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

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ABSTRACT

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 needs to be managed by decreasing the marketing resource allocations toward the customers making the returns. However, recent research suggests 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, we conducted a large-scale customer selection and optimal resource allocation field experiment with 26,000 customers over 6 months from an online retailer. We found 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. Further, we found that by including this risk, rather than simply implementing traditional CLV-based models generically, the firm can target more profitable customers.

Keywords: Customer Perceived Risk, Product Returns, Field Experiment, Optimal Resource Allocation, Customer Lifetime Value
When managers make decisions on customer selection and marketing resource allocation, the main objective is often profit maximization. And, these decisions are based on the premise that the profit objective function that firms are trying 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, often ignoring customer product return behavior or even treating customer product return behavior only as a cost that needs to be managed. This is supported by the qualitative evidence we gathered from a survey of 56 retailers suggesting that less than half of the retailers (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*.

--- Insert Table 1 about here ---

Further, we find that even when they 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 that needs to be managed and avoided rather than having the view that customer product return behaviors have the potential to provide value from lowering the customer’s perceived risk of purchase.

Product returns are no small part of the firm-customer exchange process currently costing firms about $100 Billion annually in reverse logistics, an average drain of roughly 3.8% for every retailer (Blanchard 2007). And, this is likely a conservative figure since the cost of
reverse logistics often does not include the value of lost profit 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).

One reason for customers returning products might be low product quality. If this were the case, then more investments could be focused on improving product quality to reduce product returns. However, a recent survey showed that the top two reasons customers cited for returning products were “No Trouble Found” and “Buyer’s Remorse”, which accounted for around 95% of the responses (Lawton 2008). This suggests that product returns are a necessary part of the exchange process as product returns do not frequently result from product quality issues. Instead product returns seem to be primarily driven by a lack of fit that the consumer only realizes after purchase. However, is it truly necessary to manage customers based on their individual product return behavior?

One solution to this problem is that managers could just choose to write off their losses from product returns and continue to manage customers based only on their purchase behavior and responsiveness to marketing initiatives, as a traditional customer profitability framework would suggest (e.g. Venkatesan and Kumar (2004)). However, it does not seem clear that this would be an ideal solution to increase firm profitability. While product returns do have a direct negative impact on firm profitability through an increase in logistics costs and losses in margins, research suggests 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 (Nasr 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, making this an issue that has to be dealt with across all customers. We surveyed managers from three different firms operating in three different industries. We 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 B2B firm, 64% of customers returned a product; and for a general merchandise retailer, 75% of customers returned a product. This means that about 2 out of every 3 (or more) customers are likely to return a product in their lifetime with the firm (see Web Appendix A for more details). 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 that the customer’s perceived risk related to product returns plays in the firm-customer exchange process, we develop and empirically test a conceptual framework which represents the entire firm-customer exchange process that includes firm-initiated marketing communications, customer buying behavior, and customer product return behavior. The theoretical framework which 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 impact pre- and post-purchase decisions (Nasr Bechwati and Siegal 2005), the willingness of a customer to purchase at a given price (Anderson, Hansen, and Simester 2009), the perception 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 the differences in ongoing customer behavior (both future purchase and product return behavior) and responsiveness to marketing efforts, in turn resulting in a significant loss in a firm’s ability to maximize its profitability.

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 over 6 months from an online retailer, a key contribution of this study. Few other studies actually use field experiments to conduct customer selection and optimal resource allocation, both with B2B high-tech firms (Kumar et al. 2008; Kumar, Venkatesan, and Reinartz 2008). The goal of this field experiment was to see whether improvements in understanding the ongoing relationships between firms and customers can be profitable in the future. After the field experiment, we found that the firm was able to increase profit in both the short-term (6-month profit increased on average by over 45% per customer) and long-term (actual profit over 3 years increased on average by over 29% per customer), when accounting for product return costs and a customer’s perceived risk (Proposed Model). This suggests that the firm’s current strategy (Recency, Frequency and Monetary Value (RFM)-based with product returns managed as a cost), as well as the strategies of the several other firms we found from our qualitative study (as summarized by Table 1) of ignoring a customer’s perceived risk is suboptimal (represented by two benchmark models).

Further, 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, i.e. the
correlations between the different customer selection strategies were weak at best. This
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 not only changes the optimal amount of marketing
resources that each customer should receive to maximize profitability, but it also changes
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). Further, 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 and service
level, and also the longer-term implications of purchase including both the potential benefits
and sacrifices (Sweeney, Soutar, and Johnson 1999). In the immediate situation, a key risk
the customer faces is whether the product provides a sufficient level of post-purchase utility
so that a decision can be made to keep, rather than return, the product (Anderson, Hansen,
and Simsteer 2009). In the longer-term, a key risk the customer faces is whether future
purchases will have a high enough post-purchase 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 pre-purchase, purchase, and post-
purchase, making it necessary to manage customer perceptions throughout the firm-customer
exchange process (Petersen and Anderson 2013).
**Pre-Purchase.** Before a purchase decision is even made, consumers often use past 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 since the firm wants to increase the burden of the return cost to the customer in order to influence the customer not to return the product (Wood 2001). Thus, while 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 the perceived risk is a key factor when a customer is making 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 then increases the customer’s willingness to buy. In fact, the authors find that lowering the perceived financial risk has the highest impact on increasing perceived value for the money. Further, Anderson, Hansen, and Simester (2009) find that when faced with a purchase decision, customers assign a certain value to being able 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 a customer is to make the decision to purchase the product.

**Post-Purchase.** Even after purchase occurs, customers are often faced with information which affects their level of perceived risk. For instance, customers may receive disconfirming information post-purchase that may cause the customer to want to return the product (Nasr Bechwati and Siegal 2005). And, research has shown that the customers who
are forced to pay for their own product return (fee-based) tend to decrease their post-return spending by about 75-100% and the customers who have free-based product returns tend to increase their post return spending by about 158-457% (Bower and Maxham 2012). However, we note that this increase in post-return purchases did include the purchase replacement products suggesting that the gains from free-based are still significant, although should be slightly more conservative. Further, increasing the hassle to return products also has been shown to affect other customer behaviors outside of purchase including customer referrals (Petersen and Kumar 2010).

While it is the case product returns provide a direct cost to firms through reverse logistics costs and losses in profit, this research suggests that the ability to and experience with returning products lowers a customer’s perceived risk, leading to an increase in the customer’s commitment and trust with a firm (Selnes 1998) and increasing the probability of future purchase.

A Field Experiment

Purpose

The goal of this field experiment is 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 in their customer selection and optimal resource allocation decisions. We do this by creating several objective functions which will be used for customer selection and optimal resource allocation which are built on the foundational CLV frameworks already in the marketing literature. Further, we run a 6-month long 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. Then, at the end of the field experiment we observe exactly which resource allocation algorithm is able to maximize profit over a 6-month time period (i.e. short-term).

**Design**

This field experiment was set up using a classical experimental design using a random set of 26,000 customers from the focal firm of the study. The experiment was run in the following way. First, the 26,000 customers were randomly segmented into one of the following five groups (giving 5,200 customers per group). The groups were selected to represent the common ways which retailers measure customer value (as seen in 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-based\(^1\) objective function without considering product returns (*CLV w/o Product Returns*)
4. **Benchmark Model 2 Group** – Targeted using a CLV-based objective function with considering the cost of product returns (*CLV w/Net Buying*)
5. **Proposed Model Group** – Targeted using a CLV-based objective function with considering perceived risk and the cost of product returns (*CLV w/Product Returns*)

The design of this field experiment is depicted in Figure 1 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 different groups will be allocated marketing resources (except for the Control Group), in this case emails and catalogs, over a period of 3 months from May 2009 to July 2009. The decision on the amount of marketing resources to allocate will depend on in which group the customer is randomly segmented. Then, all the groups will be observed for an additional 3 months from August.

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\(^1\) The CLV-based objective function measures the profit (revenue – transaction costs) from purchases and when applicable profit lost from product returns (revenue lost + transaction costs).
2009 to October 2009 where no group will be allocated any marketing resources before a second measurement is taken. We would like to point out that we only optimize marketing communications to customers for 3 months and then observe behavior for another 3 months (6 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. While we do not optimize the marketing communications across the entire 6-month time period, we do not expect the wear-out of the marketing efforts to vary across segments in the second 3 months.

At the end of October 2009, we tabulate the purchase behavior, product return behavior, and marketing efforts to quantify the impact of the 5 different treatment conditions to quantify the short-term effects of resource allocation using each of the different objective functions. Additionally, we recomputed each customer’s CLV at the end of October 2009 to see whether there was also long-term impact which resulted from the different resource allocations. Further, 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 (3 years). We did this to see whether our prediction of CLV at the end of the experiment is close to the actual profit provided by the customers.

-- Insert Figure 1 about here --

Measurement

In this section, our goal is to describe the measurement of the objective functions that we will be optimizing for each of the five groups in the field experiment. Since 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 (Recency, Frequency, and Monetary Value) score which 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 which is derived from a 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, $\text{Marketing}_t$ represents the expected marketing costs incurred by the firm. Finally, $r$ 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. relationship indicator$^2$). This will not directly affect the estimation

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$^2$ The relationship indicator is different from the probability a customer will purchase in a given time period. The probability a customer will purchase in a given time period is contained in the measure for $\pi_1(\text{Purchases}_{st})$ and is time varying. The relationship indicator represents a decision by the customer at the start of the prediction window as to the degree to which the customer wants to continue the entire relationship.
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 which will need to be estimated. The first dependent variable is for $\pi_1(\text{Purchases}_{it})$, the second dependent variable is for Marketing$_{it}$, and the third dependent variable is for $\text{P(\text{Relationship}_{i,t=1})}$. Thus, we get the following equation for Benchmark Model 1:

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

where:
- $CLV_{i,0} =$ Customer lifetime value 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
- $\text{P(\text{Relationship}_{i,t=1})} =$ The probability customer $i$ is active in the relationship at $t = 1$

Benchmark Model 2. The second benchmark model that we use is 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 this, 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. By not having a separate measure for purchases and returns, the objective function cannot differentiate between 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 that can be lowered after satisfactory product return experiences. However unlike Benchmark Model 1,
it does account 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, $\pi_2(NetPurchases_{it})$ represents the expected stream of profit from purchases minus the profit lost from returns over time. Second, Marketing$_{it}$ represents the expected marketing costs incurred by the firm. Finally, $r$ represents the discount rate. Thus, we get the following equation for Benchmark Model 2:

$$CLV_{i,t=0} = P(Relationship_{i,t=1}) \times \sum_{t=1}^{T} \frac{\pi_2(NetPurchases_{it}) - Marketing_{it}}{(1 + r)^{(t-1)}}$$

where:
- $CLV_{i,t=0}$ = Customer lifetime value for customer $i$ at time $t = 0$
- $\pi_2(NetPurchases_{it})$ = 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
- $P(Relationship_{i,t=1})$ = The probability customer $i$ is active in the relationship at $t = 1$

Proposed Model. The Proposed Model we developed separates $\pi_2(NetPurchases_{it})$ into two different variables: $\pi_1(Purchases_{it})$ and $\pi_3(Returns_{it})$. 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 $[\pi_1(Purchases_{it}) - \pi_3(Returns_{it})]$, here we just observe and model the two metrics separately. Further, 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 between the two customers described earlier which have the same overall profitability but different product return profiles. For instance, say customer 1 has

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3 Here the profit lost from product returns includes both the revenue lost from the return of money to the customer and the cost of the reverse logistics (return shipping and restocking fees).
$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 $100, but have different return profiles. Unlike the Proposed
Model which splits purchases and returns, Benchmark Model 2 would not be able to
differentiate between the two customers in this example. Next, Marketing$\_it$ represents the
expected marketing costs incurred by the firm over time. Finally, $r$ represents the discount
rate. Thus, we get the following equation for the Proposed Model:

$$CLV_{i,t=0} = P(\text{Relationship}_{i,t=1}) \times \sum_{t=1}^{T} \left( \frac{\pi_1(Purchases_{i,t}) - \pi_3(Returns_{i,t}) - Marketing_{i,t}}{(1+r)^t} \right)$$

where:
- $CLV_{i,t=0}$ = Customer lifetime value for customer $i$ at time $t = 0$
- $\pi_1(Purchases_{i,t})$ = Expected profit from purchases by customer $i$ in time $t$
- $\pi_3(Returns_{i,t})$ = 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
- $P(\text{Relationship}_{i,t=1})$ = The probability customer $i$ is active in the relationship at $t = 1$

Model Development

In order to run the experiment, we need to compute each customer’s CLV based on the	hree different models (Benchmark Model 1, Benchmark Model 2, and Proposed Model). To
do this, we estimate a model with the drivers of the key variables in the objective functions
and make sure the model is able to accurately predict each customer’s CLV. If the model can
accurately predict a customer’s CLV, then the differences in the results from the field
experiment can be attributed more to the treatment effects rather than to prediction error.

In order to properly model each part of the three objective functions and predict each
customer’s CLV more accurately for the field experiment, we need to accommodate four
challenges common in the CRM 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.

**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. And, this perceived utility of a product can be initially greater than 0, 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 due to past product return behavior). Additionally, we expect that a customer is likely to keep the product only when the realized post-purchase utility remains greater than 0. Thus, the firm’s expectation is that the marketing effort will lead to increasing a customer’s perceived utility for a given product. The value of this marketing effort, usually 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. While a customer can observe several attributes of the product before purchase, e.g. price, the customer does not directly observe ‘fit’ until after the purchase occurs. Thus, once the customer observes the ‘fit’ of the product post-purchase, the utility is modified either upward or downward to reflect the actual fit. In the cases where the customer’s utility of the product is modified downward to the point where the utility becomes negative, the customer chooses to return the product. Conversely, where the utility is still positive, the customer chooses to keep the product.
To accommodate this setup, we use a Type-1 Tobit model to estimate the profit obtained from purchases ($\pi_1(Purchases_{it})$), the profit lost and costs incurred from product returns ($\pi_3(Returns_{it})$), and the marketing efforts allocated toward customers ($Marketing_{it}$), where we augment the data in cases where the value of the dependent variable is either censored or unobserved. The Type-1 Tobit model allows 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 a purchase, return, or marketing effort occurs. For instance, in the case of purchases, the model technically estimates the following equation: $\pi_1(Purchases_{it}) = P(Purchase_{it}) * E(Profit_{it}|Purchase_{it} = 1)$ 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 the purchase occurs, i.e. $Purchase_{it} = 1$.

**Unobserved Dependence between Marketing, Buying, and Product Returns.** In any firm-customer exchange process, the decision of the firm to initiate marketing communications, the decision for a customer to purchase and the decision for a customer 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 $Marketing_{it}$, $\pi_1(Purchases_{it})$, and $\pi_3(Returns_{it})$.

**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

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4 We choose a Type-1 Tobit model (instead of a Type-2 Tobit model) as we expect the underlying drivers of the probability and the conditional expectation for each equation are similar. Using a Type-2 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.
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 a customer is still in the relationship (i.e. the probability the customer will make any future purchases) with the firm independent of the decision of the customer 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 a customer is still in the relationship with the firm starting at the beginning of the CLV prediction window or field experiment time period. The result of this computation is distinct from the probability of a purchase, return, or marketing effort in a given time period, which is accommodated by the Type-1 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 behave independently from each other and a customer value framework needs to accommodate these differences – both unobserved and observed heterogeneity. We follow an approach similar to Rust and Verhoef (2005), where 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, based on 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 SUR Tobit Model with data augmentation. This model allows for us to uncover the drivers of each of the components of the firm-customer exchange process for each customer. Next, for each of the modeling frameworks we compute \( \text{P(Relationship}_{i,t}=1) \) based on 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 BG/NBD model as described by Fader, Hardie, and Lee (2008). We describe these models in the following two sections.

**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:

\[
y_{it} = X_{it} \beta + \epsilon_{it}, \quad \epsilon_{it} \sim N(0, \Omega) \tag{4}
\]

\[
\beta_i = Z_i \delta + \tau_i, \quad \tau_i \sim N(0, \Sigma) \tag{5}
\]

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 \( t \)
\[ \pi_3(\text{Returns}^*_it) = \text{The latent value of profit lost and costs incurred from product returns for customer } i \text{ in time } t \]
\[ \text{Marketing}^*_it = \text{The latent value of marketing costs for customer } i \text{ in time } t \]
\[ X_{it} = A \text{ matrix of the covariates for each customer } i \]
\[ \beta_i = A \text{ matrix of coefficients for each customer } i \text{ that explain } y_{it} \]
\[ Z_i = A \text{ matrix of customer specific demographic variables} \]
\[ \delta = A \text{ vector of coefficients that explain } \beta_i \]
\[ i = \text{Represents each customer} \]
\[ t = \text{Represents each period, in this case quarter} \]

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 \( \beta \), we have the following:
\[ X_{it} = \text{diag}(x_{it}^{\text{Purchases}}, x_{it}^{\text{Returns}}, x_{it}^{\text{Marketing}}) = \begin{bmatrix} 0 & 0 & 0 \\ 0 & 0 & 0 \\ 0 & 0 & 0 \end{bmatrix} ; \beta_i = (\beta_{i1}, ..., \beta_{in})' = \begin{bmatrix} \beta_{i1} & \cdots & \beta_{in} \end{bmatrix} \]

In the case of Benchmark Models 1 and 2, we only have two equations instead of 3. For the purposes of this study, we can implement a Gibbs sampler in a series of 7 steps that are iterated until convergence. For Benchmark Models 1 and 2, there are 6 steps (these two benchmark models skip Step 2). These steps are:

1. Augment \( \pi(Purchases^*_it) \) using the following algorithm:
\[ \pi_i(Purchases^*_it) = \begin{cases} \pi_i(Purchases^*_it), & \text{if } \pi_i(Purchases^*_it) > 0 \\
TN_{[-\infty,0]}(\mu_i(Purchases^*_it), \sigma^2_{\text{Returns}(Purchases^*_it)}), & \text{if } \pi_i(Purchases^*_it) = 0 
\end{cases} \]
where:
\[ \mu_i(Purchases^*_it) = \frac{x_{it}^{\text{Purchases}} \beta_{i1} + \sigma_{\text{Purchases-Purchases}}^{-1} \sum_{Purchase_i} (\tilde{y}_i^{\text{Purchases},it} - E(y_i^{\text{Purchases},it}))}{\sigma_{\text{Purchases-Purchases}}^2} \]
\[ \sigma^2_{\text{Return}(Purchases)} = \sigma^2_{\text{Purchases-Return}} \sigma_{\text{Purchases-Purchases}}^{-1} \sigma_{\text{Purchases-Purchases}}^2 \]
\[ \tilde{y}_i^{\text{Purchases},it} = \pi_i(\text{Returns}^*_it) ; \Sigma_{\text{Purchases}} = \begin{bmatrix} \sigma^2_{\text{Returns}} & \sigma_{\text{Returns-Marketing}} \\ \sigma^2_{\text{Returns-Marketing}} & \sigma^2_{\text{Marking}} \end{bmatrix} \]

When we observe a purchase, the latent value of \( \pi_i(Purchases^*_it) \) takes the observed value. In the cases where we do not observe a purchase, the latent value of \( \pi_i(Purchases^*_it) \) 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 \( \pi_i(Purchases^*_it) \).
2. Augment $\pi^*_j(\text{Returns}^*_i)$ using the following algorithm (only for the Proposed Model):

$$
\pi_j(\text{Returns}^*_i) = \begin{cases} 
\pi_j(\text{Returns}^*_i), & \text{if } \pi_j(\text{Returns}^*_i) > 0 \\
\max(\text{NetProfit}^*_i, TN_{j \in \mathcal{S}_j}(\mu_{\text{Returns}}, \sigma_{\text{Returns}}^2)) & \text{if } \pi_j(\text{Returns}^*_i) = 0 \text{ and } \text{NetProfit}^*_i > 0 \\
0, & \text{otherwise}
\end{cases}
$$

where:

$$
\text{NetProfit}^*_i = \sum_{j=0}^{i} \pi_j(\text{Purchases}^*_j) - \sum_{j=0}^{i} \pi_j(\text{Returns}^*_j)
$$

$$
\mu_{\text{Returns}}(\text{Returns}) = x_{it}^\text{Returns} \beta_{\text{Returns}}^j + \sigma_{\text{Returns} - \text{Returns}} \sum_{j=0}^{i} \pi_j(\text{Returns}^*_j) (y_{\text{Returns},it}^* - E(y_{\text{Returns},it}^*))
$$

$$
\sigma_{\text{Returns} - \text{Returns}}^2 = \sigma_{\text{Returns} - \text{Returns}}^2 - \sigma_{\text{Returns} - \text{Returns}} \sum_{j=0}^{i} \pi_j(\text{Returns}^*_j) \sigma_{\text{Returns} - \text{Returns}}^2
$$

$$
y_{\text{Returns},it}^* = \begin{bmatrix} \pi_j(\text{Purchases}^*_j) \\ \mu_{\text{Marketing}}^j \end{bmatrix}; \Sigma_{\text{Returns} - \text{Returns}} = \begin{bmatrix} \sigma^2_{\text{Purchases}} & \sigma_{\text{Purchases} - \text{Marketing}} \\ \sigma_{\text{Marketing} - \text{Purchases}} & \sigma^2_{\text{Marketing}} \end{bmatrix}
$$

In this case, when we observe a product return the latent value of $\pi_j(\text{Returns}^*_i)$ takes the observed value. In the cases where 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, NetProfit$_{it} = 0$, where NetProfit$_{it}$ is the total profit from purchases from customer i up to time t minus the total profit lost from customer i for product returns up until time t-1. When NetProfit$_{it} = 0$, we do not augment the value for product returns. When NetProfit$_{it}$ is positive (meaning that products can still be returned by the customer), we draw from a truncated normal distribution (Tanner and Wong 1987) and compare the value of the draw with -NetProfit$_{it}$. The greater value between –NetProfit$_{it}$ and the draw from the truncated normal is kept for $\pi_j(\text{Returns}^*_i)$, as a draw from the from the truncated normal that is smaller than –NetProfit$_{it}$ would mean the customer is able to return more products than they previously purchased.

3. Augment Marketing$_{it}^*$ using the following algorithm:
When marketing resources are allocated to a customer, the latent value of Marketing\textsuperscript{*} takes the observed value. In the cases where the firm allocates no resources, the latent value of Marketing\textsuperscript{*} is drawn from a truncated normal distribution (Tanner and Wong 1987).

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

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

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

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 non-informative priors for $v_0, R_0^{-1}, \rho_0,$ and $D_0^{-1}$ so that all inferences are driven by the data. We repeat steps 1 through 7 until convergence is reached, where the fit and convergence of the model were judged visually and by using the Geweke Test (Geweke 1992). We iterate 10,000 times with the first 5,000 iterations considered burn-in and dropped from the results. We see 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 which will help to compute the drivers of $\pi_1(\text{Purchases}_{it}), \pi_2(\text{NetPurchases}_{it}), \pi_3(\text{Returns}_{it}),$ and Marketing\textsubscript{it} for predicting an individual customer’s stream of profit over a given period of time. However, that model does not
account for the fact that a customer can choose to end the relationship with the firm, where
the 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. By treating \( P(\text{Relationship}_{i,t=1}) \) as independent of the
expected stream of profit, it allows us to multiply the two independent processes together and
obtain a prediction of CLV for each customer. We do this 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 2). We tested the correlations in the following manner by using the
data from the empirical study. Since 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 to \( P(\text{Relationship}_{i,t=1}) \).

--- Insert Table 2 about here ---

There is a very low correlation between \( P(\text{Relationship}_{i,t=1}) \) and the other three dependent
variables. This 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 while 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 model (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. This is done in the following manner:

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

(6)

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 > 0
- \( t_x \) = The time of the last transaction
- \( T \) = The end of the observation time window \((t = 0)\)
- \( r \) = The shape parameter from the gamma distribution
- \( \alpha \) = The scale parameter from the gamma distribution
- \( a, b \) = Shape parameters of the beta distribution

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. We then multiply this prediction of the probability that a customer is active at time \( t = 1 \) with the NPV 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 comes from two different samples in two time periods from a B2C company that sells footwear, apparel, and other accessories through the Internet and mail-order catalogs and is aggregated by quarter. The return policy of this store is considered very lenient in that they are willing to give 100% of your money back for any reason if, at any time after the purchase, you do not want to keep the product. The data for this cohort comes from Q2, 2003 to Q1, 2006. To remove any

---

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

6 We 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) since it is measuring the probably of obtaining a stream of profits. If the firm wants to compute CLV again in the future, they would calculate \( P(\text{Relationship}_{i,t=1}) \) at the beginning of expected stream of future profits.
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 products per customer. These purchases generated about $1.94M in profit or about $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 about $343k or about $197 per product return. This means, on average, about 1 of 6 products purchased was returned for a refund or an exchange (1,741/9,943 or about 17.5%) – falling within the expected range (4-25%) of direct marketers (Fenvessy 1992). In addition, these customers received a total of 41,837 catalogs and emails between Q2, 2003 and Q1, 2006: about 45 catalogs and emails per customer or 15 catalogs and emails per customer per year.

**Variable Selection and Operationalization.** The variables selected as predictors in each of the models ($\pi_1(Purchases^*_it)$, $\pi_2(NetPurchases^*_it)$, $\pi_3(Returns^*_it)$, and Marketing$^*_it$) are based on the commitment-trust theory of relationship marketing (Morgan and Hunt 1994). We select these variables as research has shown that a customer’s perceived risk plays a significant role in a customer’s commitment and trust with a firm. A reduction in a customer’s perceived risk acts a mechanism to build feelings of commitment and trust between the customer and the firm (Selnes 1998). Further, this increase in trust provides value to the customer increasing the customer’s 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

---

7 There was an average of 5.4 transactions per customer or about 2 products per transaction. Each customer made at least 1 transaction since the sample includes customers who made their first purchase during Q2, 2003.
summarize the list of variables selected and how each variable is operationalized for each of the three equations in Table 3. We note that the intention here was to be inclusive of variables previously used in CLV models and not to introduce new variables.

-- Insert Table 3 about here --

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. While these variables can help to significantly increase the model fit, they can also potentially help managers in acquisition strategies when the demographic profiles of the prospects are known and there are no purchase histories to rely on for prediction. For the purpose of this study, we only use demographic 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 4A and 4B. We choose to use the same set of variables for each model (except adding the product return-related variables as needed⁸) 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 4A. 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 generally affects the dependent variables. We find that the results are similar to

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⁸ We include product returns as an explanatory variable in the Marketing equation for Benchmark Model 2 as 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 as it captures the impact of product return behavior on future purchase behavior.
those in past studies, offering some external validation. For instance, we see in the Proposed Model that product returns have a negative impact on future marketing expenditures and a positive impact on future purchase behavior. This highlights the exact trade-off between the firm managing the costs of product returns and the firm benefiting from higher future purchase behavior as a result of lowering a customer’s perceived risk that we are studying.

We present the results of the estimation of \( P(\text{Relationship}_{i,t=1}) \) in Table 4B. The results show that there is a significant difference between the likelihoods of different customers being active at the start of the prediction period (mean = 0.81; min = 0.002; max = 0.95). Further, we test for the potential presence of endogeneity of marketing efforts using the Wu-Hausman test\(^9\). We found the posterior of the parameter estimate on the error from the marketing equation as an independent variable in the purchase equation to be not significant from 0 (\( p > 0.41 \)), suggesting that endogeneity bias is not an issue in this study.

--- Insert Tables 4A and 4B about here ---

**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 to the benchmark models. To do this, 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 starting right 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.\(^{10}\) Additionally, we compute \( P(\text{Relationship}_{i,t=1}) \) directly from the results of the estimation found in Table 4B and

\(^9\) We thank one of the anonymous reviewers for raising this issue.

\(^{10}\) We provide details of the prediction algorithm in *Web Appendix B*. 

25
from the historical transaction information from each customer, i.e. \( x, t_s, \) 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 5).

--- Insert Table 5 about here ---

We see from the results in Table 5 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 see that the model has an average deviation of 3.61 for marketing costs (MAPE\(^{11}\): 21.1\%) and 27.91 for profit from purchases (MAPE: 17.1\%). For Benchmark Model 2, we see that the model 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, for the proposed model, we see that the 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 re-estimate the models for a new and larger sample of customers and use the customer-level parameter estimates from the models to 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. This data contains 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 following 5 groups described earlier:

---
\(^{11}\) MAPE is computed only conditional on a purchase, product return, or market effort actually occurring.
1. **Control Group** (No Formal Measure)
2. **Firm Strategy Group** (RFM)
3. **Benchmark Model 1 Group** (CLV w/o Product Returns)
4. **Benchmark Model 2 Group** (CLV w/ Net Buying)
5. **Proposed Model Group** (CLV w/ Product Returns)

To determine whether each group of customers were similar in past and predicted behavior, we measured the average total past profit and projected the average long-term profitability over 3 years (i.e. CLV) for each customer in each group using our Proposed Model objective function and the general estimation framework as described earlier in this paper (see Table 6). We provide details on the prediction algorithm for each customer’s CLV in *Web Appendix C*.

-- Insert Table 6 about here --

The results from Table 6 show that each of the five groups of customers is 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. Since 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*, the customer selection and resource allocation algorithm is based on the RFM score, common for many direct marketing firms. This rewards Recent, Frequent, and high spending (Monetary value) customer purchase behavior. In addition, this firm also had a policy which 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 earlier in this paper (see Eq. 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. 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 6-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:

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

(7)

where:

- \( \pi_1(\text{Purchases}_{i,t}) \) = Expected profit from purchases by customer i in time t
- \( \pi_3(\text{Returns}_{i,t}) \) = 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 \( T = 1 \) quarter)
- \( P(\text{Relationship}_{i,t=1}) \) = Computed probability a customer is in the relationship with the firm at the beginning of the field experiment (t = 1)

\[\text{12 For the resource allocation, the marketing equation is not used since marketing is the decision variable. The marketing model is only relevant in the design of the study to understand the dynamics between marketing efforts, customer purchase behavior, and customer product behavior.}\]
There were two constraints placed 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 which were less than or equal to the optimal marketing spend in order to 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 email is $1.00,\textsuperscript{13} the customer would receive two emails at the total cost of $2.00 to the firm. Second, we only optimized the allocation of resources to customers for a single time period (1 quarter), but observed the continued purchasing and product return behavior of customers for two periods (2 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. Finally, many customers have already chosen whether to receive catalogs, emails, or both. In the cases where the customers choose one or the other, the customers only received the desired marketing effort. In the case where there was no preference or where the customers wanted to receive both, an equal number of catalogs and emails were sent.

\textsuperscript{13} We note that the cost of an email ($1.00) and the cost of a catalog ($3.00) were estimated by the firm. We do note that the marginal cost of sending an email is very low (almost nothing) and most of the cost of the email is a fixed cost of setting up the email campaign. However, it is not appropriate to just send each email to each customer given the low marginal cost since the cadence of contacting customers (and not over-contacting) is important in maintaining the relationship.
We then ran the study over the 6 month time period, where catalogs were mailed and emails were sent during the first 3 months based on the respective resource allocation algorithms described earlier and purchases and returns were observed over the 6 month time period. One reason we chose to allow 3 months to pass with no catalogs, is that managers of the focal firm in this field experiment stated that, after an email or catalog is mailed, approximately 87% of the purchases occur within 8 weeks (2 months) and 95% of the purchases after a catalog or email is sent occur within 12 weeks (3 months). Further, managers stated that approximately 90% of product returns occur within 8 weeks after purchase (2 months) and 98% of product returns occur within 12 weeks after purchase (3 months). Second, recent research suggests 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 3 months after the last potential catalog or email is sent to each customer, we should likely observe at least 95% of all of the purchase and over 90% of the product return behavior that result from sending these catalogs or emails to the customers.\textsuperscript{14} It is unlikely to determine exactly the wear-out time of emails 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 emails during this time same period.

Field Experiment Results

After the 6 month time period elapsed, we analyzed the number of emails 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

\textsuperscript{14} We find 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 1 month.
experiment (see Table 7). Using the control group as the benchmark for our comparisons, we see that the 5,200 customers from the control group made purchases totaling $1.60M, product returns totaling $403.2k, and received no catalogs or emails 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 emails were sent to the 5,200 customers resulting in a slight increase in profit from purchases ($1.62M) and decrease in profit lost and costs incurred from product returns ($373.2k) compared to the control group. As a result, we see an increase in the average profit per customer to $240.55 or about 2%. While we did see 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 emails and catalogs did cause the profitability to increase only marginally above the control group.

Using the strategy with Benchmark Model 1 (CLV w/o Product Returns), 17,199 catalogs and emails were sent to the 5,200 customers resulting in an increase in profit from purchases ($1.71M) and decrease in profit lost and costs incurred from product returns ($290.16k) from the control group. As a result, we see an increase in the average profit per customer to $273.48 or about 16%. When compared to the firm’s strategy, we see that Benchmark Model 1 is able to send fewer catalogs and emails 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 w/ Net Buying), 14,664 catalogs and emails were sent to the 5,200 customers resulting in an increase in profit from purchases ($1.80M) and decrease in profit lost and costs incurred from product returns ($270.21k) from the control group. As a result, we see an increase in the average profit per customer to
$294.21 or about 25%. When compared to the firm’s original strategy, we see that Benchmark Model 2 is also able to send fewer catalogs and emails to the customers to obtain a higher average customer through increases in purchases and decreases in product returns. In addition, when compared to Benchmark Model 1, we see that Benchmark Model 2 provides a higher average profit per customer during the 6 month time period. This suggests that accounting for purchases net product returns (versus just purchases in Benchmark Model 1) does provide a slightly higher profit over the short-run.

Using the strategy with the Proposed Model (CLV w/ Product Returns), 12,090 catalogs and emails were sent to the 5,200 customers resulting in an increase in profit from purchases ($2.02M) and decrease in profit lost and costs incurred from product returns ($201.16k) from the control group. As a result, we see an increase in the average profit per customer to $352.77 or about 50%. When compared to the firm’s original strategy, we see that the Proposed Model is also able to send fewer catalogs and emails to the customers to obtain a higher CLV through increases in purchases and decreases in returns. In addition, when compared to Benchmark Model 1 and Benchmark Model 2, we see 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 based on the proposed objective function which accounts for both the cost of product returns and the role of a customer’s perceived risk in their 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 see significant differences in the profitability of each group. For the Control Group the firm
obtained $1.22M, for the Firm Strategy Group the firm obtained $1.25M, for the Benchmark Model 1 Group the firm obtained $1.42M, for the Benchmark Model 2 Group the firm obtained $1.53M, and for the Proposed Model Group the firm obtained $1.83M. We see that by using the Proposed Model, the firm was able to get about $300k 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, we see from the results in Table 7 that when firms account for the costs of product returns they are able to significantly lower the total dollars of products returned, from $290.16k for Benchmark Model 1 to $270.21k for Benchmark Model 2. As expected, when the costs of product returns impact expected profitability resources will be reallocated to minimize the cost of product returns. However, we also see 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 $270.21k for Benchmark Model 2 to $201.16k for the Proposed Model. This suggests that understanding the dynamics between product return behavior and purchase behavior over time allows firms to distinguish between customers that 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 where the benefits to customer profitability are coming from. There are three ways a firm can realize a higher profit from a given customer using the profit function from the Proposed Model: (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 8).

--- Insert Table 8 about here ---

With regard to profit from purchases, the Proposed Model offered increases of 26.3% over the Control Strategy, 24.7% of 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 above 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 lowering of a customer’s perceived risk (i.e. gains from Benchmark Model 2 to Proposed Model). If we focus only on the average gains in profit during the 6 month time period we see that the gains from managing the costs of returns increase profit by about 7.6% and the gains from accounting for a customer’s perceived risk increase profit by about 19.9%. This suggests that managing costs are important, but understanding how customers respond to product return experiences can generate significantly higher (more than 2x) increase in profit for the firm.

**How Would the Proposed Model Allocate Resources in Other Groups?** These results also raise the question as to whether the Proposed Model causes a substantial shift in how
marketing resources are allocated. For instance 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 9). 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.

-- Insert Table 9 about here --

The results here suggest that the marketing efforts allocated using the Firm Strategy are
relatively uncorrelated to the marketing efforts allocated using the Proposed Strategy. We
note that the correlation of 0.03 is significant from a statistical perspective, but that is more
likely due to the sample size of 5,200 than it is due to the fact that they 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 to a CLV-based strategy. Research has shown that
there is some correlation between RFM and CLV, as Recency, Frequency, and Monetary
Value are often key drivers of CLV. However, this correlation is not always terribly high.
Second, and perhaps more importantly, the firm lowers the resource allocations to customers
who return products. The results of the estimation in Table 4A show that past product returns
are positively related to future purchase behavior. Thus, many of the customers who received
fewer marketing efforts in the Firm’s Strategy due to product return behavior received
significantly more marketing efforts using the Proposed Model.
The marketing efforts allocated using Benchmark Model 1 is only weakly correlated (0.27, p < 0.01) 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 being directed at customers who return products as the resource allocation algorithm does not punish customers for over-returning since the costs of product returns do not affect the allocation decision. As a result, the deviations between the Proposed Model and Benchmark Model 1 are a result of over-spending on customers who return too many products and under-spending on customers who are profitable, but do not return many products.

The marketing efforts allocated using Benchmark Model 2 is moderately correlated (0.42, p < 0.01) with the marketing efforts allocated using the Proposed Strategy. There seems to be one main reason for this finding. While product returns now enter the profit objective function as a cost through \(\text{NetPurchases}\) 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.

**Are the Different Models Targeting the Same Customers?** One other interesting result from the resource allocation field experiment is with regard to who is targeted with marketing efforts. For instance, we find in many cases 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 are usually in 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 which find that moderate return rates tend to generate the most profitable customers in the future (Petersen and Kumar 2009).

On the other hand, 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 into the future. This suggests that the Proposed Model wants the firm to target a different type of customer than the benchmark models – not just reallocate 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 which 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 short-term profitability of customers. In addition to showing that including the customer’s perceived risk related to product returns positively affects firm profit in the short-term, we want to see whether the Proposed Model also creates some long-term customer value. To do this we compute 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 (see Table 6 for the pre-field test CLV values), we used the Proposed Model algorithm to compute each customer’s CLV (see Web Appendix C for details on the CLV computation). We then compare the newly computed CLV from October 2009 to the previously computed CLV from May 2009.
As we saw in Table 6, the average CLV per customer for each of the 5 segments was about the same suggesting that each segment of customers 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 6 months of the field experiment. The goal here is to see 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 (see Table 7 for the average CLV for customers in each group). We notice from the results that the post-study 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), it 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 if the long-term benefits shown in the prediction of CLV after the field experiment are actually realized by the firm. 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 due to the fact that 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 from the end of the field experiment (End of Oct 2009 to End of Oct 2012). We found that this group had an average actual profit of $1,353.66 which is similar to the predicted CLV $1,402.96. This suggests that the resource allocation strategy resulting from the objective function in the Proposed Model which accounts for the perceived risk and cost of product returns is actually generating long-term customer value as well.

**Implications to Managers and Academics**

This study has several important implications to both managers and the marketing literature on measuring and maximizing customer value. First, this study has shown that product returns play a significant role in the firm-customer exchange process both in the short-term and long-term. This suggests that ignoring the impact of customer product return behavior on a customer’s perceived risk of purchase when measuring and maximizing customer value is short-sighted. It also suggests that many of the retailers who were surveyed in our qualitative study (see Table 1) that do not use product returns in their measure of customer value (even as a cost that needs to be managed) are missing an opportunity to enhance customer and firm profitability. It is especially short-sighted when the desire of the firm is to build long-term and profitable relationships over time. Including product returns as a customer’s perceived risk of purchase and a cost that needs to be managed in the CLV objective function and optimal resource allocation algorithm positively changed the trajectory of a customer’s value to the firm. Further, the customer profitability framework outlined in this study can be generalizable to situations where 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.

Additionally, this study shows the value of applying marketing research in practice. First and foremost, this study provides a framework which managers can use for customer selection and optimal resource allocation to maximize customer and firm profit which is actionable. Second, this study provides an example to other marketing researchers on how to design an experiment in practice which 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). Finally, this study showed the significant increase in profits obtained from customers by more effectively allocating resources to customers.

**Limitations and Future Research**

We acknowledge that this study was only carried out with a single B2C retail firm. While this limits the potential generalizability of the study, it requires significant effort to run a field experiment with a single firm, a key contribution. Future research can replicate this study in other settings to further enhance the generalizability of this study. For instance, it would be worth studying situations where the costs of returns are not entirely recoverable (e.g. after commissions are paid to salespeople or margins are paid to distributors), when return policies are stricter (e.g. 15% restocking fee), or where the costs of returns are significantly high (e.g. in a grocery context where the salvage value of perishable products is $0).
Further, it would important to note where the framework for this study is less applicable. While we believe that firms in service industry could easily adapt this framework to measure the cost of complaints (instead of product returns), there two general cases some cases where firms who 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 they 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 textbooks, where firms, in that case publishers, need not worry as much about returns as customers can resell books to 3rd party retailers for resale.

Additionally this study only used 2 benchmark models to test the ability of the proposed framework to increase firm profitability through customer selection and optimal resource allocation. We agree that there can be other benchmark models which are reasonable alternatives for comparison with our Proposed Model. However, the number of benchmark models used reflects the limitations of conducting a field experiment. Future research can also test additional models to enhance the viability of the proposed framework, such as understanding 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 or splitting the marketing effort and seeing how emails and catalog work independently and together to drive customer profitability through purchase and product return behavior.
References


Blanchard, David (2007), "Supply Chains Also Work in Reverse," in *Industry Week*.


FIGURE 1: Experimental Design of Field Experiment

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<thead>
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<th></th>
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<td>x₅</td>
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</table>

Note: Oᵢa represents the value of a Customer i, and xᵢ represents the type of treatment that was applied to customer i.

TABLE 1: Number of Retailers who Use a Given Customer Selection and ORA Strategy

<table>
<thead>
<tr>
<th>Resource Allocation Strategy</th>
<th>No Formal Allocation Model</th>
<th>Based on Rank-order</th>
<th>Use an ORA Algorithm</th>
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<td>No Formal Measure</td>
<td>2</td>
<td>0</td>
<td>0</td>
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<tr>
<td>RFM/PCV</td>
<td>11</td>
<td>12</td>
<td>0</td>
</tr>
<tr>
<td>CLV w/o Product Returns</td>
<td>5</td>
<td>5</td>
<td>1</td>
</tr>
<tr>
<td>CLV w/ Net Buying</td>
<td>10</td>
<td>7</td>
<td>1</td>
</tr>
<tr>
<td>CLV w/ Product Returns</td>
<td>0</td>
<td>0</td>
<td>2</td>
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</tbody>
</table>

RFM = Recency, Frequency, and Monetary Value; PCV = Past Customer Value
CLV = Customer Lifetime Value; ORA = Optimal Resource Allocation

Table 2: Correlations Between P(\text{Relationship}_{t=1}), Purchases, Returns, and Marketing

<table>
<thead>
<tr>
<th>Correlations</th>
<th>P(\text{Relationship}_{t=1})</th>
<th>Avg(Purchases)</th>
<th>Avg(Returns)</th>
<th>Avg(Mktg)</th>
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</thead>
<tbody>
<tr>
<td>P(\text{Relationship}_{t=1})</td>
<td>1</td>
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<td></td>
</tr>
<tr>
<td>Avg(Purchases)</td>
<td>0.08</td>
<td>1</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Avg(Returns)</td>
<td>0.03</td>
<td>0.42</td>
<td>1</td>
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<tr>
<td>Avg(Mktg)</td>
<td>0.04</td>
<td>0.61</td>
<td>0.66</td>
<td>1</td>
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<td>Variable</td>
<td>Operationalization</td>
<td></td>
<td></td>
<td></td>
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<tr>
<td>----------------------------------------------</td>
<td>------------------------------------------------------------------------------------</td>
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<tr>
<td><strong>Variable Operationalization</strong></td>
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<tr>
<td><strong>Model: $\pi_1(\text{Returns}_{it})$</strong></td>
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</tr>
<tr>
<td>Average Value of Past Product Returns</td>
<td>The average value of profit lost and costs incurred from product returns of customer i up to the current time period</td>
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<td></td>
</tr>
<tr>
<td>Net Value of Past Product Returns</td>
<td>The total profit lost and costs incurred from product returns from customer i up to the current time period</td>
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<td></td>
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</tr>
<tr>
<td>Log Marketing Costs</td>
<td>The log (marketing costs + 1) from the current time period for customer i</td>
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<td></td>
<td></td>
</tr>
<tr>
<td>GM from Purchasing</td>
<td>The profit from the purchases in the current time period for customer i</td>
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<tr>
<td>Lag of Purchase Indicator</td>
<td>An indicator of whether customer i purchased a product in the last time period</td>
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<tr>
<td>Lag of Product Return Indicator</td>
<td>An indicator of whether customer i returned a product in the last time period</td>
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<tr>
<td>Average Inter-return Time</td>
<td>The average time between product returns for customer i in (months)</td>
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<tr>
<td>Average Inter-return Time²</td>
<td>The square of the average time between purchases for customer i</td>
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</tr>
<tr>
<td>Crossbuying</td>
<td>The number of product categories purchased by customer i from time 0 to t</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Multichannel Shopping</td>
<td>The number of distribution channels purchased by customer i from time 0 to t</td>
<td></td>
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<td></td>
</tr>
<tr>
<td>Crossbuying * Multichannel Shopping</td>
<td>The interaction between crossbuy (number of product categories purchased) and multichannel (the number of distribution channels purchased) for customer i</td>
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</tr>
<tr>
<td>Holiday Indicator</td>
<td>A dummy variable that is 1 when the time period is quarter 4, 0 otherwise</td>
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<tr>
<td><strong>Model: $\pi_2(\text{Purchases}<em>{it})$ or $\pi_3(\text{NetPurchases}</em>{it})$</strong></td>
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<tr>
<td>Average Value of Past Purchases</td>
<td>The average value of profit from purchases of customer i up to the current time period</td>
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<tr>
<td>Net Value of Past Purchases</td>
<td>The total profit from purchases of customer i up to the current time period</td>
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<tr>
<td>Log Marketing Costs</td>
<td>The log (marketing costs + 1) from the current time period for customer i</td>
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<tr>
<td>Lag of GM from Purchasing</td>
<td>The profit from the purchases in the previous time period for customer i</td>
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<tr>
<td>Lag of GM Lost from Product Returns</td>
<td>The profit lost and costs incurred from product returns in the previous time period for customer i</td>
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<tr>
<td>Average Interpurchase Time</td>
<td>The average time between purchases for customer i in (months)</td>
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<td><strong>Model: Marketing$^e_{it}$</strong></td>
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<tr>
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<td>The average value of profit from purchases of customer i up to the current time period</td>
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<tr>
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<td>An indicator of whether customer i purchased a product in the last time period</td>
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<td>Lag of Marketing Costs</td>
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<tr>
<td>Income</td>
<td>Income of the customer at the first time period of the analysis</td>
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### TABLE 4A: HB SUR Tobit Model Estimation Results
Means and (Standard Deviations) are from Distributions of Parameters Estimates across Customers

<table>
<thead>
<tr>
<th>Variable</th>
<th>Benchmark Model 1</th>
<th>Benchmark Model 2</th>
<th>Proposed Model</th>
</tr>
</thead>
<tbody>
<tr>
<td>Model: $\pi_1(\text{Returns}^*_i)$</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Intercept</td>
<td>-37.10 (7.31)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Average Value of Past Purchases</td>
<td>0.63 (0.01)</td>
<td>0.03 (0.004)</td>
<td></td>
</tr>
<tr>
<td>Net Value of Past Product Returns</td>
<td></td>
<td>2.68 (0.09)</td>
<td></td>
</tr>
<tr>
<td>Log Marketing Costs</td>
<td></td>
<td>0.07 (0.02)</td>
<td></td>
</tr>
<tr>
<td>GM from Purchasing</td>
<td>16.49 (5.44)</td>
<td>52.94 (3.79)</td>
<td></td>
</tr>
<tr>
<td>Lag of Purchase Indicator</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Lag of Product Return Indicator</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Average Inter-return Time</td>
<td>9.52 (1.70)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Average Inter-return Time*</td>
<td>-0.26 (0.43)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Crossbuying</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Multichannel Shopping</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Crossbuying * Multichannel Shopping</td>
<td>3.53 (1.25)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Holiday Indicator</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Model: $\pi_2(\text{Purchases}^<em>_i)$ or $\pi_2(\text{NetPurchases}^</em>_i)$</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Intercept</td>
<td>15.13 (5.02)</td>
<td>30.01 (9.05)</td>
<td>15.34 (4.93)</td>
</tr>
<tr>
<td>Average Value of Past Purchases</td>
<td>0.75 (0.03)</td>
<td>0.58 (0.03)</td>
<td>0.77 (0.03)</td>
</tr>
<tr>
<td>Net Value of Past Purchases</td>
<td>0.07 (0.005)</td>
<td>0.014 (0.005)</td>
<td>0.06 (0.004)</td>
</tr>
<tr>
<td>Log Marketing Costs</td>
<td>0.53 (0.06)</td>
<td>0.41 (0.04)</td>
<td>0.54 (0.07)</td>
</tr>
<tr>
<td>Lag of GM from Purchasing</td>
<td>0.12 (0.013)</td>
<td>0.035 (0.01)</td>
<td>0.15 (0.01)</td>
</tr>
<tr>
<td>Lag of GM Lost from Product Returns</td>
<td>---</td>
<td>---</td>
<td>0.05 (0.001)</td>
</tr>
<tr>
<td>Average Interpurchase Time</td>
<td>22.74 (2.04)</td>
<td>6.23 (1.99)</td>
<td>23.63 (1.99)</td>
</tr>
<tr>
<td>Average Interpurchase Time*</td>
<td>-0.60 (0.09)</td>
<td>-0.13 (0.02)</td>
<td>-0.68 (0.09)</td>
</tr>
<tr>
<td>Crossbuying</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Multichannel Shopping</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Crossbuying * Multichannel Shopping</td>
<td>17.85 (2.08)</td>
<td>7.06 (2.04)</td>
<td>17.55 (2.08)</td>
</tr>
<tr>
<td>Holiday Indicator</td>
<td>56.58 (2.22)</td>
<td>31.12 (2.17)</td>
<td>56.44 (2.21)</td>
</tr>
<tr>
<td>Model: $\pi_3(\text{Marketing}^*_i)$</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Intercept</td>
<td>-0.47 (0.09)</td>
<td>-0.51 (0.09)</td>
<td>-0.46 (0.08)</td>
</tr>
<tr>
<td>Average Value of Past Purchases</td>
<td>0.01 (0.0002)</td>
<td>0.008 (0.0002)</td>
<td>0.008 (0.0002)</td>
</tr>
<tr>
<td>Lag of Purchase Indicator</td>
<td>1.62 (0.09)</td>
<td>1.57 (0.08)</td>
<td>1.61 (0.08)</td>
</tr>
<tr>
<td>Lag of Product Return Indicator</td>
<td>---</td>
<td>-1.01 (0.13)</td>
<td>-0.98 (0.13)</td>
</tr>
<tr>
<td>Lag of Marketing Costs</td>
<td>0.75 (0.01)</td>
<td>0.74 (0.01)</td>
<td>0.75 (0.01)</td>
</tr>
<tr>
<td>Average Interpurchase Time</td>
<td>0.64 (0.02)</td>
<td>0.64 (0.02)</td>
<td>0.63 (0.02)</td>
</tr>
<tr>
<td>Average Interpurchase Time*</td>
<td>-0.04 (0.01)</td>
<td>-0.04 (0.01)</td>
<td>-0.03 (0.01)</td>
</tr>
<tr>
<td>Holiday Indicator</td>
<td>1.15 (0.09)</td>
<td>1.14 (0.09)</td>
<td>1.15 (0.09)</td>
</tr>
</tbody>
</table>

* NS denotes not significantly different from 0  
** --- denotes that variable is not included in the model

### TABLE 4B: BG/NBD Estimation Results for P(\text{Relationship}_i,t=1)

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Estimate</th>
</tr>
</thead>
<tbody>
<tr>
<td>$r$</td>
<td>4.794</td>
</tr>
<tr>
<td>$\alpha$</td>
<td>6.777</td>
</tr>
<tr>
<td>$\beta$</td>
<td>17.385</td>
</tr>
<tr>
<td>$b$</td>
<td>294.443</td>
</tr>
<tr>
<td>Log-Likelihood</td>
<td>-7515.8</td>
</tr>
<tr>
<td>$\mu$ of P(\text{Relationship}_i,t=1)</td>
<td>0.81</td>
</tr>
<tr>
<td>Min of P(\text{Relationship}_i,t=1)</td>
<td>0.002</td>
</tr>
<tr>
<td>Max of P(\text{Relationship}_i,t=1)</td>
<td>0.95</td>
</tr>
</tbody>
</table>
TABLE 5: Model Comparison – MAD/(MAPE) of Out-of-Sample Prediction
(Results based on prediction for each customer in each quarter during holdout time period)

<table>
<thead>
<tr>
<th>MODEL</th>
<th>Marketing $(\mu = 17.11)$</th>
<th>NetPurchases $(\mu = 133.70)$</th>
<th>Purchases $(\mu = 162.81)$</th>
<th>Returns $(\mu = 29.11)$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Benchmark Model 1 (without Returns)</td>
<td>3.61 (21.1%)*</td>
<td>-</td>
<td>27.91 (17.1%)</td>
<td>-</td>
</tr>
<tr>
<td>Benchmark Model 2 (Net Purchases)</td>
<td>3.60 (21.0%)</td>
<td>45.82 (34.3%)</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>Proposed Model (with Returns)</td>
<td>3.54 (20.7%)</td>
<td>-</td>
<td>27.35 (16.8%)</td>
<td>6.94 (23.8%)</td>
</tr>
</tbody>
</table>

* Numbers in parentheses represent MAPE values

TABLE 6: Past Profit and Predicted CLV of Each Customer Group

<table>
<thead>
<tr>
<th>Customer Group</th>
<th>Average Past Profit (Std. Dev.)</th>
<th>Average CLV (Std. Dev.)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Control</td>
<td>$1,226.96 (512.86)</td>
<td>$1,721.28 (683.88)</td>
</tr>
<tr>
<td>Firm’s Strategy</td>
<td>$1,206.57 (514.75)</td>
<td>$1,697.31 (701.23)</td>
</tr>
<tr>
<td>CLV w/o Product Returns</td>
<td>$1,201.65 (517.44)</td>
<td>$1,675.11 (692.57)</td>
</tr>
<tr>
<td>CLV w/ Net Purchases</td>
<td>$1,216.80 (503.37)</td>
<td>$1,680.84 (704.68)</td>
</tr>
<tr>
<td>CLV w/ Product Returns</td>
<td>$1,221.62 (521.49)</td>
<td>$1,719.78 (699.25)</td>
</tr>
</tbody>
</table>

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

TABLE 7: Field Experiment Results

<table>
<thead>
<tr>
<th>Customer Group</th>
<th>Total Profit from Purchases in 6 Months</th>
<th>Total Profit Lost from Product Returns in 6 months</th>
<th>Total Catalogs and Emails Sent in the First 3 Months</th>
<th>Average Profit Per Customer During the 6 Months</th>
<th>Average CLV Per Customer Post Study</th>
</tr>
</thead>
<tbody>
<tr>
<td>Control</td>
<td>$1.60M</td>
<td>$403.20k</td>
<td>0</td>
<td>$235.20</td>
<td>$1,088.89</td>
</tr>
<tr>
<td>Firm’s Strategy</td>
<td>$1.62M</td>
<td>$373.20k</td>
<td>19,760</td>
<td>$240.55</td>
<td>$1,087.03</td>
</tr>
<tr>
<td>Benchmark Model 1 (without Returns)</td>
<td>$1.71M</td>
<td>$290.16k</td>
<td>17,199</td>
<td>$273.48</td>
<td>$1,172.17</td>
</tr>
<tr>
<td>Benchmark Model 2 (Net Purchases)</td>
<td>$1.80M</td>
<td>$270.21k</td>
<td>14,664</td>
<td>$294.21</td>
<td>$1,223.16</td>
</tr>
<tr>
<td>Proposed Model (with Returns)</td>
<td>$2.02M</td>
<td>$201.16k</td>
<td>12,090</td>
<td>$352.77*</td>
<td>$1,402.96*</td>
</tr>
</tbody>
</table>

* The values found for average profit per customer during the 6 months and average CLV per customer post study for the Proposed Model are statistically significantly larger from each of the other segments
** The actual CLV per customer in the Proposed Model Group over an extended period of 3 years after the end of the field experiment was $1,353.66
### TABLE 8: Relative Gains for the Proposed Model

<table>
<thead>
<tr>
<th>MODEL</th>
<th>Profit from Purchases</th>
<th>Profit Lost from Product Returns</th>
<th>Marketing Costs</th>
<th>Average Profit Per Customer</th>
<th>Average CLV Per Customer</th>
</tr>
</thead>
<tbody>
<tr>
<td>Control</td>
<td>26.3%</td>
<td>-50.1%</td>
<td>N/A</td>
<td>51.5%</td>
<td>28.8%</td>
</tr>
<tr>
<td>Firm’s Strategy</td>
<td>24.7%</td>
<td>-46.1%</td>
<td>-38.8%</td>
<td>46.6%</td>
<td>29.1%</td>
</tr>
<tr>
<td>Benchmark Model 1 (without Returns)</td>
<td>18.1%</td>
<td>-30.7%</td>
<td>-29.7%</td>
<td>28.5%</td>
<td>19.7%</td>
</tr>
<tr>
<td>Benchmark Model 2 (Net Purchases)</td>
<td>12.2%</td>
<td>-25.6%</td>
<td>-17.6%</td>
<td>19.1%</td>
<td>14.7%</td>
</tr>
</tbody>
</table>

The percentages in each cell represent the benefit the Proposed Model strategy provides the firm relative to the other strategy.

### TABLE 9: Correlation of Resource Allocations with Proposed Model

<table>
<thead>
<tr>
<th>MODEL</th>
<th>Firm’s Strategy</th>
<th>Benchmark Model 1</th>
<th>Benchmark Model 2</th>
</tr>
</thead>
<tbody>
<tr>
<td>Proposed Model</td>
<td>0.03</td>
<td>0.27</td>
<td>0.42</td>
</tr>
</tbody>
</table>

*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 < 0.01
Web Appendix

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

Web Appendix A: Qualitative Insights from Marketing Practice

How prevalent are product returns for retailers?

To answer this question, we reached out to three managers from three different firms: a catalog apparel retailer, a high-tech B2B firm, and a general merchandise retailer. We asked each manager to determine the percentage of customers in the entire database that had made at least 1 product return since that customer made his or her first purchase. We found that 70% of customers at the catalog apparel retailer return a product, 64% of customers from the high-tech B2B firm returned a product, and 75% of customers from the general merchandise retailer returned a product. Thus, many different types of firms experience product returns from the majority of their customer base. This suggests that any policy by the firm to manager product return behavior is likely to affect the majority of the customer base.

What are retailers currently doing to measure and maximize customer value?

To answer this question, the firm which conducted the field experiment in collaboration with us conducted interviews with retailers during the first quarter of 2009. In total, we surveyed 74 managers over the telephone from 56 retailers who sold products (i.e. dealt with customer product returns) from industries including, but not limited to home and gardening, apparel, arts and crafts, grocery, supermarkets, furniture, lighting and fan, electronics, retail department, footwear, and auto parts stores. The telephone survey was scheduled after making the initial contact with the retailer corporate office. The contact information was obtained from the company website. Each interview lasted anywhere from 12 minutes to 20 minutes. In some retail firms, we obtained two interviews to validate the responses. The retailers were located all over the U.S. The annual revenue for the smallest retailer exceeded $120 million and they have been in business for over 10 years. We asked each of the retailers the following two open-ended questions which are key to this study:

1. How do you measure the value of your customers?
2. How do you allocate marketing resources to customers?

We collected the responses from the survey and then grouped the responses from each question into one of several categories from our prior experience working with retailers. First
with regard to measuring customer value, we grouped the responses into 5 categories: (1) No Formal Measure, (2) RFM-based or Past Customer Value (PCV)-based, (3) CLV-based without considering product returns, (4) CLV-based with considering the cost of product returns, and (5) CLV-based with considering the cost and perceived risk of product returns. No Formal Measure is defined as the case where the firm applies no formal customer value measurement process. In general, these firms usually allocated marketing resources to every customer at each time a marketing campaign was initiated (i.e. all customers get all emails). RFM-based or PCV-based is defined as the case where the firm applies a backward-looking measure of customer value, i.e. only past purchase behavior or past profits help the firm value a given customer. In this case, RFM (Recency, Frequency, and Monetary Value) and PCV (Past Customer Value) are used to represent this category as they are the two most common backward-looking measures the retailers we surveyed use.1 CLV-based without considering product returns is defined as the case where the firm uses a forward-looking measure of customer value, i.e. predicts future behavior, but only considers customer purchase behavior and firm-initiated marketing efforts. CLV-based with considering the cost of product returns is defined as the case where the firm uses a forward-looking measure of customer value and includes product returns in one of the following two ways: (1) either it is subtracted from purchases where purchases become net buying behavior or (2) the average product return behavior across all customers is reflected in the gross profit margin as a cost of doing business. As an example, Alan Beychok, the CEO of Benchmark Brands, said to us:

“We net out the cost of product returns from the sales revenue for each customer and then apply the gross margin percent to work with the gross contribution margin. We use this gross contribution margin as one of the inputs in deciding the number of catalogs to mail out.”

In this case, the firm cannot differentiate between two types of customers who generate profit of $100: (a) a customer with $200 in profit from purchases and $100 in profit lost from product returns or (b) a customer with $100 in profit from purchases and no product returns. CLV-based with considering the cost and perceived risk of product returns is defined as the

---

1 RFM-based models score customers based on recency of purchase, frequency of purchases, and monetary value of purchases. Customers received more points for purchases which are more recent, more frequent, and have a higher monetary value. Customers are then ranked from the highest to lowest RFM scores. PCV-based models measure the total net present value (NPV) of past profit of each customer has provided to the firm and rank order customers based on the highest to lowest total past profit (in today’s dollars).
case where the firm uses a forward-looking measure of customer value and integrates a separate measure of customer-level product return cost as part of the CLV measure. In this case, the firm not only captures a product return cost in its measure of CLV, it also captures the impact product return behavior has on future customer purchase behavior. We do note that very often, the choice of how product returns is used in computing the value of a customer, is determined by the capabilities of the database used by the retailers.

Second, with regard to how firms allocate marketing resources, we grouped the responses into 3 categories: No Formal Allocation Model, Based on Rank-order, and Use an ORA (Optimal Resource Allocation) Algorithm. No Formal Allocation Model is defined as the case where the firm does not discriminate between customers, i.e. each customer gets the same marketing efforts. Based on Rank-order is defined as the case where the firm rank-orders the customers using the customer selection metric and allocates resources to the top X% of customers based on resource constraints. Use an ORA Algorithm is defined as the case where the firm has a formal process which tries to allocate marketing resources to maximize profit from all customers.

After we grouped the retailers into each of the three categories, we populated a crosstab table with the retailers who have the different customer selection and optimal resource allocation strategies (see Table WA1). There are a few key takeaways from Table 1. First, very few retailers (3.5%) are not applying at least a basic customer selection and optimal resource allocation model. However, from a customer value measurement standpoint, we see that the majority of retailers either use a backward-looking metric like RFM/PCV (41%) or a forward-looking metric which does not directly account for product returns, i.e. CLV without considering product returns (20%). Only 35.5% either integrate product returns as a measure of net buying behavior, i.e. CLV with considering the cost of product returns (32%), or as a separate measure within CLV, i.e. CLV with considering the cost and perceived risk of product returns (3.5%). And from a resource allocation standpoint, we see that about half of the retailers (50%) do not even have a formal resource allocation strategy, i.e. all customers receive all mailings. Although close to a majority of retailers use a rank-order allocation strategy (43%), only a few retailers use the more sophisticated optimal resource allocation algorithms (7%).

**TABLE WA1: Number of Retailers who Use a Given Customer Selection and ORA Strategy**
This raises the question as to why all firms do not use a customer selection model with product returns and an optimal resource allocation algorithm. First, there can be a lack of capability to measure customer value or run a proper optimization even if the desire is there. Some retailers do not have the appropriate infrastructure to collect the appropriate data or the analysts in place to analyze the data. Second, the retailers may put a lot of effort into measuring value in a more sophisticated way since transaction data is accessible, but only use these results to run some simple resource allocation strategies (i.e. top 25% receive the marketing effort) if it is too complex or costly to apply the optimal contact strategy at an individual level. Third, the retailers may not have collected the data in a way that lends itself to integration. For instance, many retailers may have all the transaction data linked to a customer. However, these retailers may not have collected the product return data in a way where it is easy to link it back to a given customer. Finally, it may be the case that a retailer may be capable of implementing the most advanced analytics but may not be interested in doing so, as the ROI of these advanced analytics is not yet clear. Whatever the reason may be, the goal of this study is to understand the value of understanding the role of perceived risk with customer product return behavior and integrating this into a customer selection and optimal resource allocation to maximize short- and long-term customer profitability.
Web Appendix B: Prediction of the Dependent Variables

Here, we describe the process for predicting the dependent variables for each of the customers. For the case of Benchmark Model 1, we only need to predict Purchases and Marketing. For the case of Benchmark Model 2, we only need to predict NetPurchases and Marketing. And, for the case of the Proposed Model we need to predict Purchases, Returns, and Marketing and the prediction for the profit from purchases for customer i in time t is computed in the following manner. Specifically, the expected value for purchases for customer i in time t is the Monte Carlo average of the expected value over N draws:

$$ Purchases_i = \frac{\sum_{n=1}^{N} \left( \Phi \left( x^{\text{Purchases}}_n, \beta^{\text{Purchases}}_{i,n} \right) \right) }{N} $$

where:

- $$ \beta^{\text{Purchases}}_{i,n} $$ is the n\textsuperscript{th} draw of $$ \beta^{\text{Purchases}} $$ from the MCMC algorithm
- $$ \Omega = C'C $$ and $$ c^{\text{Purchases}} $$ is the diagonal element for the Purchases equation of the Cholesky root C
- $$ \lambda_{n,\text{Purchases}} = \left( \Phi \left( x^{\text{Purchases}}_n, \beta^{\text{Purchases}}_{i,n} + \lambda_{n,\text{Purchases}} c^{\text{Purchases}} \right) \right) $$

$$ N = 5,000 $$ or the number of posterior draws from the MCMC algorithm

The prediction for the profit lost and cost incurred from product returns for customer i in time t is made in the following manner. It is the Monte Carlo average of the expected value over N draws:

$$ Returns_i = \frac{\sum_{n=1}^{N} \left( \Phi \left( x^{\text{Returns}}_n, \beta^{\text{Returns}}_{i,n} \right) \right) }{N} $$

where:

- $$ \beta^{\text{Returns}}_{i,n} $$ is the n\textsuperscript{th} draw of $$ \beta^{\text{Returns}} $$ from the MCMC algorithm
- $$ \Omega = C'C $$ and $$ c^{\text{Returns}} $$ is the diagonal element for the Returns equation of the Cholesky root C
- $$ \lambda_{n,\text{Returns}} = \left( \Phi \left( x^{\text{Returns}}_n, \beta^{\text{Returns}}_{i,n} + \lambda_{n,\text{Returns}} c^{\text{Returns}} \right) \right) $$

$$ NetProfit_i = \sum_{j=0}^{t} \hat{Purchases}_i - \sum_{k=0}^{t-1} \hat{Returns}_{i,k} $$

$$ N = 5,000 $$ or the number of posterior draws from the MCMC algorithm

The prediction for the marketing cost allocated for customer i in time t is computed in a similar fashion. Specifically, the expected value for the marketing cost allocated for customer i in time t is the Monte Carlo average of the expected value over N draws:
\[ \text{Marketing}_n = \sum_{n=1}^{N} \left( \Phi \left( \frac{x_{n \text{Marketing}} \beta_{n \text{Marketing}}}{\sigma_{n \text{Marketing}}} \right) \right) \left( \frac{x_{n \text{Marketing}} \beta_{n \text{Marketing}}}{\sigma_{n \text{Marketing}}} + \lambda_{n \text{Marketing}} \sigma_{n \text{Marketing}} \right) / N \]

where:

- \( \beta_{i,n}^{\text{Marketing}} \) is the \( n^{th} \) draw of \( \beta_i^{\text{Marketing}} \) from the MCMC algorithm
- \( \Omega = C' C \) and \( c_{n \text{Marketing}} \) is the diagonal element for the Marketing equation of the Cholesky root \( C \)
- \( \lambda_{n \text{Marketing}} = \phi \left( \frac{x_{n \text{Marketing}} \beta_{n \text{Marketing}}}{\sigma_{n \text{Marketing}}} \right) / \Phi \left( \frac{x_{n \text{Marketing}} \beta_{n \text{Marketing}}}{\sigma_{n \text{Marketing}}} \right) \)

\( N = 5,000 \) or the number of posterior draws from the MCMC algorithm
Web Appendix C: Prediction Algorithm for CLV

Here, we describe the process for compute the CLV for a given customer. In order to compute the CLV for each customer, we first need to predict the expected value of each of the key variables in the objective function. To predict the three dependent variables in each time period, we use a stepwise approach. We predict values in time t using the predicted values in time t-1. For the variables that are not predicted, we assume that the value does not change in future time periods. For the purpose of this analysis, we predict CLV over a 3-year, or 12 quarter, window. We use the predictions of the three dependent variables for each customer in each of the 12 quarters along with the computation of \( P(\text{Relationship}_{i,t=1}) \) at May 2009 for the initial CLV prediction and at October 2009 for the final CLV prediction. For quarter 1, we use the observed values for the customers in the final time period of the observation window as the independent variables. Starting with the quarter 2 prediction, we update the independent variables which are based on the three dependent variables we are predicting using the newly predicted values and keep the values of the other independent variables constant. At the end of the 12th quarter, we sum the discounted value of the stream of Purchases, Returns, and Marketing and multiply it with \( P(\text{Relationship}_{i,t=1}) \) to arrive at the prediction of CLV.

Using the data from the original sample of 935 customers, the results from Tables 4A and 4B suggest that our model is able to accurately predict the three dependent variables we need to compute CLV. We test to see if, when combined with \( P(\text{Relationship}_{i,t=1}) \), we are able accurately predict each customer’s CLV in the holdout period for this group of customers. Here the holdout time period starts in Q2 2006 and goes until Q1 2009. Using the predictions of each of the dependent variables as described above, we compute each customer’s expected CLV in the holdout time period for the original sample of 935 customers. We compare the predicted CLV with the actual CLV (see Table C.1).

<table>
<thead>
<tr>
<th>MODEL</th>
<th>MAD</th>
<th>MAPE</th>
<th>Predicted Mean</th>
</tr>
</thead>
<tbody>
<tr>
<td>Benchmark Model 1 (without Returns)</td>
<td>$98.45</td>
<td>9.81%</td>
<td>$1,081.40</td>
</tr>
<tr>
<td>Benchmark Model 2 (Net Purchases)</td>
<td>$108.26</td>
<td>10.79%</td>
<td>$1,098.85</td>
</tr>
</tbody>
</table>

TABLE C.1: Comparison of CLV Models – MAD of Out-of-Sample Prediction
(Results based on prediction of CLV for each customer for all quarters during holdout time period)
The results of this CLV prediction show that each of the three models is effective in predicting CLV, with the Proposed Model offering the most accurate prediction (MAPE of Benchmark Model 1: 9.81%, MAPE of Benchmark Model 2: 10.79%, and MAPE of Proposed Model: 5.42%). While it is not surprising that a model with additional variables predicts more effectively, there are two findings from this result. First, we see that including product returns as a separate dependent variable and accounting for the probability of a customer still being in the relationship seems to eliminate the over-prediction bias that is common in the previous CLV modeling frameworks. Second, we see from Benchmark Model 1 to the Proposed Model that the inclusion of product returns as a dependent variable achieves two results: (1) increases the predictive accuracy of Marketing and Purchases and (2) allows for the prediction of Returns. Also, by separating Purchases and Returns, the Proposed Model has a slightly higher predictive accuracy for CLV than Benchmark Model 2. This suggests that understanding the perceived risk related to product returns significantly improves prediction. As a result, we confidently use this CLV prediction framework for predicting CLV for the customers in each of the 5 groups in the field experiment.