this finding. Although product returns enter the profit objective function as a cost through NetPurchases, which limits the spending on customers who return too many products, it ignores the fact that the drivers of $\pi_1(\text{Purchases}_{it})$ and $\pi_3(\text{Returns}_{it})$ are different. Thus, many of the deviations between the proposed model and Benchmark Model 2 are a result of the proposed model better capturing the dynamics between marketing efforts, purchase behavior, and product return behavior.

Do the different models target the same customers? Another notable result from the resource allocation field experiment involves which customers are targeted with marketing efforts. For example, we find in many cases that the differences between the marketing resource allocations of Benchmark Model 2 and the proposed model are not differences in magnitude of spending on a given customer. Rather, the differences usually pertain to which customers are selected to receive marketing resource allocations in the first place. Specifically, the proposed model tends to target customers with moderate levels of product return rates (~10%–15%) who continue to increase purchase rates into the future. This offers some validation to other studies that have found that moderate return rates tend to generate the most profitable customers in the future (Petersen and Kumar 2009).

In contrast, Benchmark Model 2 tends to target customers who make few or no product returns after larger purchases and are more likely to decrease purchase rates in the future. This suggests that the proposed model drives the firm to target a different type of customer than those targeted in the

benchmark models rather than just reallocating the same resources to the same customers. This is further evidence that there are significant differences in short- and long-term customer behavior between customers who return products and customers who do not return products that have a significant impact on the profitability of a given customer.

Long-term profit implications. The results of the field experiment suggest that even minor changes to the profit objective function can lead to significant changes in the resource allocation strategy and customers' short-term profitability. In addition to showing that including the customer's product return-related perceived risk positively affects firm profit in the short run, we wanted to determine whether the proposed model also creates some long-term customer value. To do this, we computed the long-term expected profit (i.e., CLV) from the customers in the field experiment at the end of the field experiment (October 2009). Similar to the CLV computation before the field experiment (for the pre-field test CLV values, see Table 8), we used the proposed model algorithm to compute each customer's CLV (for details on the CLV computation, see Web Appendix C). We then compared the newly computed CLV from October 2009 with the previously computed CLV from May 2009.

As Table 8 illustrates, the average CLV per customer for each of the five segments was approximately the same, suggesting that the customer segments were similar, at least in their expected long-term profitability to the firm before the field experiment. After the field experiment, we recomputed each customer's CLV using the additional information we gathered over the six months of the field experiment. Our goal was to determine whether a change in the strategy to manage the customers results in a change in the long-term profitability of the customers in each segment.

We find that there are significant differences in the predicted CLVs across customer segments (for the average CLV for customers in each group, see Table 9). The results show that the poststudy CLV is highest for the customers from the proposed model. This suggests that using the proposed model, which accounts for the customer's perceived risk and cost of product returns, not only provides some short-term value through an increase in purchases and decrease in product returns at a lower investment (i.e., increase in average profit during the field experiment) but also positively changes the trajectory of the future profitability of the average customer. This suggests that accounting for the customer's perceived risk and cost of product returns offers a sustainable advantage to a firm.

It is also important to determine whether the firm actually realizes the long-term benefits shown in the CLV prediction after the field experiment. In other words, are the results valid or are they driven by something else, such as a measurement error? Given the results of the field experiment, the focal firm in this study chose to implement the proposed model to allocate resources to all customers moving forward. This makes it difficult to determine the accuracy of the CLV prediction for all customers except the group of customers who were in the proposed model group during the field experiment. This is because the resource allocation algorithm changed after the CLV prediction for all customers except those in the proposed model group. Thus, to

determine the accuracy of the CLV prediction, we collected data on the actual profitability of the customers in the proposed model group for three years after the end of the field experiment (end of October 2009 to end of October 2012). We found that this group had an average actual profit of \$1,353.66, which is similar to the predicted CLV of \$1,402.96. This suggests that the resource allocation strategy that results from the proposed model's objective function (which accounts for the perceived risk and cost of product returns) actually generates long-term customer value as well.

IMPLICATIONS FOR MANAGERS AND ACADEMICS

This study has several important implications for both managers and the marketing literature on measuring and maximizing customer value. First, we show that product returns play a significant role in the firm–customer exchange process both in the short run and the long run. This suggests that it is shortsighted to ignore the impact of customer product return behavior on a customer's perceived risk of purchase when measuring and maximizing customer value. Our results also indicate that the many retailers surveyed in our qualitative study (see Table 1) that do not use product returns in their measure of customer value (even as a cost to be managed) are missing an opportunity to enhance customer and firm profitability. It is especially shortsighted when the aim of the firm is to build long-term and profitable customer relationships over time. Including product returns as both a customer's perceived risk of purchase and a cost that must be managed in the CLV objective function and optimal resource allocation algorithm positively changed the trajectory of a customer's value to the firm. Furthermore, the customer profitability framework outlined in this study can be generalizable to situations in which firms sell mainly services and product returns are scarce. Product returns and customer complaints of service have similar consequences to future customer behavior (Fornell and Wernerfelt 1987; Petersen and Kumar 2009). Thus, managers can substitute the customer's perceived risk and cost of product returns with the customer's perceived risk and cost of customer complaints in this framework to more accurately understand the firm–customer exchange process for a service firm.

In addition, this study shows the value of applying marketing research in practice. First and foremost, this study provides an actionable framework that managers can use for customer selection and optimal resource allocation to maximize customer and firm profit. Second, this study provides an example to other marketing researchers regarding how to design an experiment in practice that can isolate the value of a key metric (in this case, the customer's perceived risk and cost of product returns) and a treatment (in this case, optimal resource allocation). Third, this study shows the significant increase in profits from customers by more effectively allocating resources to customers.

LIMITATIONS AND FURTHER RESEARCH

We acknowledge that this study was only carried out with a single business-to-customer retail firm. Although this limits the potential generalizability of the study, significant effort is required to run a field experiment with a single firm, which is a key contribution. Additional research can

replicate this study in other settings to further enhance the generalizability of this study. For example, it would be worthwhile to examine situations in which the costs of returns are not entirely recoverable (e.g., after commissions are paid to salespeople, after margins are paid to distributors), return policies are stricter (e.g., 15% restocking fee), or the costs of returns are significantly high (e.g., in a grocery context where the salvage value of perishable products is \$0).

Furthermore, it is important to note contexts in which the framework for this study is less applicable. Although we believe that firms in service industry could easily adapt this framework to measure the cost of complaints (instead of product returns), there are two general cases in which firms that sell products might not fully realize the value of this framework. First, firms need to be able to attribute the product return instance to a given customer. If a firm cannot link the product return to the customer, the best it can do is to manage the cost of product returns (but not the customer's perceived risk). Second, in some contexts there is already a significantly developed used-product market, such as for textbooks; firms in these contexts—in this case, publishers—need not worry as much about returns because customers can resell books to third-party retailers for resale.

In addition, this study only used two benchmark models to test the ability of the proposed framework to increase firm profitability through customer selection and optimal resource allocation. We agree that other benchmark models could be reasonable alternatives for comparison with our proposed model. However, the number of benchmark models used reflects the limitations of conducting a field experiment. Further research could test additional models to enhance the viability of the proposed framework, such as determining whether the value of understanding a customer's perceived risk comes from the splitting of purchases and product returns or the inclusion of product returns as an explanatory variable. Alternatively, research could split the marketing effort to determine how e-mails and catalogs work independently and together to drive customer profitability through purchase and product return behavior.

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