Product Returns and Bad Debts in Direct Marketing: Implications for the Targeting Dilemma and Return Policies

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The goal of this dissertation is to investigate the role of product returns and bad debts (i.e., customers default, keeping the products without paying for them) in direct marketing. The dissertation constructs several models to study return and bad debt behaviors as well as its combined impact on firm profitability.

The dissertation consists of two essays, which have a common research objective, but differ in the theoretical focus and methodology. Essay #1, “Targeting Dilemma at the Bottom of the Pyramid,” sets up a seemingly unrelated regression model and a logit framework to measure the differential impact of bad debt information on the profitability of a firm’s targeting policies in a cross-sectional empirical context. While response is cross-sectional, this data involves multiple waves of targeting of consumers by the firm, the essay solves the endogeneity problem of non-random targeting. Results reveal a positive correlation between customer preferences for the return option and those for the bad debt option. We suggest that the firm should target customers with more payments or more returns in the past when the product return is not allowed.

Essay #2, “A Structural Model of Default and Product Return Options with Implications for Return Policies,” further studies the trade-offs between the return and default option by developing a structural model and applying it to a panel dataset from a co-operative database in direct mail. Our research finds that customers have lower price sensitivity and higher transaction
fit uncertainty if we ignore defaults. Furthermore, this essay shows that customers’ trade-offs between return and default option are influenced by their return and default costs as well as the transaction fit of the product. Our research illustrates the importance of including the default option when estimating demand and studying the optimal return policies for firms.

Overall, the dissertation helps researchers understand how customers trade off costs in choosing the return and bad debt option in direct marketing, and helps managers incorporate these behaviors jointly in making targeting decisions and return policies.
Product Returns and Bad Debts in Direct Marketing: Implications for the Targeting Dilemma and Return Policies

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Submitted in Partial Fulfillment of the Requirements for the Degree of
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University of Connecticut

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Product Returns and Bad Debts in Direct Marketing: Implications for the Targeting Dilemma and Return Policies

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Introduction Chapter

In the ‘direct response’ industry which largely serves the needs of customers who may have limited or no access to credit card debt, many firms use a ‘bill me later’ payment mechanism and allow customers to pay by check after receiving the product. This introduces a risk of costs that could be incurred due to customers’ defaults (i.e., customers keep the products without paying for them), termed the risk of ‘bad debt’ for firms.

Bad debts and product returns consume substantial resources, and lead to continual inefficiency and sub-optimal profits for firms. Academic research has largely focused on the effect of returns, detailing conditions under which return behavior can be profitable. Less is known about the latter, even though predicting bad debt is an important marketing activity for firms in the direct response industry.

The objective of this dissertation is to investigate return and default behaviors as well as its combined impact on firm profitability. The dissertation consists of the follow essays:

Essay #1. Targeting Dilemma at the Bottom of the Pyramid, and


Essay #1 measures the differential impact of bad debt information on the profitability of a firm’s targeted marketing policies. We construct a logit framework and make an empirical application to a dataset in a co-operative database. While response is cross-sectional, this data involves multiple waves of targeting of consumers by the firm, the essay solves the endogeneity problem of non-random targeting. We also model customer responses to firm targeting using a
seemingly unrelated regression (SUR) approach. The models are estimated by the maximum likelihood procedure which selects the set of values for the model parameters that maximizes the likelihood function. One major contribution of Essay #1 is that we find a positive correlation between customer preferences for the return option and those for the bad debt option, which implies that the bad debt option cannot be ignored in the study of product returns. This raises the interesting question: what would be the impact on firm profits if it does not allow product returns, thus effectively removing the return choice from the customer’s choice set?

As a first step towards understanding the answer to this question, we simulate probability changes for the three options (bad debt, paid, and no order) after removing the return option, then study the firm’s optimal targeting scheme when the return option is removed. Our results show that removing the return option may actually increase the firm’s profit. Our framework suggests that the firm should target customers with more payments or more returns in the past when the product return is not allowed.

Essay #2 further studies the trade-offs between the default option and return option in direct mail utilizing panel data on customer return and defaults. We set up a structural model with both return and default options included, and compare it with the model in Anderson, Hansen, and Simester (2009), which does not have a default option. We empirically apply the two models to a panel dataset from a co-operative database. We use a Markov Chain Monte Carlo algorithm for estimation.

A key contribution of Essay #2 is that we find out how customers choose between the return and default option. Customers compare their return costs and default costs, and prefer the option with a lower cost. Meanwhile, when the product fits the customer’s preferences better, customers are more likely to keep the product, which means a preference for default over return. We find
estimates of product fit uncertainty and demand elasticities can be biased when we do not consider the default option. This further illustrates the importance of including the default option in customers’ choice set of responding to direct mail.

Essay #2 also contributes to helping firms design return policies when considering defaults. We find that allowing product returns can increase customers paying probabilities. In addition, having a strict return policy for product categories with higher uncertainty of transaction fit can increase firms’ profits. As return costs are higher, customers may make orders more cautiously, thus less likely to make returns afterwards, which helps reduce firms’ loss from product returns.

Overall, this dissertation helps researchers understand how customers choose between the return and default options in direct marketing, and helps managers make targeting decisions and return policies to reduce product return and bad debt costs.
Chapter 1

Targeting Dilemma at the Bottom of the Pyramid
Abstract

Dealing with ‘demon customers’ (Selden and Colvin 2003) consumes substantial resources, and leads to continual inefficiency and sub-optimal profits for firms. Undesirable behavior exhibited by such customers can manifest in two major types of behavior – unwarranted returns and bad debt. Academic research has largely focused on the effect of returns, detailing conditions under which return behavior can be profitable (Petersen and Kumar 2009). Less is known about the latter, even though predicting bad debt is an important marketing activity for firms in the direct response industry, which markets products to a substantial segment of customers with limited access to credit card debt. For such customers transaction specific ‘credit rating’ is not predetermined (as in credit cards), but is rather an integral part of the targeting process through the ‘bill me later’ payment mechanism. Thus little is also known about the following research question: what is the combined impact of both return and bad debt behaviors on firm profitability? We study this important question with the help of a unique dataset from a co-operative database, and find that direct response firms may benefit from reconsidering their return policies by factoring in customer bad debt propensities and costs.

Keywords: Product return; Bad debt; Direct mail; Targeted Marketing
1. Introduction

Firms targeting customers trade off maximizing response with minimizing costs due to undesirable customers. Increasing credit card usage by US consumers (Durkin 2000) implies that for most commonly studied firms costs of targeting undesirables are restricted to the costs of returns, since the risk of non-payment is assumed by credit card companies. However there is a substantial and largely understudied industry called the ‘direct response’ industry that largely serves the needs of customers who may have limited or no access to credit card debt. Many firms in this industry use a ‘bill me later’ payment mechanism that does not require a credit card. Rather, customers most often pay by check after receiving the product. This introduces an additional risk in the targeting decision of costs that could be incurred due to non-payment by customers, termed risk of ‘bad debt’. Thus firms in the direct response industry grapple with dual issues of minimizing returns and bad debt in crafting their targeting algorithms.

This dual optimization constitutes a non-trivial challenge to targeted marketing. Previous research has underscored the need to account for propensity to return in targeted marketing, as returns, while helping to reassure customers and build relationships under some conditions, can also be potentially costly for firms. Product returns cost firms an estimated $100 billion annually due to product depreciation and costs incurred in managing the return process can reach 35% of revenues for some catalog retailers (Anderson, Hansen, and Simester 2009). Retailers allow the product return option because customers are more likely to order the products when they have a return option (e.g. Anderson, Hansen, and Simester 2009). Firms may penalize excessive return behavior through various disincentives such as a penalty for returned products. Managing product returns is complex since there is a non-linear (inverted U) relationship between the number of product returns and a customer’s profitability to a firm.
By contrast bad debt has been relatively less studied in the marketing literature. Recent research (Liu, Pancras, and Houtz 2015) has shown that firms can substantially improve profits by incorporating information on customer bad debt behaviors in their targeting policies. When examining the undesirable behaviors of returns and bad debt in tandem, the question that is of paramount importance from the direct response firm’s point of view is the relative magnitude of the costs of return and bad debt. In many cases the answer may not be as obvious as it may seem at first glance. In fact in some situations the bad debt option can cost less than the return option for the firm! This may be due to high labor costs related to operations such as product handling or restocking costs, which may end up exceeding the cost of the product itself. This raises the counter-intuitive research question that is addressed in this paper: what would be the impact of a firm’s policy to not allow product returns?\footnote{Note that this would allow customers to retain products without payment (become ‘bad debts’) if they choose to do so. While somewhat counterintuitive, this may be a plausible alternative for firms for whom the cost of collecting bad debt is greater than the cost of the product.}

In this paper we measure the differential impact of bad debt information on the profitability of a firm’s targeted marketing policies. We first calibrate the impact of return information, largely replicating the relationships reported in earlier research (Petersen and Kumar 2009). Then we measure the impact of adding bad debt information incrementally demonstrating its value in predicting returns, then providing evidence for the need to explicitly incorporate bad debt prediction into the targeting algorithm.

The major contributions of this paper to the literature on returns and customer targeting are as follows. To our knowledge our study is the first to find a positive correlation between customer preferences for the return option and those for the bad debt option, which implies that the bad debt option cannot be ignored in the study of product returns. We also find that removing...
the return option may actually increase the firm’s profit: our framework suggests that the firm should target customers with more payments or more returns in the past when the product return is not allowed. Substantively this study is also, to our knowledge, one of the first to study unique marketing issues related to the substantial segment of customers (of up to 28% of the US population) who have limited or no access to credit card debt, and we term this segment as the ‘bottom of the pyramid’.

In section 2, we describe the related literature on product returns and targeting in direct marketing. In Section 3, we construct the discrete choice modeling framework and compare the possible models. In section 4, we estimate the models using data obtained from a Spanish book company. In section 5, we use the estimates in section 4 to perform a simulation study of removing the return option. In section 6, we discuss the optimal targeting scheme when the return option is removed. We conclude in section 7.

2. Industry Background, Theory and Literature Review

2.1 The response/screening tradeoff in the direct response industry

Firms employing targeted marketing face a key tradeoff in terms of credit screening and customer response. With the widespread use of credit cards in both online and offline commerce, credit screening has largely been outsourced to the banks and companies that issue credit cards. However the proportion of customers who do not own a credit card due to low income or past credit issues is still about 28% of US consumers (Holmes 2014), which amounts to 65.8 million consumers. Companies that serve this sizeable consumer segment have to find ways to screen out consumers who are bad debts among these from those who will pay.
In addition to this structural targeting issue, there is likely an under-researched propensity of customers to respond when they are invited to ‘buy now and pay later’, which could be perceived as being given a ‘pass’ on screening. This is likely to exist not only among the 65.8 million customers who do not own a credit card, but also probably a sizeable proportion among the 33% who own 1-2 credit cards and who may have limited credit. The ‘bill me later’ payment mechanism is likely to cue impulse purchase (Rook 1987; Gilbride et al 2015) though we are not aware of research that explicitly studies the mechanism underlying this tradeoff. However the tradeoff exists, as is evidenced by the existence of the sizeable ‘direct response industry’ that is described in the following section. While tracing this mechanism is, we believe, a fruitful area for future research, in this paper we focus more on the managerial implications of this tradeoff in a real field study using appropriate econometric methods to accurately document the response of customers to targeted marketing in a direct response context. We also identify bad debt prediction and management through refining targeting algorithms as one unique feature of this segment that may be termed the ‘bottom of the pyramid’.

While the terms ‘catalog marketing’ and ‘direct response’ are used in similar contexts, catalog marketing often requires payment with a credit card or a check upfront. This is to be distinguished from the direct response industry, where the payment terms are often on a ‘bill me later’ basis. Essentially here the credit rating component of the commercial transaction is not outsourced, but instead is made an integral part of the targeting process. In other words, targeting

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2 We draw on terminology that was used by Prahalad and Hammond (2002) and Prahalad (2009) regarding the potential benefits of targeting a large number of customers with lower purchasing power in developing countries. However we apply the concept to the large segment of customers in the US with lower purchasing power and limited access to credit card debt that often pose unique challenges to marketing practitioners. We believe many of these challenges in targeting this ‘bottom of the pyramid’ in the West such as the bad debt-return targeting tradeoff that we study represent under-researched opportunities for academic marketing research.
has to be optimized to not just maximize response, but also to minimize the possibility of bad debt.

This paper examines bad-debt and return policies in the context of the direct response industry, which approached $2 billion in revenues in 2014 (Statista 2013). We focus on a subset of this industry known as the ‘bill-me-later’ market. These are direct response product or service offers which do not require payment prior to order shipment. Bill-me-later offers expose the marketer to the risk of consumer bad-debt, but simultaneously increases response rates. Many well-known companies promote bill-me-later offers. MBI (collectibles, jewelry, gifts, Bradford Exchange (collectibles, jewelry, gifts), Boardroom (newsletters) and Publishers Clearing House (magazines, merchandise) have combined revenue approaching $1.5 billion³. Furthermore, many of the 7,000 magazines published in the U.S. also offer bill-me-later options. The bill-me-later business model has also morphed into major applications outside of the direct response industry as well, probably to take advantage of its ability to increase response rates. A striking example of this was the 2008 purchase by the leading online payments system company Paypal of ‘Bill Me Later’, a company that extends credit on a transaction by transaction basis for almost $1 billion (Bruene 2008).

2.2 Product returns and bad debts

³ Industry sources and online links were accessed to obtain this estimate. See the following links: https://www.statista.com/topics/1265/magazines/, http://www.mbi-inc.com/, https://www.google.com/?gws_rd=ssl&q=publishers+clearing+house+revenue, all accessed November 4, 2016.
Two questions have dominated the research on product returns: (1) Should the firm offer a return option? (2) Should the firm charge for the product return? Firms generally offer a return option because customers are less likely to order products if the return option is not allowed (Anderson, Hansen, Simester 2009). Firms also allow product returns from retailers if there is a viable used market for the product, where customers have a high willingness to pay for used products (Gümüs, Ray, and Yin 2013). Furthermore, product return behavior can be managed to increase lifetime value of customers; Petersen and Kumar (2009) find that customer value is maximized at an intermediate level of returns, rather than either a complete absence or an extremely high level of returns.

As product returns can be costly, many retailers charge a restocking fee for the product return. The return penalty may be more severe when product returns are salvaged by a channel member because the retailer misses out on the generous refund from the manufacturer when the retailer salvages returned units without the help of the manufacturer (Shulman, Coughlan, and Savaskan 2010). However, things are different for online retailers. They should either institute a policy of free product returns or at least examine their customer data to determine their customers' responses to return fees (Bower and Maxham III 2012). This is because customers who paid for their product returns decreased their post-return spending at that retailer; and those who had free returns increased their post-return spending.

The extant literature on returns does not consider the bad debt option when studying returns. Liu, Pancras, and Houtz (2015) have shown that the firm can significantly increase its profit after incorporating bad debt behaviors. However they do not address the issue whether bad debt and return behavior are related, or trace out consequent implications for firm targeting. An intriguing possibility arising from this perspective of considering bad debt and returns as possibly related
behaviors is whether the firm may actually prefer bad debt to product return when the cost of return is greater. This could occur if the firm were to find it optimal to not allow product returns under certain conditions, which would provide a counterpoint to the recommendations of the previous literature on product returns.

2.3 Non-random targeting in catalog mailing

Past responses of customers to firm targeting reveal their preferences, and it is common practice in industry for firms to target customers based on their responsiveness to past targeting by firms. While this is intuitive, the practice can cause bias in customer response models that do not account for this non-random firm targeting behavior. Firms employing customer response models to make targeting decisions thus have to correct for their own targeting behavior in the past. In other words, before the firm decides to send a mailing to a certain customer, it should consider how many mailings have been sent to that customer. Ignoring the targeted histories in the modeling process for individual level targeting biases the parameter estimates (Dong, Manchanda, and Chintagunta 2009). Several papers provide possible reasons for these biases. For example, customers have an adverse reaction to direct mail activity because of heavy direct mail activity by the firm in the past (Hartmann, Nair, and Narayanan 2011). But the effect can be temporary. The negative influence of extra mailings on future responding decisions dies out after one year (van Diepen, Donkers, and Franses 2009). When the firm sends mail intermittently and achieves its full impact instead of continually mailing and diminishing their effectiveness, the total response is higher (Ansari, Mela, and Neslin 2008). Firms can increase the profits when targeting over multiple periods as opposed to a single period (Gonul, Frenkel Ter Hofstede 2006). In contrast to the earlier literature, which corrects for bias in purchase decisions only, our
study shows the effect of such bias in two additional response options, return and bad debt customer response.

Most of the previous literature suggests that the firm should target customers with higher probability to response. For example, Bodapati (2008) suggests that the firm should target customers whose purchase probabilities will increase if they receive the targeted mailings. We use sensitivity of purchase probabilities and measure the customers’ response probabilities under the scenario where product returns are not allowed. A summary of major contributions of this study with respect to the extant literature discussed above is given in Table 1.1.

*** INSERT TABLE 1.1***

3. Data and Models

The data is obtained from a co-operative database contributor which sells Spanish books by direct mail\(^4\), and contains customers’ historical transaction information such as the number of historical cancels/returns, the number of historical payments, the total return count and so on. The company selected certain customers to send direct mail promotions on six dates\(^5\). There are 140208 customers and 200,779 observations in total.

We adopt a two-pronged modeling strategy to study the research question about the interplay between return and bad debt modeling in the targeting decision of firms. In the first we model as continuous dependent variables the responses of customers to firm targeting in terms of

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\(^4\) The book is a single book called a ‘hints and tips type book’, written in Spanish. The type of promotion is often called a ‘solo offer’, where just one item promoted in the mail piece.

\(^5\) These are termed archive dates by the company.
the number of orders placed, the number of returns and the number of bad debts. In the second approach we model the probabilities of incidence of each of these discrete responses. We report major findings from each approach below. Below we develop a conceptual framework and utilize the framework to select predictors for the continuous and discrete response models which are developed in subsequent sections.

3.1 Continuous response model

We model customer responses to firm targeting using a seemingly unrelated regression (SUR) approach. The simultaneous equations comprising this method are:

\[ \text{Order}_{it} = \alpha_0 + \alpha_1 TON_{it} + \alpha_2 (TON_{it}^2)^{1/3} + \alpha_3 HON_{it} + \alpha_4 (HON_{it}^2)^{1/3} + \alpha_5 ORN_{it} + \]
\[ \alpha_6 (ORN_{it}^2)^{1/3} + \alpha_7 TB\text{N}_{it} + \alpha_8 (TB\text{N}_{it}^2)^{1/3} + \beta' Z_{OR} + \epsilon_{OR} \] (1)

\[ \text{Return}_{it} = \delta_0 + \delta_1 ORN_{it} + \delta_2 (ORN_{it}^2)^{1/3} + \delta_3 TON_{it} + \delta_4 (TON_{it}^2)^{1/3} + \delta_5 HON_{it} + \]
\[ \delta_6 (HON_{it}^2)^{1/3} + \delta_7 TB\text{N}_{it} + \delta_8 (TB\text{N}_{it}^2)^{1/3} + \lambda' Z_{RE} + \epsilon_{RE} \] (2)

\[ \text{Bad\text{d}eb}_{it} = \omega_0 + \omega_1 TB\text{N}_{it} + \omega_2 (TB\text{N}_{it}^2)^{1/3} + \omega_3 ORN_{it} + \omega_4 (ORN_{it}^2)^{1/3} + \omega_5 TON_{it} + \]
\[ \omega_6 (TON_{it}^2)^{1/3} + \omega_7 HON_{it} + \omega_8 (HON_{it}^2)^{1/3} + \phi' Z_{BD} + \epsilon_{BD} \] (3)

Where \((\epsilon_{OR}, \epsilon_{RE}, \epsilon_{BD})' \sim \text{iidN}(0, \Omega'')\)

Descriptions and descriptive statistics of each of the dependent and independent variables are given in Table 1.2 below. The average number of returns is 0.05, and of bad debts is 0.03. Note that ‘Hispanic order number’, indicating the number of Hispanic book orders, is comparatively lower (mean of 2.24) compared to total order number (mean of 22.93). The number of payments for related category (Hispanic) products is 1.84, showing that there is some

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6 More details of the analyses are available on request.
bad debt in historical related category purchases. The average number of previous mailings is 0.36, while the length of residence is 9.86 years on average.

***INSERT TABLE 1.2***

We first present model comparison results, with Model 1 estimating only Equation 1 and 2, where coefficients are estimated using SUR without historical bad debt information in independent variables. In Model 2, we add one-off bad debt ratio to model 1 to estimate the system of equations. Finally in Model 3 we add Equation 3 also to the model and estimate the simultaneous system of equations. In Table 1.3 below, we present the model comparison which shows the predictive power of using bad debt information. This is especially apparent in the comparison of Models 1 and 2, both of which predict the number of orders and the number of returns. Model 2 however uses bad debt information (one-off bad debt ratio) to predict the number of returns. Model 2 is clearly better than Model 1 in terms of log likelihood and AIC and BIC measures. Model 3 demonstrates the importance of predicting the number of bad debts in addition to the number of orders and number of returns.

***INSERT TABLE 1.3***

The results are fairly consistent across the three models, so we describe the results of Model 3. In the first panel of Table 1.4 below we present the results of predicting the number of orders using model 3. The total number of historical orders positively impacts the number of orders, as expected. The number of orders of Hispanic items negatively impacts the number of orders when the non-linearity is taken into account. The positive significant coefficient for the number of previous mailings suggests that the firm has been targeting customers who are of higher potential. Both the number of recent returns (in the last 5 transactions) and the ratio of bad debts have
positive effect on the number of orders. This shows the importance of accounting for bad debt information in predicting the number of orders, since those with a tendency to bad debt tend to place a larger number of orders.

In the second panel we present results of predicting the number of returns. The number of recent returns (in the last 5 transactions) is the strongest predictor of the number of returns. The number of previous orders, especially previous orders of Hispanic products, also is predictive of the number of returns. However the interesting result from this study’s point of view is that there is a positive relationship between the ratio of bad debts and the number of returns. In other words, customers who have more bad-debts tend to return a lot. This is different from the firm’s belief that customers who return are conscientious while those who bad debt are not. In the third panel we present results of predicting the number of bad debts. The main predictors of the number of bad debts are historical behaviors of bad debt (one-off bad debt ratio) and payments, especially for Hispanic products. The number of orders, especially that of Hispanic products, is also positively related to the number of bad debts.

It has been difficult for the firm to use characteristics of a “returner” to model for returns, because they returned products due to the gap between product quality and their expectations. It may help the firm to predict returns with customers’ bad debt information as we find evidence for a positive relationship between the return and bad debt options. Our finding raises the question involving measurement of this effect: how will incorporating information about the interaction of bad debt write-offs and returns impact targeting strategies of a direct marketing firm? To answer this important question, we next utilize a discrete response approach that will estimate probabilities of response of individual customers under different information conditions, and develop targeting strategies based on these estimated individual-level probabilities.
3.2 Discrete response model

While the previous section modeled continuous response of customers, targeting algorithms used in direct marketing are often based on customers’ discrete response to firm direct mailings, which may take the form of not ordering (‘no order’), returning (‘return’), ordering but defaulting on payment (‘bad debt’) and ordering and paying for the product (‘paid’). A discrete choice modeling framework based on the multinomial logit model is thus suitable for modeling this discrete customers response. Figure 1 shows the three possible structures for the logit model according to the customers’ decision making process. We model customer choice among the four options in a single stage as in Figure 1.1. As discussed in the Web Appendix, this single stage model fits the data in our empirical context better than the alternative choice hierarchies shown in Figure 1.2 and 1.3. Our discrete choice model incorporates heterogeneity in customer response, and also incorporates the firm’s targeting policy in the two models to correct for possible endogeneity.

3.2.1 Logit choice model

We utilize the logit model as the basic building block for our discrete choice modeling framework. As shown in Figure 1.1, there are four discrete choice options (no order, return, bad debt, and paid). As is standard, the intercept is normalized to zero for the last alternative (no order choice) for identification. Intercepts for the other three alternatives (return, bad debt and paid choice) are common across customers and capture the unobserved cost of each alternative that must be overcome for the relevant choice to occur. Consider customer $i$ who is mailed the
promotion \( t_i \) times, \( t_i=1,\ldots, T_i \), where \( T_i \) could be 1,2,3,4,5,6. We assume the utilities of the four response alternatives for customer \( i \) who receives mailings \( t \) times as:

\[
U(\text{Return})_{it} = R + \mu_{R_{it}} + \varepsilon_{R_{it}} \tag{4}
\]

\[
U(\text{Bad debt})_{it} = B + \mu_{B_{it}} + \varepsilon_{B_{it}} \tag{5}
\]

\[
U(\text{Paid})_{it} = P + \mu_{P_{it}} + \varepsilon_{P_{it}} \tag{6}
\]

\[
U(\text{No order})_{it} = 0 \tag{7}
\]

\( R, B, \text{ and } P \) are the intercepts for the three options, while \( \mu_{R_{it}}, \mu_{B_{it}}, \text{ and } \mu_{P_{it}} \) capture the influence of the independent variables on each option. The independent variables are listed in Table 1.2. \( \varepsilon_{R_{it}}, \varepsilon_{B_{it}}, \text{ and } \varepsilon_{P_{it}} \) are the error terms which are assumed to follow a type I extreme value distribution. The respective probabilities of each of the four choice alternatives for customer \( i \) who receives mailings \( t \) times is

\[
\pi_N = Pr(\text{No order})_{it} = \frac{e^{U(\text{No order})_{it}}}{e^{U(\text{Paid})_{it}} + e^{U(\text{No order})_{it}} + e^{U(\text{Return})_{it}} + e^{U(\text{Bad debt})_{it}}} \tag{8}
\]

\[
\pi_R = Pr(\text{Return})_{it} = \frac{e^{U(\text{Return})_{it}}}{e^{U(\text{Paid})_{it}} + e^{U(\text{No order})_{it}} + e^{U(\text{Return})_{it}} + e^{U(\text{Bad debt})_{it}}} \tag{9}
\]

\[
\pi_B = Pr(\text{Bad debt})_{it} = \frac{e^{U(\text{Bad debt})_{it}}}{e^{U(\text{Paid})_{it}} + e^{U(\text{No order})_{it}} + e^{U(\text{Return})_{it}} + e^{U(\text{Bad debt})_{it}}} \tag{10}
\]

\[
\pi_P = Pr(\text{Paid})_{it} = \frac{e^{U(\text{Paid})_{it}}}{e^{U(\text{Paid})_{it}} + e^{U(\text{No order})_{it}} + e^{U(\text{Return})_{it}} + e^{U(\text{Bad debt})_{it}}} \tag{11}
\]

Next we set up the likelihood function that will be maximized to estimate the model coefficients. The indicator variables capturing the four mutually exclusive customer choices will be as follows. \( Y_P \) is the customer’s choice of paying for the product, taking a value \( Y_P = 1 \) if paid, otherwise \( Y_P = 0 \). \( Y_N \) is the customer’s choice of not ordering to the product: \( Y_N = 1 \) if no
order, otherwise \( Y_N = 0 \). \( Y_R \) is the customer’s choice of returning the product: \( Y_R = 1 \) if returned, otherwise \( Y_R = 0 \). \( Y_B \) is the customer’s choice of bad debt: \( Y_B = 1 \) if bad debt, otherwise \( Y_B = 0 \).

\[
\ln(\text{Likelihood}) = \ln( (\pi_P)^{Y_P} \times (\pi_N)^{Y_N} \times (\pi_R)^{Y_R} \times (\pi_B)^{Y_B} (1 - \pi_P)^{(1 - Y_P)} \times (1 - \pi_N)^{(1 - Y_N)} \times (1 - \pi_R)^{(1 - Y_R)} \times (1 - \pi_B)^{(1 - Y_B)})
\]  

(12)

The model is estimated by the maximum likelihood procedure which selects the set of values of the model parameters that maximizes the likelihood function. In this way, we can obtain a logit model that fits best with the observed data. With individual level panel data, it is particularly important to account for possible biases due to heterogeneity and endogeneity, and we describe how our model incorporates these aspects below.

### 3.2.2 Conceptual Framework and Variables Selection

Since direct response firms use discrete choice models to develop their targeting algorithms, we develop a conceptual framework in Figure 1.4 to describe the drivers of such targeting policies. While the variables will be developed using this framework for the discrete choice models, the framework in Figure 1.4 is also applicable to the continuous response models developed in the previous sub-section.

The no order option is set as the baseline, and we select four to five independent variables for each of the other three options (return, bad debt, and paid), as listed in Table 1.5. The independent variables are classified into two types. The first type of variable shows the information of the firm’s target activities (number of previous mailings). The second type of independent variables include customers’ historical behavior of previous choices (return, bad debt, and paid) which will accommodate lagged interactions between the different choices. For example, a customer’s past return behaviors could influence his current bad debt choices. These
variables are selected to be consistent with the targeting framework shown in Figure 1.4. The details of the independent variables for each of the three options (return, bad debt, and paid) are discussed below.

***INSERT FIGURE 1.4 ***

There are four variables for the return option: previous mailings, bad debt number, Hispanic payment number, and one-off return amount. Previous research (van Diepen, Donkers and Franses 2009) shows that the extra mailings would irritate customers, leading to a lower response rate. So here we expect the number of previous mailings the customer received in the past to have a negative influence on his return option. Hispanic payment number also has a negative influence on a customer’s return option in the continuous response study. Since the customer who frequently returned products in the past is more likely to return products, the one-off return amount is expected to positively influence a customer’s probability of return. The one-off bad debt number is a variable indicating the customer’s historical bad debt behavior. This variable is expected to positively affect probability of return.

Four variables are selected as drivers of bad debt: previous mailings, payments, one-off bad debt ratio, and one-off return number. As mentioned above, we expect previous mailings to negatively influence a customer’s probability of response. The one-off bad debt ratio is expected to positive influence probability of bad debt, while the payments variable is expected to have negatively influence probability of bad debt. These are based on arguments of inertia in customer behavior, i.e. customers who exhibited bad debt in the past continue to exhibit bad debt behavior, while those who tend to pay in the past tend to continue paying for the product in future. Note that this may just represent observed heterogeneity in these behaviors over time rather than state dependence. The one-off return number is included here to explore the relationship between the
bad debt and return, and we expect this relationship to be positive, since there is a positive link between these two undesirable customer behaviors.

Four independent variables are used to parameterize the utility for the paid option: number of previous mailings, book bad debt number, Hispanic order number, total return number. The number of previous mailings variable is expected to have a negative influence on the paid option (van Diepen, Donkers and Franses 2009). The book bad debt number and total return number are variables concerned with the customers’ historical bad debt and return behavior. We expect the customers who frequently returned or wrote off in the past to be less likely to pay for the product. Next we describe the discrete choice model components.

*** INSERT TABLE 1.5 ***

**Heterogeneity**

We incorporate heterogeneity in the intercepts R, B, P by assuming that they follow a multivariate normal distribution across customers:

\[
\beta_1 = \begin{bmatrix} R \\ B \\ P \end{bmatrix} \sim N(\mu_1, \Omega_1)
\] (13)

This model has been termed the ‘mixed logit’ model by Train (2009), and simulated maximum likelihood method can be used to estimate the mixed logit model. Here the expected value of the likelihood is replaced by an arithmetic mean calculated from the sample. If D draws (in our application D equals 20) are made from \( N(\mu_1, \Omega_1) \), probabilities can be computed conditional on each draw, and the average yields the simulated probability

\[
\tilde{P}_{ij} = \frac{1}{D} \sum_{r=1}^{D} L_{ij}(\beta^r)
\] (14)
Endogeneity

While the model developed so far will capture heterogeneity in customer response behaviors, it does not account for the type of endogeneity problem that has been labeled ‘non-random response’ modeling (Manchanda et al 2004; Donkers et al 2006), which requires the model to account for the firm’s targeting strategy. Rather than inefficiently sending out mailings randomly to customers (an assumption of the standard discrete choice model developed above), the firm targets some customers with its mailings by selecting customers based on past observed behaviors. Not accounting for the firm’s targeting decisions will result in an upward bias in the effect of a variable on the customer choice variable such as paid choice, bad debt or return. Therefore it is important that the model be augmented to correct for the endogeneity problem caused by the firm’s targeting.

Figure 1.5 shows the number of customers targeted in each of the six waves of mailings in our data. The numbers of customers who received mailings in each wave are 2439, 1901, 1686, 1259, 1084, and 1413. Note that the last wave shows a heightened level of targeting activity on the part of the firm, presumably to try and maximize response. In the first wave, we do not know the firm’s full targeting decisions because there is no information about the customers who are not targeted. Consequently we only model customers’ responses for the first wave. For the second to sixth wave, we model both customers’ responses and the firm’s targeting. The number of customers who were targeted by the firm from the second to sixth wave are: 341, 577, 553, 575, and 736 (shown in Figure 1.5). For example, in the third wave, the firm targeted 577 customers from the customers who received mailings in wave one or wave two.
As described earlier we utilize the conceptual framework in Figure 1.4 to develop predictors for firm targeting policies; the variables were decided upon based on inputs of the firm tasked with developing the targeting algorithms. We use five independent variables to account for the firm’s targeting: Previous mailings, total return number, recent bad debts, payments, and whether the customer responded recently (responded recently). Previous mailings is motivated by Van Diepen et al 2009b, who found that customers may be irritated by extra mailings, in which case the firm would do well to avoid further targeting of such customers. We therefore expect previous mailings to have a negative effect on the firm’s targeting decisions. The remaining variables are related to customers’ response behaviors to direct mail. The coefficient signs we expect for these variables are fairly intuitive: total return number and recent bad debts are expected to negatively influence the firm’s targeting, while payments and recently responded are expected to positively influence the firm’s targeting decisions, since the firm prefers to target customers who have a track record of payments.

We use a logit model to describe the firm’s targeting. Let $I_{it}$ (t=2, 3, 4, 5, 6) denote the targeting decisions of the firm for the wave $t$. The indicator variable $I_{it}$ equals 1 if the firm sends a mailing to customer $i$ at wave $t$, and equals 0 otherwise. The utility for the firm to send a mailing to customer $i$ at wave $t$ is:

$$U(I_{it} = 1) = b + \mu_{it} + \epsilon$$

(15)

where

$$\mu_{it} = \gamma_1 \text{Previous mailings} + \gamma_1 \text{Total return number} + \gamma_2 \text{Recent bad debts} + \gamma_3 \text{Payments} + \gamma_4 \text{Recently responded}$$

(16)

The intercept $b$ is assumed to follow a normal distribution:
\[ b \sim N(\mu_b, \sigma_b) \]  \hspace{1cm} (17)

The utility of not targeting a customer is zero.

\[ U(l_{it} = 0) = 0 \]  \hspace{1cm} (18)

The probability that the firm targets customer \( i \) at wave \( t \) is

\[ \pi_1 = Pr(l = 1)_{it} = \frac{e^{U(l_{it}=1)}}{1+e^{U(l_{it}=1)}} \]  \hspace{1cm} (19)

The probability that the firm will not target customer \( i \) at wave \( t \) is

\[ \pi_2 = Pr(l = 0)_{it} = \frac{1}{1+e^{U(l_{it}=1)}} \]  \hspace{1cm} (20)

The likelihood for the firms targeting model is

\[ (\text{Likelihood})_T = (\pi_1)^I \times (1 - \pi_1)^{(1-I)} \]  \hspace{1cm} (21)

Equation 12 provides the likelihood for the customer response model. As in Donkers et al (2006), we can combine the likelihoods for the customer response model from Equation 12 with the likelihood for the firm targeting model in Equation 21 to obtain the log likelihood of the full model:

\[ \ln(\text{Likelihood})_{Full} = \ln(\text{Likelihood}) + \ln(\text{Likelihood})_T \]  \hspace{1cm} (22)

### 4. Discrete Choice Model Results

The results for mixed logit model which incorporates both heterogeneity and endogeneity correction are shown in Table 1.6. The results are fairly intuitive, with variables capturing
tendency to previously engage in a behavior positively influencing probability of the relevant customer discrete response. For example, one-off return amount (coefficient 0.03; t-value 4.999) positively impacts probability of return, one-off bad debt ratio (coefficient 2.003; t-value 6.258) positively impacts probability of bad debt. Similarly, Payments (coefficient -0.401; t-value -3.677) negatively impacts probability of bad debt while Hispanic order number captures the tendency to buy (and pay for) related product categories.

***INSERT TABLE 1.6***

Apart from these intuitive effects, interactions between the different choices provide some interesting and less obvious predictors of customer discrete response. One-off bad debt number (coefficient 0.459; t-value 2.37) positively impacts probability of returns, indicating that customers who tend to bad debt in the past also tend to return the product. This could be due to a malicious intent of procuring the product with the intention of using it and returning it once their needs are satisfied, or due to a genuine lack of fit between the actual product (once it is delivered) and their needs. It is beyond the scope of the data at hand to determine which of these motivations drives their behavior. However the data shows evidence of this link between historical bad debt and tendency to return. Another less obvious predictive phenomenon is the impact of total return number on the probability of paid choice. While again the exact reason for this predictive link is beyond the scope of the dataset we utilize, this link is not inconsistent with the findings of the recent literature on returns. Kumar and Petersen (2009) discuss the dual impact of returns on customer value, with moderate levels of returns acting as an enabler of relationship building between the firm and the customer and the consequent creation of switching costs for the customer. This beneficial effect of returns up to a threshold is predicated on the customer being well-intentioned and ‘genuine’ in terms of their return behavior, in the
sense that with respect to the purchase, *a priori* they try to maximize their utility, but *a posteriori* find that there is lack of fit between the actual product and their needs. This is qualitatively different from the *a priori* malicious intention of the customer who is either irresponsible in terms of purchase and therefore returns inordinate quantities of products, or who wants to use the product for a particular (social or consumption) occasion and then return the product, effectively gaining ‘something for nothing’. There is some evidence from our results that in our empirical context customers may be exhibiting this type of beneficial relationship between returns and paid choice. One other piece of evidence that is suggestive in this context is the coefficient of *one-off return number* in predicting the probability of bad debt choice probability. While this coefficient (-0.608; *t*-value -1.525) is not statistically significant, the negative sign appears to provide some evidence of the possible beneficial impact of returns in this dataset.

The firm targeting model coefficients in the bottom panel of Table 1.6 illustrate the preoccupations and challenges of a direct marketing firm in terms of its targeting options. The firm heavily mails those who have been mailed earlier (coefficient 0.563; *t*-value 11.564) and those who have made their payments historically (coefficient 0.057; *t*-value 4.182). They also avoid irritating customers by not targeting those who have responded recently (coefficient -0.097; *t*-value -1.875). The fact that total return number and bad debt in last five transactions have negative coefficients approaching significance shows that while the firm is trying to avoid such undesirable customers, it is still casting a wide targeting net as long as the customer has made a sufficient number of historical payments.

5. Discussion
In this section we discuss implications of our demand analyses by conducting simulations utilizing the estimates from our discrete response model.

5.1 Comparative statics

From Table 1.6 we can infer that there is a positive relationship between propensity to return and to bad debt, since customers who frequently took on bad debts in the past are more likely to return products. Strategically this raises the interesting question: what would be the impact on firm profits if it does not allow product returns, thus effectively removing the return choice from the customer’s choice set? As a first step towards understanding the answer to this question, we simulate probability changes for the three options (bad debt, paid, and no order) after removing the return option, then study the firm’s optimal targeting scheme when the return option is removed.

One empirical issue that the researcher needs to deal with in this dataset is the existence of many zeros in the independent variables. For each of the variables, we choose the top 100 customers and the bottom 100 customers after removing the zeroes in the data. For example, in the case of one-off return amount, we sort the 10023 observations by the one-off return amount variable. The top 100 customers have a mean of 60.381 dollars of one-off return amount, while the bottom 100 customers have a mean of 27.400 of one-off return amount. We calculate the probabilities of the three options (no response, bad debt, paid) for each individual after removing the return option, and list the mean probabilities for the top 100 customers and the bottom 100 customers in Table 1.7. We also perform t-tests to examine whether the distributions for the top group and the bottom group are different, and p-values are listed in the table.

***INSERT TABLE 1.7***
Our key result from this simulation is that the firm can make greater profits by removing the return option. We first study the three variables concerned with the historical return behavior. The variable one-off return number decreases the probability change for bad debt while increasing the probability change for paid. Since there is no nesting structure in the discrete choice model, customers can consider the return option with the other options simultaneously, which results in the return variables having greater influence. The one-off return number slightly decreases the probability change for the no response option while slightly increasing the probability change for the paid option. Customers who returned a lot in the past are more likely to choose the paid option if the return option is removed, and are less likely to choose the no response option. The number of previous mailings increases the probability change for the no response option and decrease the probability changes of bad debt and paid choice.

Next we study the impact of historical bad debt behavior. The book bad debt number slightly increases the probability of bad debt if the return option is removed. This is not surprising because the customers who frequently took on bad debt can still choose bad debt after the return option is removed. Finally, we look at the variables concerned with historical payment or order behaviors. All these variables (Hispanic payment number, Hispanic order number, and payments) negatively influence the no response probability while positively influencing the paid choice probability. We then rank by the variable one-off bad debt number, and we find that the customers with higher one-off bad debt number are more likely to take on bad debts.

5.2 Impact on profits

Next we simulate the firm’s targeting strategy by assuming the costs/profit of the four options and calculate the expected profit of each customer. The customers are targeted on the basis of positive expected profits. There is a mailing cost and targeting cost for no response, and
we assume this cost to be $c = 0.5$ based on current mailing costs. For the bad debt option, there is a cost for the product (a Spanish magazine) in addition to the mailing cost, so we assume the total cost to be $b = 5$. The return option is even more costly due to handling and restocking cost, so we assume it to be $r = 8$. It is to be noted that these costs, though seemingly somewhat counter-intuitive, were obtained based on feedback from the management of the direct response company and reflect actual costs for this particular company. The paid option is the only profitable option, and we assume the profit to be $v = 15$ for each magazine. The number of customers targeted and the profits are listed in Table 8. We find that the total profit is $7883$ if product returns are allowed, but it increases to $10628$ when product returns are not allowed.

Assume the utilities of customers’ options are $u_1, u_2, u_3,$ and $u_4$, then the expected profit increase when product returns are not allowed is

$$\Delta EP = \frac{e^{u_2}}{(e^{u_1} + e^{u_2} + e^{u_3} + e^{u_4})(e^{u_1} + e^{u_2} + e^{u_3} + e^{u_4})} \times \frac{-c}{r} \times e^{u_1} \times e^{u_2} \times \frac{b}{r} \times e^{u_3} + \frac{v}{r} \times e^{u_4} + e^{u_1} + e^{u_2} + e^{u_3} + e^{u_4}}$$

(23)

Since $\frac{e^{u_2}}{(e^{u_1} + e^{u_2} + e^{u_3} + e^{u_4})(e^{u_1} + e^{u_2} + e^{u_3} + e^{u_4})} > 0$ and $r > 0$, the expected profit will decrease only if $\left(-\frac{c}{r} \times e^{u_1} - \frac{b}{r} \times e^{u_3} + \frac{v}{r} \times e^{u_4} + e^{u_1} + e^{u_2} + e^{u_3} + e^{u_4}\right) < 0$.

We have found that the firm can increase profit by not allowing product returns with the option cost set at the set of values given by $\{c = 0.5, b = 5, r = 8, v = 15\}$. Next, we will change the option cost set to study whether the profit will decrease when product returns are not allowed. We will fix $r$ and change $c, b,$ and $v$ respectively to see how profit changes.

Firstly, we study how profit will change with variation in bad debt cost $b$. When we fix profit $v$, we have results shown in Figure 1.6. The horizontal axis shows the ratio of bad debt
cost to return cost (b/r), while the vertical axis shows the ratio of the profit when product returns are not allowed to the profit when product returns are allowed. We find that the profit ratio slightly decreases when bad debt cost increases. However, whether the profit ratio will be less than 1 is mainly decided by the ratio of targeting cost to return cost (c/r) instead of the ratio of bad debt cost to return cost (b/r). When we fix c, we have results shown in Figure 1.7, which are similar to those in Figure 1.6. Therefore the bad debt cost has little influence on the profit ratio.

Next we study how profit changes with changes in the targeting (and mailing) cost c. Since b has little effect on profit, we fix b=c. Figure 1.8 shows that the profit ratio decreases steeply when targeting cost c increases. That is, the company cannot increase profit by not allowing product returns when targeting cost is higher. A possible reason is that customers are less likely to order products when product returns are not allowed. However, the total cost for the company is higher as targeting (and mailing) cost increases, and therefore the company can lose profit if product returns are not allowed.

Last we study how profit changes when v changes. Since b has little effect on profit, we fix b=c. Figure 1.9 shows that when v is high, the company can increase profit by not allowing product returns, which is the main finding of our paper.

***INSERT FIGURES 1.6, 1.7, 1.8, 1.9***

Although this analysis has some limitations since it is not a field experiment, the simulation analyses demonstrate that the customers who are likely to return products are likely to pay for the products rather than become bad debts when there is no return option. It should be noted that this result has an intuitive appeal, since customers who take the time and effort to repack a product, go to the post office and mail it, are more conscientious than customers who bad-debt.
This leads us to the conclusion that as long as the firm has a small cost of ‘no response’ (as captured by mailing and targeting costs), it can increase profit by adopting the strategy of not allowing product returns.

5.3 Return -bad debt tradeoff: simulation diagnostics

The results show that the one-off bad debt number has a significantly positive influence on the return option, while a similar variable one-off bad debt ratio has a significantly positive influence on the bad debt option. Across the continuous and discrete response studies, there is some evidence that historical returns behavior negatively influences propensity to bad debt.

The simulation results show that the customers with high bad debt numbers would still choose the bad debt option if the return option is removed. However, the customers with high return numbers would choose to pay for the products rather than take on bad debts. And the customers with high payment numbers are also more likely to pay for products. Therefore the firm should target customers with more returns and more payments in the past.

The cost of bad debt option seems to have little influence on the profit change when the firm does not allow product returns. Only when the cost of no order is as high as half of the return cost will the firm suffer losses by not allowing product returns. Since the no response cost is generally not very high, the firm can increase profits by not allowing product returns.

There is some limitation to the simulation study. In the simulation study, we obtain the estimates when there are four choices in the model, remove the return option and assume the estimates do not change when the return option is removed. However, as the Lucas’ critique states, economic agents who observe the new policy (no return option is offered) may change their response to the stimulus (targeted offers). In other words, the estimates of the demand
model that captures customer response may differ from that estimated in this reduced form model. Therefore the probability changes for the three options (no order, bad debt, and paid) may be different from those obtained in the demand analysis. There are two methods to address this issue: one, a structural model that builds up customer response from primitives of customers and firm behavior. And two, a field experiment that allocates customers randomly to conditions where the return option is present/absent. We position our work as the first evidence of a positive link between the two undesirable customer behaviors of bad debts and returns, and believe that the structural approach and/or field experiment approach can be fruitful avenues for future research.

Our paper suggests the firm remove the return option, which is at odds with the findings in Anderson, Hansen, Simester (2009). They find that the customers are less likely to respond when the return option is not allowed, thus suggesting the return option should be offered. However, they do not consider the bad debt option, which in our application costs much more than the no order option. Table 7 shows that the targeted customers have a higher mean probability of no order when the return option is removed, which is consistent with the findings in the earlier literature. However, the mean bad debt probability of the targeted customers only increases a little when product returns are not allowed. As a result, the loss caused by the product returns and bad debts are greatly reduced when the return option is not offered. This implies that even though the customers are less likely to respond on average, the firm can make a greater profit by not offering the return option.

5.4 Return and bad debt: a ‘bottom of the pyramid’ phenomenon?

Customers could react in several different ways when they receive a catalog. They could ignore the catalog or they could place an order from it. In the latter case, they may choose to
keep the product or return it. Customers could be conscientious, honestly frustrated or exploitative in their return behavior, and the difficulty of managing this process stems largely from the difficulty in ascertaining ‘good’ intentions from ‘bad’ ones. Studies on product returns have generally been conducted for target segments for whom payment is not an issue, as most payments are made by credit card, and the decision regarding credit-worthiness of the customer is predetermined by the company that issued the credit card on which the purchase was made. When such merchants who rely mostly on credit cards for payment engage in targeted marketing, their targeting algorithms do not need to consider whether the customer is credit-worthy. In contrast, firms engaging in direct response marketing often target a segment of the market that are of lower income, and who may often not have, or use credit cards for discretionary purchases. In these types of ‘bill me later’ transactions, the product is purchased first, and the payment is made, usually by check, on receipt of the product. In these direct response transactions, the estimation of credit-worthiness of the customer is endogenized into the targeting algorithm. Motivations for the other undesirable behavior of ‘bad debt’, where customers just keep the product without paying for it, are less ambiguous, stemming either from sheer forgetfulness or a clear-cut intention to cheat the firm. Yet bad debts can also be difficult to predict and to manage, especially in the case of “buy-now-pay-later” payment option that is often offered for small ticket items. While tracing out motivations for these undesirable behaviors is an important research question, it is beyond the scope of the data utilized in this study. Our analyses do present some findings that throw some light on possible inter-relationships between these undesirable behaviors and raise questions about whether this phenomenon could be unique to customers with limited or no credit card debt availability, i.e., the ‘bottom of the pyramid’. Customers could be utilizing separate mental accounts (Thaler 1985) for bad debt and returns
where they trade off actual costs as well as psychic costs they might incur in each scenario. Optimization of such costs across transactions could lead to some of the linkages between undesirable behaviors that our analysis uncovers.

Our results support the findings of the literature on returns by providing a further piece of evidence - that customers who return are largely customers who tend to pay rather than bad debt. This is so even among customers with low (or no) access to credit card debt. Our recommendations that firms should seriously consider dropping the return option for at least some of their ‘bill me later’ campaigns is based on the economics of return costs rather than on the profile of customers who tend to return products. Our research finding may not apply to bigger ticket items, where the temptation to bad debt may be higher if there is no return option. However it should be noted that in those cases the economics of the transaction would mean that there are likely to be greater collection efforts on the part of the firm. The other interesting implication of our finding has to do with the online ‘bill me later’ options such as the one proposed by the company acquired by Paypal in 2008. It is to be noted that in this case the linkage between undesirable behaviors that we detect in the case of a single firm is still likely to exist. However the tradeoff of the greater risk of bad debt versus higher response rate would now occur across two firms. These are the online ‘bill me later’ firm that guarantees credit and is responsible for collection of debt, and the targeting firm that enjoys the higher response rate, and that pays some of the returns from this as a fee to the ‘bill me later’ company.

6. Conclusion
This paper studies the customers’ responses to direct mail considering both the bad debt and return options by utilizing the historical transaction information variables that influence the customers’ return, bad debt, and paid options. We find that customers with high payment numbers are less likely to make returns or bad debts, while those who frequently took on bad debts in the past are more likely to take on bad debts and more likely to return products. Also, customers who ordered a lot of products in the past are less likely to pay for the products. Overall, we believe that the challenges to targeted marketing uncovered by this study constitute the beginning of a possibly rich set of research questions that can arise from studying the ‘bottom of the pyramid’ marketing phenomenon, i.e., unique challenges and variants of marketing concepts that are applied in marketing to customers with limited or no access to credit card debt.

The paper also studies the impact of removing the product return option. The results show that the customers with high return numbers in the past are more likely to pay rather than take on bad debts if the product return is not allowed. The customers with high write-off numbers may become bad debts, while the customers with high payment numbers are more likely to pay for products. Therefore customers with high return numbers and high payment numbers are the most profitable for the firm. We also demonstrate that the firm can increase its profit by forbidding product returns if the no response cost is not too high.

There are some limitations in this research. First, we only consider the heterogeneity in the intercepts in this paper. We can improve this by assuming all of the coefficients to follow distributions in future research. Second, the customer demand functions estimated can be considered a first approximation due to the reduced form approach and applicability of the Lucas Critique. Nevertheless, this paper provides the first step in the measurement of the tradeoff between bad debts and returns in the targeting literature. In spite of the limitations, the paper
contributes to product returns in direct mail by considering the bad debt option together with the return option. We find some positive interactions between the customers’ historical return behaviors and their possibilities to take on bad debts. We also provide evidence for a counterintuitive strategy whereby the company reduces return costs by not allowing the product returns, and thus increase profits. Firms that resort to this option may explore other avenues for relationship building such as loyalty programs to substitute for the relationship-building component of returns behavior described in Petersen and Kumar (2009).
References


Appendix 1: Nested logit models

In the first structure, customers decide to choose one of the four options in a single stage. In the second structure, customers decide to order or not in the first stage and then choose the other options in the second stage. In the third structure, customers make all the decisions in three stages. We are using the first structure in this paper, and the reason is shown in the appendix.

1. Nested Logit Model B

There is a two-level nesting structure (Figure 1.2) in the nested logit model B. When a customer receives a direct mailing, she will first decide to order or not. If she does not order, she takes a no order option. If she orders the product, she will have three options in the second level: return, bad debt, and paid. The intercepts are still the same for all customers in this model.

Consider customer i who is mailed the product $t_i$ times, $t_i = 1, \ldots, T$, where $T_i$ could be 1, 2, 3, 4, 5, 6. We assume the utilities of the three response alternatives in the second level for customer i who receives mailings $t$ times as:

$$U(\text{Return})_{it} = R + \mu_{Rit} + \epsilon_{Rit} \quad (A1)$$

$$U(\text{Bad debt})_{it} = B + \mu_{Bit} + \epsilon_{BIt} \quad (A2)$$

$$U(\text{Paid})_{it} = \mu_{Pit} + \epsilon_{Pit} \quad (A3)$$

The probability of returning the product is conditional on ordering the product for customer i who receives mailings $t$ times:

$$Pr(\text{Return}|\text{Order})_{it} = \frac{e^{U(\text{Return})_{it}}}{e^{U(\text{Paid})_{it}} + e^{U(\text{Return})_{it}} + e^{U(\text{Bad debt})_{it}}} \quad (A4)$$

The probability of bad debt is conditional on ordering the product for customer i who receives mailings $t$ times:

$$Pr(\text{Bad debt}|\text{Order})_{it} = \frac{e^{U(\text{Bad debt})_{it}}}{e^{U(\text{Paid})_{it}} + e^{U(\text{Return})_{it}} + e^{U(\text{Bad debt})_{it}}} \quad (A5)$$

The probability of paying for the product is conditional on ordering the product for customer i who receives mailings $t$ times:

$$Pr(\text{Paid}|\text{Order})_{it} = \frac{e^{U(\text{Paid})_{it}}}{e^{U(\text{Paid})_{it}} + e^{U(\text{Return})_{it}} + e^{U(\text{Bad debt})_{it}}} \quad (A6)$$

The inclusive value for ordering the product for customer i who receives mailings $t$ times is

$$IV(Order)_{it} = \ln(e^{U(\text{Paid})_{it}} + e^{U(\text{Return})_{it}} + e^{U(\text{Bad debt})_{it}}) \quad (A7)$$

The utility of no order for customer i who receives mailings $t$ times is

$$U(\text{No order})_{it} = N \quad (A8)$$

The probability of ordering the product for customer i who receives mailings $t$ times is

$$Pr(Order)_{it} = \frac{e^{cIV(Order)_{it}}}{e^{cIV(Order)_{it}} + e^{U(\text{No order})_{it}}} \quad (A9)$$

The probability of not ordering the product for customer i who receives mailings $t$ times is

$$\pi_N = Pr(\text{No order})_{it} = \frac{e^{U(\text{No order})_{it}}}{e^{cIV(Order)_{it}} + e^{U(\text{No order})_{it}}} \quad (A10)$$
The probability of returning the product for customer \( i \) who receives mailings \( t \) times is
\[
\pi_R = Pr(\text{Return})_{it} = \frac{e^{U(\text{Return})_{it}}}{e^{U(\text{Paid})_{it} + e^{U(\text{Return})_{it}} + e^{U(\text{Bad debt})_{it}}}} \times \frac{e^{c \times IV(\text{Order})_{it}}}{e^{c \times IV(\text{Order})_{it} + e^{U(\text{No order})_{it}}}}
\] (A11)

The probability of bad debt for customer \( i \) who receives mailings \( t \) times is
\[
\pi_B = Pr(\text{Bad debt})_{it} = \frac{e^{U(\text{Bad debt})_{it}}}{e^{U(\text{Paid})_{it} + e^{U(\text{Return})_{it}} + e^{U(\text{Bad debt})_{it}}}} \times \frac{e^{c \times IV(\text{Order})_{it}}}{e^{c \times IV(\text{Order})_{it} + e^{U(\text{No order})_{it}}}}
\] (A12)

The probability of paying for the product for customer \( i \) who receives mailings \( t \) times is
\[
\pi_P = Pr(\text{Paid})_{it} = \frac{e^{U(\text{Paid})_{it}}}{e^{U(\text{Paid})_{it} + e^{U(\text{Return})_{it}} + e^{U(\text{Bad debt})_{it}}}} \times \frac{e^{c \times IV(\text{Order})_{it}}}{e^{c \times IV(\text{Order})_{it} + e^{U(\text{No order})_{it}}}}
\] (A13)

The log likelihood is
\[
\ln(\text{Likelihood}) = \ln((\pi_P)^{Y_p} \times (\pi_N)^{Y_N} \times (\pi_R)^{Y_R} \times (\pi_B)^{Y_B} (1 - \pi_P)^{(1-Y_p)} \times (1 - \pi_N)^{(1-Y_N)} \times (1 - \pi_R)^{(1-Y_R)} \times (1 - \pi_B)^{(1-Y_B)})
\] (A14)

The model is estimated by the maximum likelihood procedure which selects the set of values of the model parameters that maximizes the likelihood function. In this way, we can obtain a logit model that fits best with the observed data.

2. Nested Logit Model C

There is a three-level nesting structure (Figure 1.3) in the nested logit model C. When a customer receives a direct mailing, she will first decide to order or not. If she does not order, she makes a no order option. If she orders the product, she will have two options in the second level: return or keep. If she decides to keep the product, she will enter the third level to have two options: bad debt or paid. The intercepts are the same for all customers in this model.

Consider customer \( i \) who is mailed the product \( t_i \) times, \( t_i = 1, \ldots, T_i \), where \( T_i \) could be 1,2,3,4,5,6. We assume the utilities of the two response alternatives in the third level for customer \( i \) who receives mailings \( t \) times as:
\[
U(\text{Bad debt})_{it} = B + \mu_{B_{it}} + \epsilon_{B_{it}}
\] (A15)

\[
U(\text{Paid})_{it} = \mu_{P_{it}} + \epsilon_{P_{it}}
\] (A16)

The probability of bad debt is conditional on keeping the product for customer \( i \) who receives mailings \( t \) times:
\[
Pr(\text{Bad debt}|\text{Keep})_{it} = \frac{e^{U(\text{Bad debt})_{it}}}{e^{U(\text{Paid})_{it} + e^{U(\text{Bad debt})_{it}}}}
\] (A17)

The probability of paying for the product is conditional on keeping the product for customer \( i \) who receives mailings \( t \) times:
\[
Pr(\text{Paid}|\text{Keep})_{it} = \frac{e^{U(\text{Paid})_{it}}}{e^{U(\text{Paid})_{it} + e^{U(\text{Bad debt})_{it}}}}
\] (A18)

The inclusive value for keeping the product for customer \( i \) who receives mailings \( t \) times is
\[
IV(\text{Keep})_{it} = \ln(e^{U(\text{Paid})_{it}} + e^{U(\text{Bad debt})_{it}})
\] (A19)

The utility of return for customer \( i \) who receives mailings \( t \) times is
\[ U(\text{Return})_{it} = R + \mu_{Rit} + \varepsilon_{Rit} \]  

(A20)

The probability of returning the product is conditional on ordering the product for customer \( i \) who receives mailings \( t \) times:

\[ \text{Pr}(\text{Return}|\text{Order})_{it} = \frac{e^{U(\text{Return})_{it}}}{e^{U(\text{Return})_{it}} + e^{c_1 \times \text{IV}(\text{Keep})_{it}}} \]  

(A21)

The probability of keeping the product is conditional on ordering the product for customer \( i \) who receives mailings \( t \) times:

\[ \text{Pr}(\text{Keep}|\text{Order})_{it} = \frac{e^{c_1 \times \text{IV}(\text{Keep})_{it}}}{e^{U(\text{Return})_{it}} + e^{c_1 \times \text{IV}(\text{Keep})_{it}}} \]  

(A22)

The inclusive value for ordering the product for customer \( i \) who receives mailings \( t \) times is

\[ IV(\text{Order})_{it} = \ln(e^{IV(\text{Keep})_{it}} + e^{U(\text{Return})_{it}}) \]  

(A23)

The utility of no order for customer \( i \) who receives mailings \( t \) times is

\[ U(\text{No order})_{it} = N \]  

(A24)

The probability of ordering the product for customer \( i \) who receives mailings \( t \) times is

\[ \pi_N = \text{Pr}(\text{No order})_{it} = \frac{e^{c_2 \times IV(\text{Order})_{it}}}{e^{c_2 \times IV(\text{Order})_{it}} + e^{U(\text{No order})_{it}}} \]  

(A25)

The probability of not ordering the product for customer \( i \) who receives mailings \( t \) times is

\[ \pi_R = \text{Pr}(\text{Return})_{it} = \frac{e^{U(\text{Return})_{it}}}{e^{U(\text{Return})_{it}} + e^{c_1 \times IV(\text{Keep})_{it}}} \times \frac{e^{c_2 \times IV(\text{Order})_{it}}}{e^{c_2 \times IV(\text{Order})_{it}} + e^{U(\text{No order})_{it}}} \times \frac{e^{c_1 \times IV(\text{Keep})_{it}}}{e^{c_1 \times IV(\text{Keep})_{it}} + e^{U(\text{Return})_{it}}} \times \frac{e^{U(\text{Return})_{it}}}{e^{U(\text{Return})_{it}} + e^{c_1 \times IV(\text{Keep})_{it}}} \times \frac{e^{c_2 \times IV(\text{Order})_{it}}}{e^{c_2 \times IV(\text{Order})_{it}} + e^{U(\text{No order})_{it}}} \]  

(A26)

The probability of returning the product for customer \( i \) who receives mailings \( t \) times is

\[ \pi_B = \text{Pr}(\text{Bad debt})_{it} = \frac{e^{U(\text{Paid})_{it}}}{e^{U(\text{Paid})_{it}} + e^{U(\text{Bad debt})_{it}}} \times \frac{e^{c_1 \times IV(\text{Keep})_{it}}}{e^{c_1 \times IV(\text{Keep})_{it}} + e^{U(\text{Return})_{it}}} \times \frac{e^{c_2 \times IV(\text{Order})_{it}}}{e^{c_2 \times IV(\text{Order})_{it}} + e^{U(\text{No order})_{it}}} \times \frac{e^{c_1 \times IV(\text{Keep})_{it}}}{e^{c_1 \times IV(\text{Keep})_{it}} + e^{U(\text{Return})_{it}}} \times \frac{e^{c_2 \times IV(\text{Order})_{it}}}{e^{c_2 \times IV(\text{Order})_{it}} + e^{U(\text{No order})_{it}}} \times \frac{e^{c_1 \times IV(\text{Keep})_{it}}}{e^{c_1 \times IV(\text{Keep})_{it}} + e^{U(\text{Return})_{it}}} \]  

(A27)

The probability of paying for the product for customer \( i \) who receives mailings \( t \) times is

\[ \pi_P = \text{Pr}(\text{Paid})_{it} = \frac{e^{U(\text{Paid})_{it}}}{e^{U(\text{Paid})_{it}} + e^{U(\text{Bad debt})_{it}}} \times \frac{e^{c_1 \times IV(\text{Keep})_{it}}}{e^{c_1 \times IV(\text{Keep})_{it}} + e^{U(\text{Return})_{it}}} \times \frac{e^{c_2 \times IV(\text{Order})_{it}}}{e^{c_2 \times IV(\text{Order})_{it}} + e^{U(\text{No order})_{it}}} \times \frac{e^{c_1 \times IV(\text{Keep})_{it}}}{e^{c_1 \times IV(\text{Keep})_{it}} + e^{U(\text{Return})_{it}}} \times \frac{e^{c_2 \times IV(\text{Order})_{it}}}{e^{c_2 \times IV(\text{Order})_{it}} + e^{U(\text{No order})_{it}}} \times \frac{e^{c_1 \times IV(\text{Keep})_{it}}}{e^{c_1 \times IV(\text{Keep})_{it}} + e^{U(\text{Return})_{it}}} \]  

(A28)

The log likelihood is

\[ \ln(\text{Likelihood}) = \ln((\pi_P)^{Y_P} \times (\pi_N)^{Y_N} \times (\pi_R)^{Y_R} \times (\pi_B)^{Y_B} (1 - \pi_P)^{(1 - Y_P)} \times (1 - \pi_N)^{(1 - Y_N)} \times (1 - \pi_R)^{(1 - Y_R)} \times (1 - \pi_B)^{(1 - Y_B)}) \]  

(A30)

The model is estimated by the maximum likelihood procedure which selects the set of values of the model parameters that maximizes the likelihood function. In this way, we can obtain a logit model that fits best with the observed data.

3. Mixed Logit Model E (with Heterogeneity)
The mixed logit model E is obtained by adding heterogeneity to model B. The variables R, B, N are varying among different customers in this model. We assume them to follow a multivariate normal distribution.

\[ \beta_2 = \begin{bmatrix} R \\ B \\ N \end{bmatrix} \sim N(\mu_2, \Omega_2) \]  

(A31)

We use the simulation method to estimate the mixed logit model. The expected value is replaced by an arithmetic mean calculated from the sample.

Draw 20 values from \( N(\mu_2, \Omega_2) \) and calculate the probability. The average is the simulated probability

\[ \tilde{p}_{ij} = \frac{1}{20} \sum_{r=1}^{20} L_{ij}(\beta^r) \]  

(A32)

4. Mixed Logit Model F (with Heterogeneity)

The mixed logit model F is obtained by adding heterogeneity to model C. The variables R, B, N are varying among different customers in this model. We assume them to follow a multivariate normal distribution.

\[ \beta_3 = \begin{bmatrix} R \\ B \\ N \end{bmatrix} \sim N(\mu_3, \Omega_3) \]  

(A33)

We use the simulation method to estimate the mixed logit model. The expected value is replaced by an arithmetic mean calculated from the sample.

Draw 20 values from \( N(\mu_3, \Omega_3) \) and calculate the probability. The average is the simulated probability

\[ \tilde{p}_{ij} = \frac{1}{20} \sum_{r=1}^{20} L_{ij}(\beta^r) \]  

(A34)

5. The comparison of the six models

Table A1 shows the values of both AIC and BIC for the six models. We find that the models with heterogeneity considerably outperform the homogeneous models. Among the heterogeneous models, the model F with a three level nesting structure is best according to AIC, but model D without any nesting structure performs best according to BIC.

We are doing a simulation study of removing the return option in this paper. When we remove the return option, the attractiveness of “order” decreases. Therefore, customers should be more likely to choose no response. However, if we use model F, more customers are going to respond when product returns are not allowed, which is in conflict with our analysis. Thus we do not use nested logit models in this paper.
Table A1: The comparison of the models without targeting policy

<table>
<thead>
<tr>
<th>Model</th>
<th>n</th>
<th>k</th>
<th>ll</th>
<th>aic</th>
<th>bic</th>
</tr>
</thead>
<tbody>
<tr>
<td>Logit model A</td>
<td>10023</td>
<td>15</td>
<td>2918.51</td>
<td>5867.02</td>
<td>5975.21</td>
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<tr>
<td>Nested logit model B</td>
<td>10023</td>
<td>16</td>
<td>2912.45</td>
<td>5856.9</td>
<td>5972.30</td>
</tr>
<tr>
<td>Nested logit model C</td>
<td>10023</td>
<td>17</td>
<td>2907.56</td>
<td>5849.12</td>
<td>5971.73</td>
</tr>
<tr>
<td>Mixed logit model D</td>
<td>10023</td>
<td>21</td>
<td>2076.48</td>
<td>4194.96</td>
<td>4346.43</td>
</tr>
<tr>
<td>Nested logit model E</td>
<td>10023</td>
<td>22</td>
<td>2072.54</td>
<td>4189.08</td>
<td>4347.76</td>
</tr>
<tr>
<td>Nested logit model F</td>
<td>10023</td>
<td>23</td>
<td>2068.8</td>
<td>4183.6</td>
<td>4349.49</td>
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<tr>
<td>Paper</td>
<td>Main question</td>
<td>Main findings</td>
<td>Type</td>
<td>Choice Alternatives</td>
<td></td>
</tr>
<tr>
<td>------------------------------</td>
<td>----------------------------</td>
<td>-------------------------------------------------------------------------------</td>
<td>----------</td>
<td>------------------------------</td>
<td></td>
</tr>
<tr>
<td>Anderson, Hansen, Simester (2009)</td>
<td>Return option value</td>
<td>The customers are less likely to order the products if the return option is removed.</td>
<td>Empirical</td>
<td>No response, buy, return</td>
<td></td>
</tr>
<tr>
<td>Gümüş, Ray, and Yin (2013)</td>
<td>Return policy and customer valuation of used products</td>
<td>The higher the customer valuation of used products is, the more likely the company would offer a return option to the retailer.</td>
<td>Analytical</td>
<td>No response, buy, return</td>
<td></td>
</tr>
<tr>
<td>Petersen and Kumar (2009)</td>
<td>Return behavior and CLV</td>
<td>As returns increase, the lifetime value of a customer increases first and then starts decreasing.</td>
<td>Empirical</td>
<td>No response, buy, return</td>
<td></td>
</tr>
<tr>
<td>Shulman, Coughlan, and Savaskan (2010)</td>
<td>Return penalty</td>
<td>The return penalty may be more severe when returns are salvaged by a channel member who derives greater value from a returned unit.</td>
<td>Analytical</td>
<td>No response, buy, return</td>
<td></td>
</tr>
<tr>
<td>Bower and Maxham III (2012)</td>
<td>Free returns vs. fee returns</td>
<td>Customers who paid for their own return decreased their postreturn spending at that retailer, and vice versa.</td>
<td>Empirical</td>
<td>No response, buy, return</td>
<td></td>
</tr>
<tr>
<td>Hartmann, Nair, and Narayanan (2011)</td>
<td>Causal marketing mix effects</td>
<td>Customers have adverse reactions to direct mail activity because of heavy direct mail activity by the firm in the past.</td>
<td>Empirical</td>
<td>No response, response</td>
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<tr>
<td>van Diepen, Donkers, and Franses (2009)</td>
<td>Dynamic effects and competitive effects</td>
<td>Each extra mailing the same charity sends negatively affects the future responding decision; but the effects die out in one year.</td>
<td>Empirical</td>
<td>No response, response</td>
<td></td>
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<tr>
<td>Gonul, Frenkel Ter Hofstede (2006)</td>
<td>Mailing strategies</td>
<td>The expected profits are higher when a longer time horizon is employed than a single-period horizon.</td>
<td>Empirical</td>
<td>No response, response</td>
<td></td>
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<tr>
<td>Ansari, Mela, and Neslin (2008)</td>
<td>Customer channel migration</td>
<td>The total response can be higher by sending e-mails intermittently than by continually e-mailing.</td>
<td>Empirical</td>
<td>No response, response</td>
<td></td>
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<tr>
<td>Bodapati (2008)</td>
<td>Targeting with purchase data</td>
<td>The targeting should be based on the sensitivity of purchase probabilities instead of the purchase probabilities.</td>
<td>Empirical</td>
<td>No response, response</td>
<td></td>
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<td>Reference</td>
<td>Targeting</td>
<td>Modeling Focus</td>
<td>Methodology</td>
<td>Empirical Results</td>
<td></td>
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<td>-----------</td>
<td>----------------</td>
<td>-------------</td>
<td>------------------</td>
<td></td>
</tr>
<tr>
<td>Dong, Manchanda, and Chintagunta (2009)</td>
<td>Targeting in the presence of firm strategic behavior</td>
<td>Ignoring firm strategic behavior in the modeling process biases the parameter estimates</td>
<td>Empirical</td>
<td>No response, response</td>
<td></td>
</tr>
<tr>
<td>This Study</td>
<td>Targeting ‘bottom of pyramid’ customers with return-bad-debt tradeoff</td>
<td>Historical bad debts predict return probabilities; firms can increase profit by dropping the return option.</td>
<td>Empirical</td>
<td>No response, paid, return, bad debt</td>
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<tr>
<td>Variable</td>
<td>Variables description</td>
<td>Mean</td>
<td>Std</td>
<td>Min</td>
<td>Max</td>
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<td>------------------------------------------------------------</td>
<td>-------</td>
<td>-------</td>
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<tr>
<td>Order</td>
<td>One-off order number</td>
<td>1.1</td>
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<td>Return</td>
<td>One-off return number</td>
<td>0.05</td>
<td>0.29</td>
<td>0</td>
<td>10</td>
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<td>Bad debt</td>
<td>One-off bad debt number</td>
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<td>0.24</td>
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<td>TON</td>
<td>Total order number</td>
<td>22.93</td>
<td>46.58</td>
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<td>877</td>
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<tr>
<td>$(TON^2)^{1/3}$</td>
<td>Cube root transformed squared total order</td>
<td>6.38</td>
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<td>91.62</td>
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<td>Hispanic order number</td>
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<td>3.01</td>
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<td>1.44</td>
<td>1.32</td>
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<td>12.84</td>
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<td>ORN</td>
<td>One-off return number of the last 5 transactions</td>
<td>0.23</td>
<td>0.66</td>
<td>0</td>
<td>5</td>
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<td>$(ORN^2)^{1/3}$</td>
<td>Cube root transformed squared one time return</td>
<td>0.19</td>
<td>0.5</td>
<td>0</td>
<td>2.92</td>
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<td>TBN</td>
<td>One-off bad debt ratio</td>
<td>0.07</td>
<td>0.25</td>
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<td>$(TBN^2)^{1/3}$</td>
<td>Cube root transformed squared one-off bad debt</td>
<td>0.08</td>
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<td>0</td>
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<td>$Z_{OR}$</td>
<td>Number of previous mailings</td>
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<td>0.64</td>
<td>0</td>
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<td></td>
<td>Length of residence</td>
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<td>Length of residence</td>
<td>9.86</td>
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<td>2.72</td>
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<td>$Z_{BD}$</td>
<td>Number of previous mailings</td>
<td>0.36</td>
<td>0.64</td>
<td>0</td>
<td>5</td>
</tr>
<tr>
<td></td>
<td>Length of residence</td>
<td>9.86</td>
<td>10.23</td>
<td>0</td>
<td>52</td>
</tr>
<tr>
<td></td>
<td>Number of payments for Hispanic products</td>
<td>1.84</td>
<td>2.72</td>
<td>0</td>
<td>45</td>
</tr>
<tr>
<td></td>
<td>Number of payments</td>
<td>2.78</td>
<td>1.6</td>
<td>0</td>
<td>5</td>
</tr>
<tr>
<td></td>
<td>Days since last order</td>
<td>397.31</td>
<td>377.3</td>
<td>0</td>
<td>1826</td>
</tr>
</tbody>
</table>
Table 1.3: Model Comparison – Continuous Response

<table>
<thead>
<tr>
<th></th>
<th>Model 1</th>
<th>Model 2</th>
<th>Model 3</th>
</tr>
</thead>
<tbody>
<tr>
<td>Order equation</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Return equation</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Bad debt equation</td>
<td>No</td>
<td>No</td>
<td>Yes</td>
</tr>
<tr>
<td>bad debt predictor in Return equation</td>
<td>No</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Log Likelihood</td>
<td>-1298.69</td>
<td>-1174.00</td>
<td>9807.80</td>
</tr>
<tr>
<td>Number of parameters</td>
<td>23</td>
<td>27</td>
<td>44</td>
</tr>
<tr>
<td>Number of observations</td>
<td>10023</td>
<td>10023</td>
<td>10023</td>
</tr>
<tr>
<td>AIC</td>
<td>2643.38</td>
<td>2402.00</td>
<td>-19527.60</td>
</tr>
<tr>
<td>BIC</td>
<td>2809.27</td>
<td>2596.74</td>
<td>-19210.24</td>
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### Table 1.4: Demand Results – Continuous Response

#### Number of Orders Equation

<table>
<thead>
<tr>
<th>Independent variables</th>
<th>Coefficient</th>
<th>t value</th>
<th>Net effect</th>
</tr>
</thead>
<tbody>
<tr>
<td>Intercept</td>
<td>0.537</td>
<td>13.407</td>
<td></td>
</tr>
<tr>
<td>Total order number</td>
<td>-0.006</td>
<td>-4.702</td>
<td>0.619</td>
</tr>
<tr>
<td>Total order number.^(2/3)</td>
<td>0.080</td>
<td>9.592</td>
<td></td>
</tr>
<tr>
<td>Hispanic order number</td>
<td>0.309</td>
<td>16.776</td>
<td></td>
</tr>
<tr>
<td>Hispanic order number.^(2/3)</td>
<td>-0.558</td>
<td>-13.235</td>
<td>-0.110</td>
</tr>
<tr>
<td>One-off recent return number</td>
<td>-1.027</td>
<td>-7.125</td>
<td>0.056</td>
</tr>
<tr>
<td>One-off recent return number.^(2/3)</td>
<td>1.544</td>
<td>8.140</td>
<td></td>
</tr>
<tr>
<td>Previous mailings</td>
<td>0.207</td>
<td>8.178</td>
<td></td>
</tr>
<tr>
<td>Length of residence</td>
<td>0.011</td>
<td>7.109</td>
<td></td>
</tr>
<tr>
<td>One-off bad debt ratio</td>
<td>-10.807</td>
<td>-10.203</td>
<td>0.066</td>
</tr>
<tr>
<td>One-off bad debt ratio.^(2/3)</td>
<td>11.382</td>
<td>10.898</td>
<td></td>
</tr>
</tbody>
</table>

#### Number of Returns Equation

<table>
<thead>
<tr>
<th>Independent variables</th>
<th>Coefficient</th>
<th>t value</th>
<th>Net effect</th>
</tr>
</thead>
<tbody>
<tr>
<td>Intercept</td>
<td>0.024</td>
<td>3.459</td>
<td></td>
</tr>
<tr>
<td>One-off recent return number</td>
<td>-0.245</td>
<td>-10.226</td>
<td>0.039</td>
</tr>
<tr>
<td>One-off recent return number.^(2/3)</td>
<td>0.505</td>
<td>16.091</td>
<td></td>
</tr>
<tr>
<td>Total order number</td>
<td>0.000</td>
<td>-0.576</td>
<td></td>
</tr>
<tr>
<td>Total order number.^(2/3)</td>
<td>0.003</td>
<td>2.268</td>
<td></td>
</tr>
<tr>
<td>Hispanic order number</td>
<td>0.032</td>
<td>7.018</td>
<td>0.015</td>
</tr>
<tr>
<td>Hispanic order number.^(2/3)</td>
<td>-0.039</td>
<td>-5.427</td>
<td></td>
</tr>
<tr>
<td>Previous mailings</td>
<td>0.006</td>
<td>1.503</td>
<td></td>
</tr>
<tr>
<td>Length of residence</td>
<td>0.000</td>
<td>1.286</td>
<td></td>
</tr>
<tr>
<td>Hispanic payment number</td>
<td>-0.012</td>
<td>-3.721</td>
<td></td>
</tr>
<tr>
<td>Payments</td>
<td>-0.011</td>
<td>-5.373</td>
<td></td>
</tr>
<tr>
<td>Independent variables</td>
<td>Coefficient</td>
<td>t value</td>
<td>Net effect</td>
</tr>
<tr>
<td>------------------------------------</td>
<td>-------------</td>
<td>---------</td>
<td>------------</td>
</tr>
<tr>
<td>Intercept</td>
<td>0.016</td>
<td>2.630</td>
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<tr>
<td>One-off bad debt ratio</td>
<td>-3.096</td>
<td>-22.605</td>
<td>0.030</td>
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<tr>
<td>One-off bad debt ratio.^(2/3)</td>
<td>3.409</td>
<td>25.210</td>
<td></td>
</tr>
<tr>
<td>One-off recent return number</td>
<td>-0.032</td>
<td>-1.735</td>
<td></td>
</tr>
<tr>
<td>One-off recent return number.^(2/3)</td>
<td>0.035</td>
<td>1.410</td>
<td></td>
</tr>
<tr>
<td>Total order number</td>
<td>-0.001</td>
<td>-4.210</td>
<td>0.018</td>
</tr>
<tr>
<td>Total order number.^(2/3)</td>
<td>0.006</td>
<td>4.812</td>
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<tr>
<td>Hispanic order number</td>
<td>0.018</td>
<td>5.070</td>
<td>0.012</td>
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<td>Hispanic order number.^(2/3)</td>
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<td>-3.491</td>
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<tr>
<td>Previous mailings</td>
<td>0.003</td>
<td>0.896</td>
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<td>Length of residence</td>
<td>0.000</td>
<td>1.722</td>
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<td>Hispanic payment number</td>
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<td>-3.284</td>
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</tr>
<tr>
<td>Payments</td>
<td>-0.012</td>
<td>-7.359</td>
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</tr>
<tr>
<td>Days Since Last Order</td>
<td>0.000</td>
<td>1.081</td>
<td></td>
</tr>
<tr>
<td>Response Model</td>
<td>Variable</td>
<td>Description</td>
<td>Mean</td>
</tr>
<tr>
<td>----------------</td>
<td>---------------------------</td>
<td>-------------------------------------------------------</td>
<td>------</td>
</tr>
<tr>
<td>Return</td>
<td>Previous mailings</td>
<td>The number of mailings the customer received in the past</td>
<td>0.36</td>
</tr>
<tr>
<td></td>
<td>One-off write-off number</td>
<td>The number of one-time write-offs in the past</td>
<td>0.03</td>
</tr>
<tr>
<td></td>
<td>Hispanic payment number</td>
<td>The number of payments for Hispanic products</td>
<td>1.84</td>
</tr>
<tr>
<td></td>
<td>One-off return amount</td>
<td>The dollar amount of one-time returns</td>
<td>1.51</td>
</tr>
<tr>
<td></td>
<td>Previous mailings</td>
<td>The number of mailings the customer received in the past</td>
<td>0.36</td>
</tr>
<tr>
<td></td>
<td>Payments</td>
<td>The number of payments in the last 5 transactions</td>
<td>2.78</td>
</tr>
<tr>
<td></td>
<td>One-off write-off ratio</td>
<td>The ratio of one-time write-off count to total write-off count</td>
<td>0.07</td>
</tr>
<tr>
<td></td>
<td>One-off return number</td>
<td>The number of cancels or returns in the last 5 one-shot transactions</td>
<td>0.26</td>
</tr>
<tr>
<td>Bad debt</td>
<td>Previous mailings</td>
<td>The number of mailings the customer received in the past</td>
<td>0.36</td>
</tr>
<tr>
<td></td>
<td>Book write-off number</td>
<td>The number of write-offs for books</td>
<td>0.22</td>
</tr>
<tr>
<td></td>
<td>Hispanic order number</td>
<td>The number of orders for Hispanic products</td>
<td>2.24</td>
</tr>
<tr>
<td></td>
<td>Total return number</td>
<td>The number of all of the returns in the past</td>
<td>1.74</td>
</tr>
</tbody>
</table>
# Table 1.6: Demand Results - Discrete Choice Model with Heterogeneity and Endogeneity Correction

<table>
<thead>
<tr>
<th>Variable/Model Component</th>
<th>Coefficient</th>
<th>t-value</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Return choice model component</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Intercept_return</td>
<td>-5.916***</td>
<td>-31.094</td>
</tr>
<tr>
<td>Previous mailings</td>
<td>0.246</td>
<td>0.952</td>
</tr>
<tr>
<td>One-off bad debt number</td>
<td>0.459***</td>
<td>2.37</td>
</tr>
<tr>
<td>Hispanic payment number</td>
<td>0.043</td>
<td>1.068</td>
</tr>
<tr>
<td>One-off return amount</td>
<td>0.030***</td>
<td>4.999</td>
</tr>
<tr>
<td><strong>Bad debt Choice model component</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Intercept_bad debt</td>
<td>-4.978***</td>
<td>-18.016</td>
</tr>
<tr>
<td>Previous mailings</td>
<td>-1.146*</td>
<td>-1.798</td>
</tr>
<tr>
<td>Payments</td>
<td>-0.401***</td>
<td>-3.677</td>
</tr>
<tr>
<td>One-off bad debt ratio</td>
<td>2.003***</td>
<td>6.258</td>
</tr>
<tr>
<td>One-off return number</td>
<td>-0.608</td>
<td>-1.525</td>
</tr>
<tr>
<td><strong>Paid Choice model component</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Intercept_paid</td>
<td>-3.883***</td>
<td>-53.575</td>
</tr>
<tr>
<td>Previous mailings</td>
<td>-0.11</td>
<td>-0.882</td>
</tr>
<tr>
<td>Book bad debt number</td>
<td>-0.051</td>
<td>-0.854</td>
</tr>
<tr>
<td>Hispanic order number</td>
<td>0.070***</td>
<td>5.791</td>
</tr>
<tr>
<td>Total return number</td>
<td>0.014*</td>
<td>1.728</td>
</tr>
<tr>
<td>Heterogeneity covariance (Choleski elements)</td>
<td>0.021</td>
<td>0.14</td>
</tr>
<tr>
<td></td>
<td>0.014</td>
<td>0.09</td>
</tr>
<tr>
<td></td>
<td>-0.018</td>
<td>-0.117</td>
</tr>
<tr>
<td></td>
<td>0.009</td>
<td>0.152</td>
</tr>
<tr>
<td></td>
<td>-0.004</td>
<td>-0.08</td>
</tr>
<tr>
<td></td>
<td>0.007</td>
<td>0.12</td>
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<tr>
<td><strong>Firm Targeting Model</strong></td>
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<td></td>
</tr>
<tr>
<td>Intercept_target</td>
<td>-2.905***</td>
<td>-60.948</td>
</tr>
<tr>
<td>Previous mailings</td>
<td>0.563***</td>
<td>11.564</td>
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<tr>
<td>Total return number</td>
<td>-0.007</td>
<td>-1.485</td>
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<tr>
<td>Bad debts in last five transactions</td>
<td>-0.042</td>
<td>-1.301</td>
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<tr>
<td>Payments</td>
<td>0.057***</td>
<td>4.182</td>
</tr>
<tr>
<td>Responded recently</td>
<td>-0.097*</td>
<td>-1.875</td>
</tr>
<tr>
<td>std variance (heterogeneity)</td>
<td>-0.008</td>
<td>-0.352</td>
</tr>
</tbody>
</table>
Table 1.7: Comparative Statics – Discrete Choice Model

| Variables                  | mean top | no order top | bad debt top | paid top | mean bottom | no order bottom | bad debt bottom | paid bottom | mean difference | no order difference | bad debt difference | paid difference | p-value top | no order top | bad debt top | paid top | mean bottom | no order bottom | bad debt bottom | paid bottom | mean difference | no order difference | bad debt difference | paid difference | p-value top | no order top | bad debt top | paid top | mean bottom | no order bottom | bad debt bottom | paid bottom | mean difference | no order difference | bad debt difference | paid difference |
|----------------------------|----------|--------------|--------------|---------|-------------|----------------|----------------|-------------|----------------|-------------------|-------------------|---------------|-------------|-------------|--------------|---------|-------------|----------------|----------------|-------------|----------------|-------------------|-------------------|---------------|-------------|--------------|------------|-----------|----------------|----------------|----------------|-------------|----------------|-------------------|-------------------|---------------|-------------|--------------|------------|-----------|----------------|----------------|----------------|-------------|----------------|-------------------|-------------------|---------------|
| One-off return amount      | 60.381   | 0.892        | 0.009        | 0.099  | 27.400      | 0.934          | 0.008          | 0.058       | 32.981         | -0.042            | 0.001            | 0.041         | 0.000       | 0.003       | 0.571        | 0.003  |
| One-off return number      | 3.870    | 0.911        | 0.010        | 0.080  | 1.000       | 0.937          | 0.009          | 0.054       | 2.870          | -0.027            | 0.001            | 0.026         | 0.000       | 0.003       | 0.757        | 0.002  |
| Total return number        | 38.420   | 0.905        | 0.010        | 0.085  | 1.000       | 0.933          | 0.009          | 0.053       | 37.420         | -0.028            | -0.003           | 0.031         | 0.000       | 0.000       | 0.385        | 0.000  |
| Previous mailings          | 3.120    | 0.956        | 0.001        | 0.043  | 1.000       | 0.944          | 0.004          | 0.052       | 2.120          | 0.012             | -0.003           | -0.009        | 0.000       | 0.008       | 0.000        | 0.046  |
| One-off bad debt number    | 1.650    | 0.885        | 0.040        | 0.075  | 1.000       | 0.901          | 0.037          | 0.062       | 0.650          | -0.015            | 0.002            | 0.013         | 0.000       | 0.008       | 0.000        | 0.046  |
| One-off bad debt ratio     | 1.000    | 0.853        | 0.053        | 0.094  | 0.361       | 0.925          | 0.015          | 0.061       | 0.639          | -0.072            | 0.038            | 0.033         | 0.000       | 0.000       | 0.000        | 0.013  |
| Book bad debt number       | 7.830    | 0.903        | 0.043        | 0.055  | 1.000       | 0.919          | 0.036          | 0.046       | 6.830          | -0.016            | 0.007            | 0.009         | 0.000       | 0.123       | 0.404        | 0.129  |
| Hispanic payment number    | 18.860   | 0.868        | 0.008        | 0.124  | 1.000       | 0.927          | 0.013          | 0.060       | 17.860         | -0.058            | -0.005           | 0.064         | 0.000       | 0.000       | 0.000        | 0.000  |
| Hispanic order number      | 20.550   | 0.856        | 0.010        | 0.134  | 1.000       | 0.925          | 0.016          | 0.059       | 19.550         | -0.069            | -0.007           | 0.075         | 0.000       | 0.000       | 0.134        | 0.000  |
| Payments                   | 5.000    | 0.749        | 0.004        | 0.247  | 1.000       | 0.906          | 0.020          | 0.074       | 4.000          | -0.157            | -0.016           | 0.173         | 0.000       | 0.001       | 0.000        | 0.000  |
Table 1.8: Impact of Product Returns Option Availability on Profits

<table>
<thead>
<tr>
<th>Scenario</th>
<th>No order</th>
<th>Return</th>
<th>Bad debt</th>
<th>Paid</th>
</tr>
</thead>
<tbody>
<tr>
<td>Product returns allowed</td>
<td>0.851</td>
<td>0.027</td>
<td>0.020</td>
<td>0.101</td>
</tr>
<tr>
<td>Product returns not allowed</td>
<td>0.872</td>
<td>N/A</td>
<td>0.021</td>
<td>0.107</td>
</tr>
</tbody>
</table>
Figure 1.4: Direct Response Targeting Tradeoffs and Drivers
Figure 1.5: The Numbers of Customers Targeted in Each Wave

Wave 1: 2439
Wave 2: 1901
Wave 3: 1686
Wave 4: 1259
Wave 5: 1084
Wave 6: 1413
Figure 1.6: Profit Changes When b Changes (v fixed)

Figure 1.7: Profit Changes When b Changes (c fixed)
Figure 1.8: Profit Changes When $c$ Changes (b fixed)

![Graph showing profit changes when $c$ changes.](image)

Figure 1.9: Profit Changes When $v$ Changes (b fixed)

![Graph showing profit changes when $v$ changes.](image)
Chapter 2

A Structural Model of Default and Product Return Options with Implications for Return Policies
Abstract

Allowing product returns benefits firms in that it encourages customers to order products. But firms have to balance between the increase in demand and the costs caused by product returns. Previous research has focused on studying customers’ return behaviors but ignored the option for customers to default. As recent research (Liu, Pancras and Houtz 2015) shows the importance of incorporating information on customer default behaviors in firms’ targeting policies, we study the question of how customers weigh their default and return options as well as how firms should design their return policies when including the default option. We construct a structural model with both return and default options included, and compare it with a model that does not have a default option (Anderson, Hansen, and Simester 2009). We estimate the two models with a sample panel dataset from a co-operative database. Our research finds that customers have lower price sensitivity and higher transaction fit uncertainty if we ignore defaults. The demand estimates can be biased and lead to a difference in firm’s optimal return policies when we do not consider the default option. We also find that customers’ trade-offs between return and default option are influenced by their return and default costs as well as the transaction fit of the product. The paper illustrates the importance of including the default option when estimating demand and studying the optimal return policies for firms. It also makes a contribution to studying the relationship between product returns and defaults.

**Keywords:** Product return; Default; Direct mail
1. Introduction

Product returns cost US retailers over $260.5 billion in 2015 according to the National Retail Federation (NRF). They are a widespread and expensive problem for firms due to product value depreciation and high labor costs corresponding to return-related operations such as product handling or restocking costs. Retailers allow the product return option because it provides customers with some value, and customers are more likely to order products with that option available (e.g. Anderson, Hansen, and Simester 2009). At the same time, firms may discourage excessive return behavior by charging a restocking fee for returned products or allowing product returns in a more limited time period.

However, prior research on product returns has not considered the default option in which customers keep the product without paying for it. These customers may either forget to pay for the product or intentionally cheat the firm. Recent research (Liu, Pancras, and Houtz 2015) has shown that firms can substantially improve profits by incorporating information on customer default behaviors into their targeting policies. While both customers who choose to default and those who return products are not willing to pay for the product, they are very different in terms of their motivations and their potential value to the firm. This raises the research question that is addressed in this paper: what is the trade-off between the default option and the return option for customers?

In this paper, we set up a structural model to study the return costs and default costs for customers, and apply the model to a sample dataset from a co-operative database in direct mail. A key contribution of this paper is that we find out how customers choose between the return and default option. When trading off between the two options, customers compare their return costs and default costs, and prefer the option with lower cost. In an empirical application, we confirm
that customers have considerable variation in their option costs for the returns and defaults. Meanwhile, customers’ uncertainty about the transaction fit increases their preferences for the return option over the default option. Transaction fit measures how much the product fits a customer’s preferences. If a customer finds the product greatly different from expected, the fit of the transaction is low.

Another contribution is that we find customers may be incorrectly classified as less price sensitive when we ignore defaults. In the music category, demand is approximately 20% less elastic when defaults are ignored. In the magazine and video categories, the differences in demand elasticities due to ignoring defaults are even larger. The direction of these differences is all negative, which can be partly explained by the nature of defaults. Because customers who choose defaults do not pay for the product, their demand does not decrease when the price increases.

This paper also contributes to helping firms design return policies when considering defaults. We find that allowing product returns can increase probability that customers will pay for their purchase, and increasing return costs at the same time can increase firms’ profits, especially for product categories with higher transaction fit uncertainty. As return costs are higher, customers make orders more cautiously, thus less likely to make returns afterwards, which helps reduce firms’ loss from product returns.

The remainder of this paper is organized as follows. In section 2, we describe the related literature on product returns and defaults. In Section 3, we construct a structural model with both return option and default option included. In section 4, we estimate the model using panel data from a co-operative database. We present our findings in section 5 and use the estimates to calculate changes in pay probabilities when the return option is removed. In section 6, we discuss
the trade-off between the default and return options for customers and optimal return policy for firms. We conclude in section 7.

2. Literature Review

Three broad questions related to product returns have been examined in the literature: (1) why do customers need a product return policy? (2) why are product returns accepted by manufacturers and retailers? and (3) how lenient should a product return policy be?

The biggest reason for product returns from customers is defective products. Fraudulent returns receive increasing attention now, but they only account for a small percentage of the total returns (NRF, 2015). In this paper, we focus on why customers find products do not fit their preferences. Customers do not fully know their preferences for the products when they make purchase decisions (Che, 1996). Especially in remote purchase environments, there are two separate decisions in the purchase decision: consumers' decisions to order and, upon receipt, their decisions to keep or return the item. Consumers' initial lack of experiential information makes product choice riskier (Wood, 2001). Allow customers to return products lowers customers' perceived risk of purchase (Petersen and Kumar, 2015). The value provided by the return option is measured by Anderson, Hansen, and Simester (2009). They find that customers value the return option more when they are more uncertain about whether the product will fit their expectations.

On the other hand, researchers have studied why manufacturers accept returns from retailers. Offering a refund for product returns can signal product quality (Moorthy and Srinivasan, 1995), though sellers can cheat by sending false signals (Wood, 2001).
Manufacturers can intensify retail competition by allowing product returns and thus improving profitability (Padmanabhan and Png, 1997 & 2004). For durable products, such as books, a returns policy option is likely to be offered to retailers because used goods are not going to lose much of their consumer valuation compared with new products (Gümüs, Ray, and Yin, 2013). For service products, the firm can increase profit by offering partial refunds for service cancellations (Xie and Gerstner, 2007). Product return behavior can be managed to increase lifetime value of customers. Customer value is maximized at an intermediate level of returns, rather than either a complete absence or an extremely high level of returns (Petersen and Kumar, 2009). Accounting for product returns can also help firms target more profitable customers (Petersen and Kumar, 2015).

As product returns cause an expensive cost for retailers and manufacturers, different return policies are adopted to discourage product returns. Manufacturers and retailers can increase return costs by offering partial credit for product returns, charging a shipping fee, or allow product returns for a limited time, etc. For manufacturers, offering a partial credit for product returns is optimal in a multi-retailer environment (Pasternack, 1985 & 2008), while a complete-credit returns policy is optimal when several manufacturers compete on the same shelf space with the same retailer (Bandyopadhyay and Paul, 2010). Retailers may charge a high return penalty for customers when product returns are salvaged by a channel member, because the retailer misses out on the generous refund from the manufacturer when the retailer salvages returned units without the help of the manufacturer (Shulman, Coughlan, and Savaskan 2010). As customers exhibit habitual behavior with respect to returning previously purchased products, a stringent return policy should be introduced if a majority of serial returners are unprofitable for the firm (Shah, Kumar, and Kim, 2014). However, retailers should be careful about raising return
costs for customers because customers who paid for their product returns decreased their post-return spending at that retailer; and those who had free returns increased their post-return spending (Bower and Maxham III 2012). Some firms are trying to provide more uncertainty-reducing information in order to reduce product returns, but uncertainty-reducing information also increases customers’ expectations and thus increases their likelihood of making returns (Shulman, Cunha Jr, and Saint Clair 2015).

Prior research seldom considers the default option when studying product returns. Customers who have defaulted may eventually pay back the debt or never pay back the debt (Zhao, Zhao, and Song, 2009). The cost of defaults can be very high for direct marketers. Liu, Pancras, and Houtz (2015) show that incorporating bad debt behaviors in a firm’s targeting can significantly increase its profit. However, this research does not address loss caused by product returns. Our paper considers both return option and default option in customers’ responses to direct mail, and studies the trade-off between the two options. We also use the results to help firms design return policies.

3. Model

We will first describe the model of product returns of Anderson, Hansen, and Simester (2009). Note that this model does not consider the default option. Then we develop a joint model of product returns and default.

3.1. Model 1 (Default not included)

Consider customer i who is deciding in period t whether to return or keep an item. We assume that

\[ U(\text{Return})_{it} = -R_i \]  

(1)
$R_i$ is the cost of returning the product and $R_i > 0$. This item varies among individuals over time.

$$U(\text{keep})_{it} = \mu_{it} + \phi_{it} + \epsilon_{it}$$

(2)

Where

$$\mu_{it} = \beta_{it}X_{it}$$

(3)

$X_{it}$ contains one variable: average transaction amount in the past, and $\epsilon_{it}$ is a standard econometric error term that is known to the customer prior to a purchase. $\phi_{it}$ measures the fit of the transaction. If the consumer finds the product greatly different from expected, the fit of the transaction is low. For example, a customer may find the content in a magazine different from what she expects, or the definition of a video not high enough. We assume that $\phi_{it}$ is only observed by the customer after receiving the product and is never observed by the researcher.

$$\phi_{it} \sim N(0, \sigma^2_{\phi})$$

(4)

When $\sigma_{\phi}$ is high, customers are more likely to receive a product that is different from their preferences, which means higher uncertainty about the transaction fit.

Whether a consumer keeps an item depends on the net utility compared to returning the item. We refer to this as $U_{it}^K$:

$$U_{it}^K = \mu_{it} + \phi_{it} + R_i + \epsilon_{it}$$

(5)

Define $\omega_{it} = \mu_{it} + \epsilon_{it}$

(6)

$$H(\omega_{it}, R_i, \sigma_{\phi}) = (\omega_{it} + R_i) \times \Phi\left(\frac{\omega_{it}+R_i}{\sigma_{\phi}}\right) + \sigma_{\phi} \times \phi\left(\frac{\omega_{it}+R_i}{\sigma_{\phi}}\right) - R_i$$

(7)

An order occurs if $\omega_{it} > \bar{\omega}_{it}$, therefore we define
$$U_{it}^0 = -\alpha(R_i, \sigma) + \mu_{it} + \epsilon_{it} \quad (8)$$

3.2 Model 2 (default included)

In this model, there are two stages in the consumer’s decision. In the first stage, the consumer decides whether to keep or return the product. If the consumer decides to keep the product in the first stage, he will decide whether to pay for the product or default in the second stage.

In the first stage, the utility for the return option is

$$U(\text{Return})_{it} = -R_i \quad (9)$$

$R_i$ is the cost of returning the product and $R_i > 0$. This item varies among individuals over time.

The utility for the keep option is obtained from the second stage. Assume the utilities for the pay option and default options as following:

$$U(\text{pay})_{it} = \mu_{it} + \epsilon_{it} + \varphi_{it} - \alpha_{it}M_{it} \quad (10)$$

$$U(\text{default})_{it} = -D_i + \mu_{it} + \epsilon_{it} + \varphi_{it} \quad (11)$$

Where

$$\mu_{it} = \beta_{it}X_{it} \quad (12)$$

$X_{it}$ contains one variable: average transaction amount in the past.

$D_i$ is the cost of bad debt and $D_i > 0$. This item varies among individuals. $M_{it}$ is the transaction amount in dollars, and $\alpha_{it}$ measures the (dis)utility of that price for consumer i at time t. We assume this random variable has a log-normal distribution:

$$\ln(\alpha_{it}) \sim N(0, \sigma_{\alpha}^2) \quad (13)$$
The mean of \( \ln(\alpha_{it}) \) is assumed to be 0 so that the utility metric is equal to the dollar metric.

\( \varepsilon_{it} \) and \( \varphi_{it} \) are the same with those in model 1.

Whether a consumer pays for an item depends on the net utility compared to default. We refer to this as \( U_{it}^P \), which is defined as

\[
U_{it}^P = U(\text{pay})_{it} - U(\text{default})_{it} = D_i - \alpha_{it} M_{it} \tag{14}
\]

A consumer has the option of paying for an item or not in his purchase decision. We can write the expected utility from keeping an item as

\[
E[U(\text{keep})_{it}] = E[U(\text{pay})_{it}|\text{pay}] Pr_{it}(\text{pay}) + E[U(\text{default})_{it}|\text{default}] Pr_{it}(\text{default})
\]

\[
E[U(\text{pay})_{it}|\text{pay}] = \mu_{it} + \varepsilon_{it} + \varphi_{it} \mathbb{1}_{[U_{it}^P > 0]} = \mu_{it} + \varepsilon_{it} + \varphi_{it} - M_{it} \times E\left[\alpha_{it}|\alpha_{it} < \frac{D_i}{M_{it}}\right] = \mu_{it} + \varepsilon_{it} + \varphi_{it} - M_{it} \times \int_{\ln\left(\frac{D_i}{M_{it}}\right)}^{\infty} \frac{du}{\sqrt{2\pi} \sigma_{\alpha}} \Phi\left(\frac{u - \ln(D_i/M_{it})}{\sigma_{\alpha}}\right)
\]

\[
\frac{D_i}{M_{it}} = \mu_{it} + \varepsilon_{it} + \varphi_{it} - M_{it} \times \int_{\ln\left(\frac{D_i}{M_{it}}\right)}^{\infty} \frac{du}{\sqrt{2\pi} \sigma_{\alpha}} \Phi\left(\frac{u - \ln(D_i/M_{it})}{\sigma_{\alpha}}\right) = \mu_{it} + \varepsilon_{it} + \varphi_{it} - M_{it} \times \exp\left(\frac{\ln(D_i/M_{it})^2}{2\sigma_{\alpha}^2}\right) \Phi\left(\frac{\ln(D_i/M_{it})}{\sigma_{\alpha}}\right) + \frac{\exp\left(\frac{\ln(D_i/M_{it})^2}{2\sigma_{\alpha}^2}\right) \Phi\left(\frac{\ln(D_i/M_{it})}{\sigma_{\alpha}}\right)}{\Phi\left(\frac{\ln(D_i/M_{it})}{\sigma_{\alpha}}\right)}
\]

Customer \( i \) expects to not pay for the order with probability

\[
Pr_{it}(\text{default}|\text{keep}) = \Pr(D_i - \alpha_{it} M_{it} < 0) = \Pr\left(\alpha_{it} > \frac{D_i}{M_{it}}\right) = 1 - \Phi\left(\frac{\ln(D_i/M_{it})}{\sigma_{\alpha}}\right) = \Phi\left(-\frac{\ln(D_i/M_{it})}{\sigma_{\alpha}}\right) \tag{17}
\]

\[
E[U(\text{default})_{it}|U_{it}^P < 0] = -D_i + \mu_{it} + \varepsilon_{it} + \varphi_{it} \tag{18}
\]
Then the expected utility of keeping the product is

\[
E[U(\text{keep})_{it}] = \left( \mu_{it} + \varepsilon_{it} + \varphi_{it} - M_{it} \times \frac{\exp\left(\frac{\sigma_{\varphi}^2}{2}\right) \times \Phi\left(\frac{\ln(D_i/M_{it})}{\sigma_{\varphi}}\right)}{\Phi\left(\frac{\ln(D_i/M_{it})}{\sigma_{\varphi}}\right)} \right) \times \left( 1 - \Phi\left(-\frac{\ln(D_i/M_{it})}{\sigma_{\alpha}}\right)\right) + [-D_i + \mu_{it} + \varepsilon_{it} + \varphi_{it}] \times \Phi\left(-\frac{\ln(D_i/M_{it})}{\sigma_{\alpha}}\right) = (\mu_{it} + \varepsilon_{it} + \varphi_{it}) - D_i \times \Phi\left(-\frac{\ln(D_i/M_{it})}{\sigma_{\alpha}}\right) - M_{it} \times \exp\left(\frac{\sigma_{\varphi}^2}{2}\right) \times \Phi\left(\frac{\ln(D_i/M_{it})}{\sigma_{\alpha}} - \sigma_{\alpha}\right) \tag{19}
\]

Assume that

\[
G(M_{it}, D_i, \sigma_{\alpha}) = -D_i \times \Phi\left(-\frac{\ln(D_i/M_{it})}{\sigma_{\alpha}}\right) - M_{it} \times \exp\left(\frac{\sigma_{\varphi}^2}{2}\right) \times \Phi\left(\frac{\ln(D_i/M_{it})}{\sigma_{\alpha}} - \sigma_{\alpha}\right) \tag{20}
\]

Then \(E[U(\text{keep})_{it}] = G(M_{it}, D_i, \sigma_{\alpha}) + \mu_{it} + \varepsilon_{it} + \varphi_{it}\) \tag{21}

Whether a consumer will keep the product depends on the net utility compared to returning the product. We refer to this as \(U^K_{it}\), which is defined as

\[
U^K_{it} = E[U(\text{keep})_{it}] - E[U(\text{return})_{it}] = G(M_{it}, D_i, \sigma_{\alpha}) + \mu_{it} + \varepsilon_{it} + \varphi_{it} + R_i \tag{22}
\]

There are two random variables \(\varepsilon_{it}\) and \(\varphi_{it}\) in equation (22). We assume the fit of transaction \(\varphi_{it}\) to follow the normal distribution:

\[
\varphi_{it} \sim N(0, \sigma_{\varphi}^2) \tag{23}
\]

The expected utility of returning the product is

\[
E[U(\text{Return})_{it} | \text{Return}] = E[-R_{it} | U^K_{it} < 0] = -R_i \tag{24}
\]

The probability of keeping the product is
\[ \text{Pr}_{it}(\text{Keep}) = \Pr(U_{it}^K > 0) = \Pr(\varphi_{it} > -[G(M_{it}, D_i, \sigma) + \mu_{it} + \varepsilon_{it} + R_i]) = \]
\[ \Phi\{[G(M_{it}, D_i, \sigma) + \mu_{it} + \varepsilon_{it} + R_i]/\sigma \phi \} \quad (25) \]

The expected utility of keeping the product is

\[ \text{E}[U(\text{Keep})_{it} | \text{Keep}] = \text{E}[G(M_{it}, D_i, \sigma) + \mu_{it} + \varepsilon_{it} + \varphi_{it} | U_{it}^K > 0] = G(M_{it}, D_i, \sigma) + \mu_{it} + \varepsilon_{it} + \varphi_{it} \]
\[ \mu_{it} + \varepsilon_{it} + \text{E} \left[ \varphi_{it} | \varphi_{it} > -[G(M_{it}, D_i, \sigma) + \mu_{it} + \varepsilon_{it} + R_i] \right] = G(M_{it}, D_i, \sigma) + \mu_{it} + \varepsilon_{it} + \varphi_{it} \]
\[ \sigma \phi \Phi\{[G(M_{it}, D_i, \sigma) + \mu_{it} + \varepsilon_{it} + R_i]/\sigma \phi \} \quad (26) \]

Therefore, the expected utility from ordering the product is:

\[ \text{E}[U(\text{Order})_{it}] = \text{E}[U(\text{Return})_{it} | \text{Return}] \text{Pr}_{it}(\text{Return}) + \]
\[ \text{E}[U(\text{Keep})_{it} | \text{Keep}] \text{Pr}_{it}(\text{Keep}) = -R_i + [G(M_{it}, D_i, \sigma) + \mu_{it} + \varepsilon_{it} + R_i] \times \]
\[ \Phi \left[ \frac{G(M_{it}, D_i, \sigma) + \mu_{it} + \varepsilon_{it} + R_i}{\sigma \phi} \right] + \sigma \phi \times \Phi \left[ \frac{G(M_{it}, D_i, \sigma) + \mu_{it} + \varepsilon_{it} + R_i}{\sigma \phi} \right] = H(\mu_{it} + \varepsilon_{it}, M_{it}, D_i, R_i, \sigma_{\phi}, \sigma_\alpha) \]
\[ (27) \]

There is one random variable \( \varepsilon_{it} \) in equation (27). We assume the econometric error term \( \varepsilon_{it} \) to follow a normal distribution:

\[ \varepsilon_{it} \sim N(0, \sigma^2) \quad (28) \]

The probability that the consumer orders a product is given by

\[ \text{Pr}_{it}(\text{Order}) = \Pr\left( \text{E}[U(\text{Order})_{it}] > 0 | M_{it}, D_i, R_i, \sigma_{\phi}, \sigma_\alpha \right) = \Pr_{it} \left( H(\mu_{it} + \varepsilon_{it}, M_{it}, D_i, R_i, \sigma_{\phi}, \sigma_\alpha) > 0 \right) = \int \Phi(\varepsilon_{it} | 0, \sigma^2) d\varepsilon_{it} \quad (29) \]

Define \( \omega_i = G(M_{it}, D_i, \sigma) + \mu_{it} + \varepsilon_{it} \quad (30) \)
\[ H(\mu_{it} + \varepsilon_{it}, M_{it}, D_i, R_i, \sigma_\varphi, \sigma_\alpha) = (\omega_i + R_i) \times \Phi\left(\frac{\omega_i + R_i}{\sigma_\varphi}\right) + \sigma_\varphi \times \Phi\left(\frac{\omega_i + R_i}{\sigma_\varphi}\right) - R_i \] 

(31)

To simplify notation, we denote the function in (31) as \( H \).

\[ \frac{\partial H}{\partial \omega_i} = \Phi\left(\frac{\omega_i + R_i}{\sigma_\varphi}\right) + (\omega_i + R_i) \times \phi\left(\frac{\omega_i + R_i}{\sigma_\varphi}\right) \times \frac{1}{\sigma_\varphi} + \sigma_\varphi \times \frac{\partial \phi\left(\frac{\omega_i + R_i}{\sigma_\varphi}\right)}{\partial \omega_i} = \Phi\left(\frac{\omega_i + R_i}{\sigma_\varphi}\right) + \]

\[ \frac{\omega_i + R_i}{\sigma_\varphi \sqrt{2\pi}} \times \exp\left(-\frac{(\omega_i + R_i)^2}{2\sigma_\varphi^2}\right) - \frac{\omega_i + R_i}{\sigma_\varphi \sqrt{2\pi}} \times \exp\left(-\frac{(\omega_i + R_i)^2}{2\sigma_\varphi^2}\right) = \Phi\left(\frac{\omega_i + R_i}{\sigma_\varphi}\right) > 0 \] 

(32)

Therefore \( H \) monotonically increases with \( \omega_i \), and one can easily find that \( H \) has a negative lower bound and a positive upper bound. Thus there is one and only one \( \omega(\sigma_i, \sigma_\varphi) \) for the \( H \) function to be 0.

When \( \omega_i > \omega_i \), \( H(\mu_{it} + \varepsilon_{it}, M_{it}, D_i, R_i, \sigma_\varphi, \sigma_\alpha) > 0 \); when \( \omega_i < \omega_i \), \( H(\mu_{it} + \varepsilon_{it}, M_{it}, D_i, R_i, \sigma_\varphi, \sigma_\alpha) < 0 \)

An order occurs when \( \omega_i > \omega_i \).

We define

\[ U_{it}^0 = -\omega(R_i, \sigma_\varphi) + G(M_{it}, D_i, \sigma_\alpha) + \mu_{it} + \varepsilon_{it} \] 

(33)

The customer will order a product if \( U_{it}^0 > 0 \). The customer will not order the product if \( U_{it}^0 < 0 \).

Then the probability of ordering the product is

\[ \Pr\left(U_{it}^0 > 0|\mu_{it}, M_{it}, D_i, R_i, \sigma_\varphi, \sigma_\alpha\right) = \Phi\left(-\frac{\omega(R_i, \sigma_\varphi) + G(M_{it}, D_i, \sigma_\alpha) + \mu_{it}}{\sigma_\varepsilon}\right) \] 

(34)

Therefore the probabilities for the four outcomes are as following:
1. No order.

\[ \Pr(U_{it}^O < 0 | \mu_{it}, M_{it}, D_i, R_i) = 1 - \Phi \left( \frac{-\sigma(R_i, \sigma \varphi) + G(M_{it}, D_i, \sigma \alpha) + \mu_{it}}{\sigma \epsilon} \right) \] (35)

2. Order and return

\[ \Pr(U_{it}^O > 0, U_{it}^K < 0 | \mu_{it}, M_{it}, D_i, R_i) = \int_{-\infty}^{0} \Phi \left( \frac{-G(M_{it}, D_i, \sigma \alpha) + \mu_{it} + \sigma \epsilon \epsilon + R_i}{\sigma \varphi} \right) \phi(\epsilon) d\epsilon \] (36)

3. Order and default

\[ \Pr(U_{it}^O > 0, U_{it}^K > 0, U_{it}^P < 0 | \mu_{it}, M_{it}, D_i, R_i) = \Phi \left( \frac{-\ln(D_i/M_{it})}{\sigma \alpha} \right) \times \int_{-\infty}^{0} \Phi \left( \frac{G(M_{it}, D_i, \sigma \alpha) + \mu_{it} + \sigma \epsilon \epsilon + R_i}{\sigma \varphi} \right) \phi(\epsilon) d\epsilon \] (37)

4. Order and pay

\[ \Pr(U_{it}^O > 0, U_{it}^K > 0, U_{it}^P > 0 | \mu_{it}, M_{it}, D_i, R_i) = \Phi \left( \frac{\ln(D_i/M_{it})}{\sigma \alpha} \right) \times \int_{-\infty}^{0} \Phi \left( \frac{G(M_{it}, D_i, \sigma \alpha) + \mu_{it} + \sigma \epsilon \epsilon + R_i}{\sigma \varphi} \right) \phi(\epsilon) d\epsilon \] (38)

3.3 Identification

To estimate the model, we make the standard assumption that \( \sigma \epsilon = 1 \). For a single category, the information is not sufficient for identification, so we use a multi-category approach to estimate the model. We select three categories: music, magazine, and video. We assume \( \sigma \varphi_c (c = 1, 2, 3) \) to vary over categories and \( \sigma \varphi_1 = 1 \). Return cost, default cost, and \( \sigma \alpha \) do not vary over categories.

We collect all these parameters in the vector
\[ \theta_{lt} = (\log(R_l), \log(D_l), \beta_{lt1}, \beta_{lt2}, \beta_{lt3}) \]  

(39)

### 3.4. The option value of returns and defaults

For the option value of returns, we compare the demand when product returns are allowed and when product returns are banned. In model 1, The probability change of a customer’s ordering and keeping an item when product returns are banned is defined as \( \Delta_1 \).

\[
\Delta_1 = \Pr(U^O > 0, U^K > 0) - \lim_{R \to \infty} \Pr(U^O > 0, U^K > 0) = \Pr(U^O > 0, U^K > 0) - \Pr(U^O > 0)
\]

(40)

In model 2, The probability change of a customer’s ordering and keeping and paying an item when product returns are banned is defined as \( \Delta_2 \).

\[
\Delta_2 = \Pr(U^O > 0, U^K > 0, U^P > 0) - \lim_{R \to \infty} \Pr(U^O > 0, U^K > 0, U^P > 0) = \Pr(U^O > 0, U^K > 0, U^P > 0) - \Pr(U^O > 0, U^P > 0)
\]

(41)

\( \Delta \) refers to the demand change due to the return option. It can be either positive or negative theoretically. Whether a customer make an order when product returns are allowed is decided by her expected utility of ordering \( H(\omega, R, \sigma_\varphi) \), while whether she makes an order when product returns are banned is decided by \( H(\omega - \pi, R, \sigma_\varphi) \). Notice that \( H(\omega, R, \sigma_\varphi) \) is monotonically increasing with \( \omega \) according to equation (32). When a customer has an \( \omega \) large enough to make \( H(\omega - \pi, R, \sigma_\varphi) > 0 \), she will make an order no matter product returns are allowed or banned. But when product returns are not allowed, she can only keep the product after ordering it. In this case, \( \Delta \) is positive and it is better for firms to ban product returns. On the other hand, if a customer has an \( \omega \) that makes \( H(\omega - \pi, R, \sigma_\varphi) < 0 \) and \( H(\omega, R, \sigma_\varphi) > 0 \), then whether product
returns are allowed makes difference for her when she decides whether to order a product. \( \Delta \) can be negative in this way and it’s better for firms to allow product returns.

For the option value of defaults, we compare the net demand when defaults are allowed and not allowed. The probability change of a customer’s ordering and keeping and paying for an item is

\[
\Lambda = \Pr(U^O > 0, U^K > 0, U^P > 0) - \lim_{B \to \infty} \Pr(U^O > 0, U^K > 0, U^P > 0) = \\
\Pr(U^O > 0, U^K > 0, U^P > 0) - \Pr(U^O > 0, U^K > 0) \quad (43)
\]

4. Empirical Application

We use panel data from co-operative databases, which include transaction information from different direct marketing firms (organized by a third party). From many product categories in the original dataset, we select three main categories: music, magazine, and video. To estimate our model, we randomly select 500 customers out of 28359 customers in the full sample data. In our data, customers have four possible options: no order, pay, return, and default. We have information about customers’ past purchase behaviors such as pay rate and return rate, and information about firms’ promotional activities such as a promotional offer. There are also some variables indicating customers’ demographical information: length of residence, age, and income.

Table 2.1 shows the summary of customers’ transactions in the three categories. We can find that customers have the lowest order rate but the highest pay rate in the magazine category. The default rate is highest in the music category and lowest in the video category.
Table 2.2.1 shows the statistics for transaction amounts of all observations. The mean of it is as high as $5.3 in the video category, while as low as $1.0 in the magazine category. Also, there is a huge variation in transaction amounts in the video category. Table 2.2.2 shows the transaction amounts of all orders.

Because the model is complicated, we select only one variable for $X$ to make the estimation more simple. The variable is the average transaction amount in the past, which is supposed to have a negative impact on the keep option, because customers might have not consumed the product at home. For example, if they still have five magazines to read, they are less likely to buy new magazines.

For estimation, we use a Markov Chain Monte Carlo algorithm of the Gibbs sampler form. Appendix 2.1 shows each conditional distribution making up the Gibbs sampler. We run the Markov Chain for a total of 30,000 iterations, dropping the first 10,000 as burn-in and then retaining every 2<sup>nd</sup> of the next 20,000 iterations for analysis. In order to verify the estimation method for our models, we first run a simulation study. There are 50 customers in the simulation dataset, and each customer has 10 transactions in each category. Simulation results are in Appendix 2.2. We believe our estimation method is statistically effective as the true values are included in 95% confidence intervals.

5. Results

Table 2.3 shows the estimates and 95% confidence intervals for the model parameters. Trace plots are in Appendix 2.3. Estimates for the covariance matrix are in Appendix 2.4. In
Table 2.3, we observe negative effects of average transaction amount in the past for the keep option in both models. This suggests that customers who have spent more for the product have less demand for it, possibly because these customers haven’t run out of the product. The ranking of the coefficients for the three categories are consistent in the two models, showing certain consistency in the two models. We also notice that the negative effects decrease in all three categories in Model 2, especially in the magazine category.

*** INSERT TABLE 2.3***

The primary parameters of interest are consumer return costs $R_i$, consumer default costs $D_i$ and the degree of product uncertainty $\sigma_{\phi}$. The means of $R_i$ and $D_i$ for customers in our sample are in Table 2.3. We plot the distributions of estimated return costs and default costs in Figure 2.1 and Figure 2.2. We observe considerable variation in return costs and default costs. We find that consumer return costs are lower in model 2, probably because the utility metric equals to the dollar metric in model 2 while there is no restriction for the utility metric in model 1. We also find that consumer default costs are lower than consumer return costs in model 2. A possible reason is that the return costs are easier for the customers to measure, such as the return shipping fee and the inconvenience of going to a post office to drop the package. However the defaults costs, such as the damage to credit, are more difficult to measure. Thus customers view a lower cost for the default option.

*** INSERT FIGURE 2.1, 2.2***

For product uncertainty, we find that customers have highest uncertainty about product fit for magazines, and lowest uncertainty about product fit for music in model 1. However, we observe different results in model 2. Especially, we find that customers’ uncertainty about the
product fit for magazine is lower than that for music. Results in model 2 seem to be more reasonable, as magazines are published on a periodical basis, and customers can better predict the product fit based on the previously published magazines. In both models, customers have higher uncertainty about product fit for video than that for music. This is consistent with what we expect, because music only contains sound, while video has both sound and picture. There is more variation in video products than music products, leading to the difference in customers’ uncertainty.

One reason for the changes in product uncertainty in the two models lies in the default option. Customers who choose to default has a lower perceived risk of buying a product that does not fit their preferences, leading to a lower uncertainty about the transaction fit. That is why $\sigma_\varphi$ decreases when we consider defaults in model 2. We also notice that the rank of $\sigma_\varphi$ is different in two models. $\sigma_\varphi$ is lowest in the music category in model 1, but lowest in the magazine category in model 2. Because customers are more likely to return products when they have higher uncertainty about the transaction fit, the rank of $\sigma_\varphi$ should be consistent with the rank of return rate in the three categories. From Table 2.1, we know that the return rate is highest (25%) in video category, and lowest (0%) in magazine category. Therefore, the estimates for $\sigma_\varphi$ in model 2 are more reasonable.

We also calculate the net demand change due to the default option defined in (43). The average pay probability of customers’ ordering and keeping and paying for an item is 0.228 when defaults are allowed while it is 0.174 when defaults are not allowed. That is, the average pay probability increases by more than 30% due to the default option, showing that it is reasonable to allow defaults in this industry.
6. Discussion

6.1. The influence of ignoring the default option

One consequence of ignoring defaults is a biased estimate for transaction fit. Comparing the estimates in table 2.3, we find that $\sigma_q$ is higher when we do not include a default option in the model. A possible reason is that a customer who chooses to default has a lower perceived risk for the product that does not fit her preferences, as the customer does not have a risk of paying for a product that she does not want. When we ignore defaults, the perceived risk is higher, which is captured in the transaction fit term, leading to higher uncertainty of transaction fit in the model without a default option.

In the case where no defaults are considered, customers who actually choose defaults are assumed to make payments in the future, so both payments and defaults are counted in net demand. In order to examine how this influences price elasticities, we calculate them using the method in Appendix 2.5, and show results in Table 2.4.

*** INSERT TABLE 2.4 ***

We find that customers are less price sensitive in each category when we ignore defaults. Specifically, the demand elasticity is 20% lower in the music category, 23% lower in the magazine category and 24% lower in the video category. A possible reason is that customers who choose defaults do not want to pay for the product no matter how price changes. These customers are far less price sensitive than those who want to pay for the products.
Overall, we find two possible consequences of ignoring defaults in consumer behavior. One is a biased estimate for the uncertainty about transaction fit, the other is that demand elasticity can be remarkably underestimated when we do not take the default option into account. Our results illustrate the importance of incorporating a default option in customers’ choice set.

6.2. Trade-off between return and default for customers

When we compare the utility functions of return and default options in (9) and (11), we can easily tell that a customer’s trade-off between the two options are influenced by her transaction fit and the difference between default cost and return cost. The influence of the option costs is more straightforward as customers are trying to choose the option with lower cost. Customers are less likely to choose the default option if their default costs are higher than return costs, vice versa. Figure 2.3 shows the difference between customers’ return costs and default costs in our data. We find that customers in our dataset have considerable variation in their default-return cost difference.

*** INSERT FIGURE 2.3 ***

The other important factor affecting a customer’s trade-off between return and default option is transaction fit. Table 2.5 shows the mean difference between default probability and return probability in each category. We find customers prefer to return rather than default when $\sigma_{\phi}$ is higher, which is reasonable because customers are more likely to return rather than keep the product when they have a higher uncertainty about the transaction fit.

*** INSERT TABLE 2.5 ***

To sum up, when customers trade off between return and default option, they compare the costs of the two options, and prefer the option with a lower cost. Meanwhile, when the
uncertainty about transaction fit is higher, customers are more likely to get a product that does not fit their preferences, so they prefer to return rather than default.

6.3. The value of the return option for firms

To study the increase in net demand due to the return option, we calculate the probability changes of customers’ paying for an item due to the return option defined as $\Delta$ in (40) and (41). Figure 2.4 shows histograms of $\Delta$ in different categories in model 1, and Figure 2.5 shows histograms of $\Delta$ in different categories in model 2.

*** INSERT FIGURE 2.4, 2.5 ***

$\Delta$ can be either positive or negative theoretically. In the results of both models, the pay probability changes are mostly positive, which means the pay probabilities mainly increase in each category when product returns are allowed. Comparing the means of the probability changes across categories, we can find that it is highest in video category and lowest in magazine category, which is consistent with the estimates for $\sigma_q$. When customers have higher uncertainty about the transaction fit, they are less likely to order the product if product returns are not allowed. As a result, the net demand increases more when product returns are allowed. For categories with higher transaction fit uncertainty, the return option offers more value for the company.

We also find two impacts when defaults are ignored. One impact is that the company can overestimate the value of return option when defaults are ignored, especially for the magazine category where transaction fit uncertainty is low. As customers who choose to default do not have the risk of paying for a product that does not fit their preferences, allowing product returns or not has little influence on their purchase decision. The other impact is that there is more
heterogeneity in the return option value when defaults are ignored. According to Table 2.3, there is an upward bias in the estimates for transaction fit uncertainty when defaults are not considered, leading to higher heterogeneity in customers’ willingness to return products. As a result, there is more uncertainty for the net demand change when product returns are not allowed.

6.4. Optimizing return policies

Firms can have different return policies by changing the return costs for customers:

\[ R_{i}^{\text{new}} = K \hat{R}, \quad i = 1, 2, \ldots, n \]

(46)

K measures how lenient the return policy is. For the current return policy, K=1, and the return costs are what we have estimated. The firm will have a more lenient return policy when K>1, and a stricter one when K<1. In order to examine the optimal return option for firms, we calculate firm profits for category j using the following formula

\[ \text{Profit}_j(K) = m_j \sum_{i=1}^{N} \text{Pay} - c_j \sum_{i=1}^{N} \text{Return} - q_j \sum_{i=1}^{N} \text{Default} \]

(47)

When K changes, we can calculate the corresponding pay number, return number, and default number. We assume that \( c_j \) is 35% of \( m_j \), and \( q_j \) is 20% of \( m_j \). The assumptions are based on feedback from the management of a direct response company. We use estimates of model 2 because defaults are not considered in model 1. Changes in the expected profit are illustrated in figure 2.6.

*** INSERT FIGURE 2.6 ***

Our research helps firms decide the extent to how lenient their return policies should be. Figure 2.6 shows that the optimal K is 3 in the music category, and 2.5 in the video category,
while the current return policy is already the optimal one in the magazine category. We observe an inverted U shape in all categories, which means that the profit increases before the optimal $K$ and decreases after the optimal $K$.

Among the three categories, we find the optimal return policy is more lenient in the music and video category. Notice that the transaction fit uncertainty ($\sigma_\varphi$) is also higher in these two compared to the magazine category. As customers are more likely to receive a product that does not fit their preferences in these categories, they are more likely to return products, causing higher loss for firms. In this situation, it is necessary to allow product returns as discussed in the previous section. But meanwhile, it is better for firms to increase return costs for customers so that they will make orders more cautiously, which can help reduce firm’s loss from product returns.

In general, firms should carefully compare different return costs in designing a return policy when they decide that product returns are allowed. They may increase their profits by tightening up the return policy in product categories where transaction fit uncertainty is high.

7. Conclusion

While previous research about product returns largely ignores default behaviors, this paper constructs a structural model that includes both the default and return options. We find that estimates for customers’ price sensitivity and transaction fit can be biased if we ignore the default option, thus demonstrating the importance of incorporating the default option in customers’ choice set. We also show that customers have considerable variation in their return costs and default costs.
When it comes to the trade-off between the return and default option, customers tend to compare their return and default costs, and choose the option with lower cost. Also, when the product fits the customer’s preferences better, customers are more likely to keep the product, which means a preference for default over return.

This paper also finds that the firm may overvalue the return option when ignoring defaults. If allowing product returns is better for the firm, they can use our model to further decide how lenient the optimal return policy should be in each category. We find that the firm should allow product returns in categories where product fit uncertainty is high. Meanwhile, they can have a stricter return policy to increase profit.

There are some limitations in this research. First, we assume that customers decide to return or keep the product first, and then decide whether to pay for the product or not. It is also possible that customers make a decision about whether to pay for the product at first, and if they determine not to pay for the product, they choose one between the return and default options. Second, we estimate our model only for three product categories. Our results may not be applicable to other product categories.

In spite of the limitations, our paper contributes to product returns in direct mail by studying the trade-offs between the default option and return option. We find customers are less price sensitive if defaults are not included, and our findings can help firms design optimal return policies for categories with different uncertainties of transaction fit.
References


Appendix 2.1: Samplings for model 2

1. Sampling $U_{ict}^0, U_{ict}^K, U_{ict}^p$

$U_{ict}^0, U_{ict}^K, U_{ict}^p$ are sampled according to the purchase behavior of customer I in period t in category c. There are four outcomes:

1.1. **No order**: Here we only need to sample $U_{ict}^0$

$$U_{ict}^0 \sim TN(\omega, \alpha_c) - \omega(R_i, \sigma_{\phi c}) + \mu_{ict} + G(D_i, \sigma_\alpha)$$ (A1)

where $TN(\omega, \alpha_c)$ denotes the normal distribution with mean $\omega$ and $\alpha$ truncated to the region (a, b).

1.2. **Order and return**: In this case, we sample the utilities as

$$U_{ict}^0 | U_{ict}^K \sim TN(0, \omega_c) (\omega(R_i, \sigma_{\phi c}) + \mu_{ict} + G(D_i, \sigma_\alpha) + \frac{1}{1+\sigma_{\phi c}^2} (U_{ict}^K - G(D_i, \sigma_\alpha) - R_i - \mu_{ict})),$$

$$\frac{\sigma_{\phi c}^2}{1+\sigma_{\phi c}^2}$$ (A2)

$$U_{ict}^K, U_{ict}^0 \sim TN(\omega, \alpha_c) (R_i + \omega(R_i, \sigma_{\phi c}) + U_{ict}^0, \sigma_{\phi c}^2)$$ (A3)

1.3. **Order and keep and pay**: In this case, we sample the utilities

$$U_{ict}^0 | U_{ict}^K \sim TN(0, \omega_c) (\omega(R_i, \sigma_{\phi c}) + \mu_{ict} + G(D_i, \sigma_\alpha) + \frac{1}{1+\sigma_{\phi c}^2} (U_{ict}^K - G(D_i, \sigma_\alpha) - R_i - \mu_{ict})),$$

$$\frac{\sigma_{\phi c}^2}{1+\sigma_{\phi c}^2}$$ (A4)

$$U_{ict}^K, U_{ict}^0 \sim TN(0, \omega_c) (R_i + \omega(R_i, \sigma_{\phi c}) + U_{ict}^0, \sigma_{\phi c}^2)$$ (A5)

$$\ln(\alpha_{ict}) \sim TN(\ln(B_i), \frac{\alpha_c^2}{\omega_{ict}})$$ (A6)

$$U_{ict}^p = D_i - \alpha_{ict}M_{it}$$ (A7)

1.4. **Order and keep and default**: In this case, we sample the utilities

$$U_{ict}^0 | U_{ict}^K \sim TN(0, \omega_c) (\omega(R_i, \sigma_{\phi c}) + \mu_{ict} + G(D_i, \sigma_\alpha) + \frac{1}{1+\sigma_{\phi c}^2} (U_{ict}^K - G(D_i, \sigma_\alpha) - R_i - \mu_{ict})),$$

$$\frac{\sigma_{\phi c}^2}{1+\sigma_{\phi c}^2}$$ (A8)

$$U_{ict}^K, U_{ict}^0 \sim TN(0, \omega_c) (R_i + \omega(R_i, \sigma_{\phi c}) + U_{ict}^0, \sigma_{\phi c}^2)$$ (A9)

$$\ln(\alpha_{ict}) \sim TN(\ln(B_i), \frac{\alpha_c^2}{\omega_{ict}})$$ (A10)

$$U_{ict}^p = D_i - \alpha_{ict}M_{it}$$ (A11)

2. Sampling $\theta_i = (\beta_{i1}, \beta_{i2}, \beta_{i3}, \ln R_i, \ln D_i)$

2.1. Sample $\beta_{ict} | \theta_{-\beta_{ict}}, \ c = 1, 2, 3.$

$$\mu_{ict} = \beta'_{ict} X_{ict}$$ (A12)

$$U_{ict}^0 + \omega(R_i, \sigma_{\phi c}) - G(D_i, \sigma_\alpha) = \mu_{ict} + \epsilon_{ict}^0$$ (A13)

The conditional distribution for $\beta_{ict}$ is normal with precision and mean:
\[ p_{ic} = \sum X_{ict} X'_{ict} + \Lambda_{\beta_{ic}} \]  
\[ \mu_{ic} = p_{ic}^{-1}(\sum X'_{ict}[U_{ict}^{0} + \omega(R_i, \sigma_{\varphi c}) - G(D_i, \sigma_{\alpha})] + \Lambda_{\beta_{ic}} \mu_{\beta_{ic}}) \]  

(A14)  
(A15)

Where \( \Lambda_{\beta_{ic}} \) and \( \mu_{\beta_{ic}} \) is the precision and mean of the prior distribution of \( \beta_{ic} \) conditional on \( \beta_{ic'}, c' \neq c \) and \( \ln R_i \), \( \ln D_i \).

2.2. Sample \( \ln R_i \)

We use a Metropolis-Hastings method to sample \( \tilde{R}_i \equiv \ln R_i \)

\[
p(\tilde{R}_i | \cdot) \propto \prod_{c=1}^{3} \prod_{t=1}^{T_{ic}} \phi(U_{ict}^{0} - \omega(\exp(\tilde{R}_i), \sigma_{\varphi c}) + G(D_i, \sigma_{\alpha}) + \mu_{ict}, 1) \times 
\prod_{t: D_{ict}^{0}} \phi(U_{ict}^{K} | \exp(\tilde{R}_i) + \omega(\exp(\tilde{R}_i), \sigma_{\varphi c} + U_{ict}^{0}, \sigma_{\varphi c}^{2})} \times \phi(\tilde{R}_i | \mu_{\tilde{R}_i}, \Lambda_{\tilde{R}_i})
\]

(A16)

where \( D_{ict}^{0} = 1 \) indicates that an order was placed. \( \Lambda_{\tilde{R}_i} \) and \( \mu_{\tilde{R}_i} \) is the precision and mean of the prior distribution of \( \ln R_i \) conditional on \( \beta_{ic}, c = 1, 2, 3 \) and \( \ln D_i \). Here we use a Metropolis-Hastings step centered at the previous draw of \( \tilde{R}_i \) with a normally distributed step size.

2.3. Sample \( \ln D_i \)

We use a Metropolis-Hastings method to sample \( \tilde{D}_i \equiv \ln D_i \)

\[
p(\tilde{D}_i | \cdot) \propto \prod_{c=1}^{3} \prod_{t=1}^{T_{ict}} \phi(U_{ict}^{0} - \omega(R_i, \sigma_{\varphi c}) + G(\exp(\tilde{D}_i), \sigma_{\alpha}) + \mu_{ict}, 1) \times 
\prod_{t: D_{ict}^{K}} pdf_{\text{lognormal}}(\exp(\tilde{D}_i) - U_{ict}^{0} | \ln M_{ict}, \sigma_{\alpha}^{2})} \times \phi(\tilde{D}_i | \mu_{\tilde{D}_i}, \Lambda_{\tilde{D}_i})
\]

(A17)

where \( D_{ict}^{K} = 1 \) indicates that an order was kept. \( \Lambda_{\tilde{D}_i} \) and \( \mu_{\tilde{D}_i} \) is the precision and mean of the prior distribution of \( \ln D_i \) conditional on \( \beta_{ict}, c = 1, 2, 3 \) and \( \ln R_i \). Here we use a Metropolis-Hastings step centered at the previous draw of \( \tilde{D}_i \) with a normally distributed step size.

3. Sampling \( \sigma_{\varphi c}, \sigma_{\alpha} \)

3.1. Sample \( \sigma_{\varphi c}, c = 2, 3 \).

\[ \tau_{\varphi c} \equiv \frac{1}{\sigma_{\varphi c}^{2}} \]  
\[ p(\tau_{\varphi c} | \cdot) \propto \prod_{t=1}^{T_{ic}} \phi(U_{ict}^{0} - \omega(R_i, \tau_{\varphi c}) + G(D_i, \sigma_{\alpha}) + \mu_{ict}, 1) \times 
\prod_{t: D_{ict}^{0}} \phi(U_{ict}^{K} | \omega(R_i, \tau_{\varphi c} + U_{ict}^{0}, \tau_{\varphi c}^{2})] \times p(\tau_{\varphi c})
\]

(A18)  
(A19)

where \( p(\tau_{\varphi c}) \) is the prior distribution of \( \tau_{\varphi c} \). We use a gamma distribution \( G(\alpha = 2, \beta = 1) \) as a prior for \( \tau_{\varphi c} \). We change the parametrization to the log scale, \( \ln \tau_{\varphi c} \), and sample \( \ln \tau_{\varphi c} \) using a random walk MH step centered on the previous value of \( \ln \tau_{\varphi c} \) with a normally distributed step size.

3.2. Sample \( \sigma_{\alpha} \)

\[ \tau_{\alpha} \equiv \frac{1}{\sigma_{\alpha}^{2}} \]  
\[ p(\tau_{\alpha} | \cdot) \propto \prod_{t=1}^{T_{ict}} \phi(U_{ict}^{0} - \omega(R_i, \sigma_{\varphi c}) + G(D_i, \tau_{\alpha}) + \mu_{ict}, 1) \times 
\prod_{t: D_{ict}^{K}} pdf_{\text{lognormal}}(D_i - U_{ict}^{0} | \ln M_{ict}, \tau_{\alpha}) \times p(\tau_{\alpha})
\]

(A20)  
(A21)
where $p(\tau_\alpha)$ is the prior distribution of $\tau_\alpha$. We use a gamma distribution $G(\alpha = 2, \beta = 1)$ as a prior for $\tau_\alpha$. We change the parametrization to the log scale, $ln\tau_\alpha$, and sample $ln\tau_\alpha$ using a random walk MH step centered on the previous value of $ln\tau_\alpha$ with a normally distributed step size.
Appendix 2.2: Simulation results

There are 50 customers in the simulation dataset, and each customer has 10 transactions in each category. For estimation, we use a Markov Chain Monte Carlo algorithm of the Gibbs sampler form. Appendix 1 shows each conditional distribution making up the Gibbs sampler. We run the Markov Chain for a total of 30,000 iterations, dropping the first 10,000 as burn-in and then retaining every 2\textsuperscript{nd} of the next 20,000 iterations for analysis. All of the true values are included in 95\% confidence intervals, so we believe our estimation method is statistically effective. The details of simulation results for our models are as follows.

1. Results for Model 1

Table A2.1: Estimates and 95\% credibility intervals for all variables

<table>
<thead>
<tr>
<th>Variable</th>
<th>True value</th>
<th>Estimate</th>
<th>95% Lower bound</th>
<th>95% Upper bound</th>
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Table A2.2: True values for covariance matrix

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Table A2.3: Estimates for covariance matrix

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Table A2.4: Lower bounds of 95% credibility intervals for covariance matrix

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Table A2.5: Upper bounds of 95% credibility intervals for covariance matrix

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2. Results for Model 2

Table A2.6: Estimates and 95% credibility intervals for all variables

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Table A2.7: True values for covariance matrix

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Table A2.8: Estimates for covariance matrix

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<tr>
<td>beta1</td>
<td>0.52</td>
<td>1.38</td>
<td>2.10</td>
<td>0.99</td>
<td>2.02</td>
</tr>
<tr>
<td>beta2</td>
<td>0.34</td>
<td>1.03</td>
<td>0.99</td>
<td>3.89</td>
<td>0.98</td>
</tr>
<tr>
<td>beta3</td>
<td>0.68</td>
<td>0.69</td>
<td>2.02</td>
<td>0.98</td>
<td>5.73</td>
</tr>
</tbody>
</table>

Table A2.9: Lower bounds of 95% credibility intervals for covariance matrix

<table>
<thead>
<tr>
<th>Covariance</th>
<th>logR</th>
<th>logD</th>
<th>beta1</th>
<th>beta2</th>
<th>beta3</th>
</tr>
</thead>
<tbody>
<tr>
<td>logR</td>
<td>0.22</td>
<td>0.21</td>
<td>0.41</td>
<td>0.25</td>
<td>0.09</td>
</tr>
<tr>
<td>logD</td>
<td>0.21</td>
<td>1.00</td>
<td>1.22</td>
<td>0.59</td>
<td>-0.44</td>
</tr>
<tr>
<td>beta1</td>
<td>0.41</td>
<td>1.22</td>
<td>1.03</td>
<td>-0.04</td>
<td>1.68</td>
</tr>
<tr>
<td>beta2</td>
<td>0.25</td>
<td>0.59</td>
<td>-0.04</td>
<td>3.30</td>
<td>-2.16</td>
</tr>
<tr>
<td>beta3</td>
<td>0.09</td>
<td>-0.44</td>
<td>1.68</td>
<td>-2.16</td>
<td>4.31</td>
</tr>
</tbody>
</table>
Table A2.10: Upper bounds of 95% credibility intervals for covariance matrix

<table>
<thead>
<tr>
<th>Covariance</th>
<th>logR</th>
<th>logD</th>
<th>beta1</th>
<th>beta2</th>
<th>beta3</th>
</tr>
</thead>
<tbody>
<tr>
<td>logR</td>
<td>0.31</td>
<td>0.34</td>
<td>0.63</td>
<td>0.43</td>
<td>1.27</td>
</tr>
<tr>
<td>logD</td>
<td>0.34</td>
<td>1.17</td>
<td>1.53</td>
<td>1.48</td>
<td>1.82</td>
</tr>
<tr>
<td>beta1</td>
<td>0.63</td>
<td>1.53</td>
<td>3.17</td>
<td>2.01</td>
<td>2.37</td>
</tr>
<tr>
<td>beta2</td>
<td>0.43</td>
<td>1.48</td>
<td>2.01</td>
<td>4.49</td>
<td>4.13</td>
</tr>
<tr>
<td>beta3</td>
<td>1.27</td>
<td>1.82</td>
<td>2.37</td>
<td>4.13</td>
<td>7.14</td>
</tr>
</tbody>
</table>
Appendix 2.3: Traceplots for two models

Figure A1: Trace plots in model 1
Figure A2: Trace plots in model 2
Appendix 2.4: Estimates of covariance matrix in two models

**Table A2.11: Estimates of covariance matrix in model 1**

<table>
<thead>
<tr>
<th>Covariance</th>
<th>logR</th>
<th>beta1</th>
<th>beta2</th>
<th>beta3</th>
</tr>
</thead>
<tbody>
<tr>
<td>logR</td>
<td>0.54</td>
<td>-1.03</td>
<td>-2.31</td>
<td>-1.51</td>
</tr>
<tr>
<td>beta1</td>
<td>-1.03</td>
<td>12.58</td>
<td>16.64</td>
<td>12.17</td>
</tr>
<tr>
<td>beta2</td>
<td>-2.31</td>
<td>16.64</td>
<td>57.88</td>
<td>27.62</td>
</tr>
<tr>
<td>beta3</td>
<td>-1.51</td>
<td>12.17</td>
<td>27.62</td>
<td>29.36</td>
</tr>
</tbody>
</table>

**Table A2.12: 95% confidence interval lower bounds of covariance matrix in model 1**

<table>
<thead>
<tr>
<th>Covariance</th>
<th>logR</th>
<th>beta1</th>
<th>beta2</th>
<th>beta3</th>
</tr>
</thead>
<tbody>
<tr>
<td>logR</td>
<td>0.43</td>
<td>-1.34</td>
<td>-2.87</td>
<td>-1.94</td>
</tr>
<tr>
<td>beta1</td>
<td>-1.34</td>
<td>10.56</td>
<td>12.55</td>
<td>8.42</td>
</tr>
<tr>
<td>beta2</td>
<td>-2.87</td>
<td>12.55</td>
<td>38.71</td>
<td>21.72</td>
</tr>
<tr>
<td>beta3</td>
<td>-1.94</td>
<td>8.42</td>
<td>21.72</td>
<td>23.29</td>
</tr>
</tbody>
</table>

**Table A2.13: 95% confidence interval upper bounds of covariance matrix in model 1**

<table>
<thead>
<tr>
<th>Covariance</th>
<th>logR</th>
<th>beta1</th>
<th>beta2</th>
<th>beta3</th>
</tr>
</thead>
<tbody>
<tr>
<td>logR</td>
<td>0.65</td>
<td>-0.74</td>
<td>-1.73</td>
<td>-1.12</td>
</tr>
<tr>
<td>beta1</td>
<td>-0.74</td>
<td>16.29</td>
<td>21.04</td>
<td>15.43</td>
</tr>
<tr>
<td>beta2</td>
<td>-1.73</td>
<td>21.04</td>
<td>71.52</td>
<td>32.99</td>
</tr>
<tr>
<td>beta3</td>
<td>-1.12</td>
<td>15.43</td>
<td>32.99</td>
<td>35.94</td>
</tr>
</tbody>
</table>

**Table A2.14: Estimates of covariance matrix in model 2**

<table>
<thead>
<tr>
<th>Covariance</th>
<th>logR</th>
<th>logD</th>
<th>beta1</th>
<th>beta2</th>
<th>beta3</th>
</tr>
</thead>
<tbody>
<tr>
<td>logR</td>
<td>0.23</td>
<td>0.01</td>
<td>-0.77</td>
<td>-1.70</td>
<td>-0.94</td>
</tr>
<tr>
<td>logD</td>
<td>0.01</td>
<td>0.89</td>
<td>1.35</td>
<td>1.47</td>
<td>1.08</td>
</tr>
<tr>
<td>beta1</td>
<td>-0.77</td>
<td>1.35</td>
<td>10.98</td>
<td>14.56</td>
<td>8.86</td>
</tr>
<tr>
<td>beta2</td>
<td>-1.70</td>
<td>1.47</td>
<td>14.56</td>
<td>55.95</td>
<td>23.52</td>
</tr>
<tr>
<td>beta3</td>
<td>-0.94</td>
<td>1.08</td>
<td>8.86</td>
<td>23.52</td>
<td>22.45</td>
</tr>
</tbody>
</table>
Table A2.15: 95% confidence interval lower bounds of covariance matrix in model 2

<table>
<thead>
<tr>
<th>Covariance</th>
<th>logR</th>
<th>logD</th>
<th>beta1</th>
<th>beta2</th>
<th>beta3</th>
</tr>
</thead>
<tbody>
<tr>
<td>logR</td>
<td>0.18</td>
<td>-0.04</td>
<td>-1.10</td>
<td>-2.34</td>
<td>-1.32</td>
</tr>
<tr>
<td>logD</td>
<td>-0.04</td>
<td>0.77</td>
<td>0.97</td>
<td>0.67</td>
<td>0.63</td>
</tr>
<tr>
<td>beta1</td>
<td>-1.10</td>
<td>0.97</td>
<td>8.81</td>
<td>11.11</td>
<td>6.45</td>
</tr>
<tr>
<td>beta2</td>
<td>-2.34</td>
<td>0.67</td>
<td>11.11</td>
<td>45.81</td>
<td>19.61</td>
</tr>
<tr>
<td>beta3</td>
<td>-1.32</td>
<td>0.63</td>
<td>6.45</td>
<td>19.61</td>
<td>17.68</td>
</tr>
</tbody>
</table>

Table A2.16: 95% confidence interval upper bounds of covariance matrix in model 2

<table>
<thead>
<tr>
<th>Covariance</th>
<th>logR</th>
<th>logD</th>
<th>beta1</th>
<th>beta2</th>
<th>beta3</th>
</tr>
</thead>
<tbody>
<tr>
<td>logR</td>
<td>0.29</td>
<td>0.06</td>
<td>-0.50</td>
<td>-1.16</td>
<td>-0.62</td>
</tr>
<tr>
<td>logD</td>
<td>0.06</td>
<td>1.02</td>
<td>1.72</td>
<td>2.29</td>
<td>1.56</td>
</tr>
<tr>
<td>beta1</td>
<td>-0.50</td>
<td>1.72</td>
<td>13.52</td>
<td>17.31</td>
<td>11.43</td>
</tr>
<tr>
<td>beta2</td>
<td>-1.16</td>
<td>2.29</td>
<td>17.31</td>
<td>65.36</td>
<td>28.47</td>
</tr>
<tr>
<td>beta3</td>
<td>-0.62</td>
<td>1.56</td>
<td>11.43</td>
<td>28.47</td>
<td>29.42</td>
</tr>
</tbody>
</table>
Appendix 2.5: Price elasticities for model 2

We first calculate the marginal effect of a price change on G.

\[ G(\mu_{it}, D_i, \sigma_\alpha) = -D_i \times \Phi \left( -\frac{\ln(D_i/\mu_{it})}{\sigma_\alpha} \right) - M_{it} \times \exp \left( \frac{\sigma_\alpha^2}{2} \right) \times \Phi \left( \frac{\ln(D_i/\mu_{it})}{\sigma_\alpha} - \sigma_\alpha \right) \]  
(A22)

Notice that \( M_{it} \) is the price.

\[ \frac{\partial G}{\partial M_{it}} = -\frac{D_i}{\sigma_\alpha M_{it}} \times \phi \left( -\frac{\ln(D_i/\mu_{it})}{\sigma_\alpha} \right) - e^{\sigma_\alpha^2/2} \times \phi \left( \frac{\ln(D_i/\mu_{it})}{\sigma_\alpha} - \sigma_\alpha \right) + \frac{e^{\sigma_\alpha^2/2}}{\sigma_\alpha} \times \phi \left( \frac{\ln(D_i/\mu_{it})}{\sigma_\alpha} - \sigma_\alpha \right) \]  
(A23)

1. The marginal effect of a price change on the order probability is

\[ \frac{\partial \Pr(U_{it}^O > 0 | \mu_{it}, M_{it}, D_i, R_i)}{\partial M_{it}} = \phi \left( \frac{-\sigma(R_i, \sigma_\phi) + G(M_{it}, D_i, \sigma_\phi) + \mu_{it}}{\sigma_\phi} \right) \times \frac{1}{\sigma_\phi} \times \frac{\partial G}{\partial M_{it}} \]  
(A24)

2. The marginal effect of a price change on the order-and-return probability is

\[ \frac{\partial \Pr(U_{it}^O > 0, U_{it}^K < 0 | \mu_{it}, M_{it}, D_i, R_i)}{\partial M_{it}} = \phi \left( \frac{-\sigma(R_i, \sigma_\phi) + G(M_{it}, D_i, \sigma_\phi) + \mu_{it}}{\sigma_\phi} \right) \times \frac{1}{\sigma_\phi} \times \frac{\partial G}{\partial M_{it}} \times \Phi \left( \frac{R_i + G(M_{it}, D_i, \sigma_\phi) + \mu_{it}}{\sigma_\phi} / \sigma_\phi / \sigma \right) \]  
(A25)

where

\[ \bar{\sigma} = \sqrt{\sigma_\phi^2 + \sigma_\epsilon^2} \]  
(A26)

\[ \mu_\epsilon = -\frac{\sigma_\epsilon}{\bar{\sigma}^2} \times (R_i + G(M_{it}, D_i, \sigma_\phi) + \mu_{it}) \]  
(A27)

3. The marginal effect of a price change on the order-and-keep-and-pay probability is

\[ \frac{\partial \Pr(U_{it}^O > 0, U_{it}^K > 0, U_{it}^P > 0 | \mu_{it}, M_{it}, D_i, R_i)}{\partial M_{it}} = -\frac{1}{\sigma_\alpha M_{it}} \times \phi \left( \frac{\ln(D_i/\mu_{it})}{\sigma_\alpha} \right) \times \]  
\[ \int_{-\infty}^{\infty} \phi \left( \frac{G(M_{it}, D_i, \sigma_\phi) + \mu_{it} + \sigma_\epsilon \epsilon + R_i}{\sigma_\phi} \right) \phi(\epsilon) d\epsilon + \phi \left( \frac{\ln(D_i/\mu_{it})}{\sigma_\alpha} \right) \times [\frac{1}{\bar{\sigma}} \times \frac{\partial G}{\partial M_{it}} \times] \]  
\[ \phi \left( \frac{R_i + G(M_{it}, D_i, \sigma_\phi) + \mu_{it}}{\sigma_\phi} / \sigma_\phi / \sigma \right) \times \phi \left( \frac{-\sigma(R_i, \sigma_\phi) + G(M_{it}, D_i, \sigma_\phi) + \mu_{it}}{\sigma_\phi} \right) \times \frac{1}{\sigma_\phi} \times \frac{\partial G}{\partial M_{it}} \]  
(A28)

4. The marginal effect of a price change on the order-and-keep-and-bad-debt probability is
\[
\frac{\partial \Pr(U^O_{it} > 0, U^K_{it} > 0, U^P_{it} < 0 | \mu_{it}, M_{it}, D_i, R_i)}{\partial M_{it}} = \frac{1}{\sigma_{\alpha_{it}}} \times \phi \left( \frac{\ln(D_i/M_{it})}{\sigma_{\alpha}} \right) \times \\
\int_{-\infty}^{\infty} \Phi \left( \frac{G(M_{it}, D_i, \sigma_{\alpha}) + \mu_{it} + \sigma_{\varepsilon} + R_i}{\sigma_{\varphi}} \right) \phi(\varepsilon) d\varepsilon + \Phi \left( -\frac{\ln(D_i/M_{it})}{\sigma_{\alpha}} \right) \times \left[ \frac{1}{\sigma_{\varphi}} \times \frac{\partial G}{\partial M_{it}} \right] \\
\phi \left( \frac{-\sigma(R_i, \sigma_{\varphi}) + G(M_{it}, D_i, \sigma_{\alpha}) + \mu_{it}}{\sigma_{\varphi}/\sigma_{\alpha}} \right) \times \Phi \left( \frac{\sigma(R_i, \sigma_{\varphi}) + R_i}{\sigma_{\varphi}} \right) \times \\
\phi \left( \frac{-\sigma(R_i, \sigma_{\varphi}) + G(M_{it}, D_i, \sigma_{\alpha}) + \mu_{it}}{\sigma_{\varphi}/\sigma_{\alpha}} \right) \times \frac{1}{\sigma_{\varepsilon}} \times \frac{\partial G}{\partial M_{it}} \right] 
\]

(A29)

Having computed the marginal effects, we can easily obtain elasticities by the following formula

\[
\text{Elasticity} = \frac{d\Pr}{dM} \times \frac{M}{P_r} 
\]  

(A30)
Table 2.1: Descriptive Statistics for Sample Data

<table>
<thead>
<tr>
<th>Category</th>
<th>Music</th>
<th>Magazine</th>
<th>Video</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td>Number of customers</td>
<td>172</td>
<td>370</td>
<td>110</td>
<td>500</td>
</tr>
<tr>
<td>Number of observations</td>
<td>16398</td>
<td>31628</td>
<td>10645</td>
<td>58671</td>
</tr>
<tr>
<td>Number of orders</td>
<td>2635</td>
<td>1480</td>
<td>1970</td>
<td>6085</td>
</tr>
<tr>
<td>Order rate (orders</td>
<td>observations)</td>
<td>16%</td>
<td>5%</td>
<td>19%</td>
</tr>
<tr>
<td>Pay rate (payments</td>
<td>orders)</td>
<td>77%</td>
<td>92%</td>
<td>72%</td>
</tr>
<tr>
<td>Return rate (returns</td>
<td>orders)</td>
<td>13%</td>
<td>0%</td>
<td>25%</td>
</tr>
<tr>
<td>Default rate (defaults</td>
<td>orders)</td>
<td>10%</td>
<td>8%</td>
<td>2%</td>
</tr>
</tbody>
</table>
Table 2.2.1: Transaction Amount in Dollars for All Observations

<table>
<thead>
<tr>
<th>Category</th>
<th>Mean</th>
<th>Median</th>
<th>Min</th>
<th>Max</th>
<th>Std</th>
</tr>
</thead>
<tbody>
<tr>
<td>Music</td>
<td>1.7</td>
<td>0</td>
<td>0</td>
<td>117.8</td>
<td>5.7</td>
</tr>
<tr>
<td>Magazine</td>
<td>1.0</td>
<td>0</td>
<td>0</td>
<td>180.0</td>
<td>6.1</td>
</tr>
<tr>
<td>Video</td>
<td>5.3</td>
<td>0</td>
<td>0</td>
<td>2733.2</td>
<td>29.4</td>
</tr>
<tr>
<td>Total</td>
<td>2.0</td>
<td>0</td>
<td>0</td>
<td>2733.2</td>
<td>13.7</td>
</tr>
</tbody>
</table>

Table 2.2.2: Transaction Amount in Dollars for All Orders

<table>
<thead>
<tr>
<th>Category</th>
<th>Mean</th>
<th>Median</th>
<th>Min</th>
<th>Max</th>
<th>Std</th>
</tr>
</thead>
<tbody>
<tr>
<td>Music</td>
<td>10.6</td>
<td>5.1</td>
<td>0.16</td>
<td>117.8</td>
<td>10.2</td>
</tr>
<tr>
<td>Magazine</td>
<td>21.9</td>
<td>19.0</td>
<td>0.01</td>
<td>180.0</td>
<td>18.5</td>
</tr>
<tr>
<td>Video</td>
<td>28.4</td>
<td>25.9</td>
<td>1</td>
<td>2733.2</td>
<td>63.4</td>
</tr>
<tr>
<td>Total</td>
<td>19.1</td>
<td>20.2</td>
<td>0.01</td>
<td>2733.2</td>
<td>38.6</td>
</tr>
</tbody>
</table>
Table 2.3: Results of Two Models

<table>
<thead>
<tr>
<th>Variable</th>
<th>Model 1 Estimate</th>
<th>95% Lower bound</th>
<th>95% Upper bound</th>
<th>Model 2 (defaults considered) Estimate</th>
<th>95% Lower bound</th>
<th>95% Upper bound</th>
</tr>
</thead>
<tbody>
<tr>
<td>ln(R)</td>
<td>0.85</td>
<td>0.77</td>
<td>0.91</td>
<td>0.44</td>
<td>0.35</td>
<td>0.52</td>
</tr>
<tr>
<td>ln(D)</td>
<td>NA</td>
<td>-1.49</td>
<td>-1.58</td>
<td>-1.40</td>
<td>-1.58</td>
<td>-1.40</td>
</tr>
<tr>
<td>β₁</td>
<td>-2.70</td>
<td>-2.97</td>
<td>-2.39</td>
<td>-2.80</td>
<td>-3.10</td>
<td>-2.54</td>
</tr>
<tr>
<td>β₂</td>
<td>-5.69</td>
<td>-6.18</td>
<td>-4.96</td>
<td>-5.70</td>
<td>-6.10</td>
<td>-5.12</td>
</tr>
<tr>
<td>β₃</td>
<td>-3.66</td>
<td>-4.08</td>
<td>-3.38</td>
<td>-3.60</td>
<td>-4.11</td>
<td>-3.24</td>
</tr>
<tr>
<td>σₓ</td>
<td>NA</td>
<td>4.36</td>
<td>4.26</td>
<td>4.45</td>
<td></td>
<td></td>
</tr>
<tr>
<td>σᵦ₁</td>
<td>Normalized as 1</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>σᵦ₂</td>
<td>1.24</td>
<td>1.19</td>
<td>1.30</td>
<td>0.58</td>
<td>0.53</td>
<td>0.63</td>
</tr>
<tr>
<td>σᵦ₃</td>
<td>1.59</td>
<td>1.51</td>
<td>1.67</td>
<td>1.13</td>
<td>1.07</td>
<td>1.18</td>
</tr>
</tbody>
</table>
### Table 2.4: Price Elasticities When Defaults Included and Not

<table>
<thead>
<tr>
<th>Category</th>
<th>Music</th>
<th>Magazine</th>
<th>Video</th>
</tr>
</thead>
<tbody>
<tr>
<td>Keep (defaults ignored)</td>
<td>-1.063</td>
<td>-1.043</td>
<td>-1.042</td>
</tr>
<tr>
<td>Keep and pay</td>
<td>-1.330</td>
<td>-1.358</td>
<td>-1.363</td>
</tr>
<tr>
<td>Change when defaults are ignored</td>
<td>-20%</td>
<td>-23%</td>
<td>-24%</td>
</tr>
</tbody>
</table>

### Table 2.5: Customers’ Preferences for Return Over Default Option

<table>
<thead>
<tr>
<th>Category</th>
<th>Music</th>
<th>Magazine</th>
<th>Video</th>
</tr>
</thead>
<tbody>
<tr>
<td>Pr(Return) - Pr(Default)</td>
<td>0.024</td>
<td>0.010</td>
<td>0.033</td>
</tr>
<tr>
<td>(\sigma_{\psi})</td>
<td>1</td>
<td>0.58</td>
<td>1.13</td>
</tr>
</tbody>
</table>
Figure 2.1: Histograms of Customer Return Costs (R) in Model 1
Figure 2.2.1: Histograms of Customer Return Costs (R) in Model 2

![Histogram of Customer Return Costs (R) in Model 2](image)

Figure 2.2.2: Histograms of Customer Default Costs (D) in Model 2

![Histogram of Customer Default Costs (D) in Model 2](image)
Figure 2.3: Histograms of $R_i - D_i$ in Model 2
Figure 2.4: Histograms of $\Delta$ in Model 1

(a) Music

(b) Magazine
Figure 2.5: Histograms of $\Delta$ in Model 2

(a) Music

(b) Magazine
Figure 2.6: Expected Firm Profits Under Different Return Policies

(a) Music

(b) Magazine

(c) Video
Concluding Chapter

This paper studies the customers’ responses to direct mail considering both the default and return options. Essay 1 demonstrates the importance of using the historical transaction information variables that influence the customers’ return, default, and pay options in firms’ targeting. It also studies the impact of removing the product return option, showing that the customers with high return numbers in the past are more likely to pay rather than default if product returns are not allowed. I find that firms can increase profits by forbidding product returns if return costs are very high. Results in essay 1 show a negative relationship between customers’ preferences for defaults and product returns, because customers who frequently return products in the past are unlikely to default.

Essay 2 further illustrates the importance of considering defaults in customers’ responses in direct mail industry and studies the relationship between customers’ default and return options. I find that estimates for customers’ price sensitivity and transaction fit can be biased if defaults are not considered. The firm may overvalue the return option when ignoring defaults. When customers choose between the return and default option, they consider two factors. One is the difference between their return and default costs. Results show that customers have considerable variation in their return costs and default costs. The other factor is transaction fit uncertainty. Customers have a preference for default over return when transaction fit uncertainty is low. Essay 2 also provides a way to decide how lenient the optimal return policy should be in each category when defaults are possible. It suggests that firms should allow product returns in categories where product fit uncertainty is high and have a stricter return policy to increase profit.
My research focuses on customers’ responses in direct mail industry and the corresponding targeting policy and return policy, but it is also helpful for studying these problems in ecommerce. Traditionally, direct marketers should carefully select customers to target because of the considerable cost of contacting customers offline. In digital marketing, the cost of contacting a customer online (such as email) is almost zero compared to the cost of a direct mail. Firms are able to contact a large number of customers at a low cost in digital marketing. However, this does not mean that targeting is no longer important. In the digital age, customers are also receiving an explosive increase of online direct marketing offers. They are much more likely to ignore these offers compared to the traditional direct mails. In order to have more responses, direct marketers should even pay more attention to targeting, sending the right offer to the right customer.

My research helps firms target customers in direct mail marketing, showing that firms should use information of customers’ three behaviors (return, default, and pay) instead of accounting for pay behavior only. This philosophy of considering customers’ various behaviors in targeting is also useful in digital marketing. It is important to use information of customers’ profitable choices such as pay to select customers. Meanwhile, it is necessary for firms to consider customers’ unprofitable choices and even some variables that are not directly related to their purchases. Nowadays online direct marketers have huge information about their customers, and it is not wise to waste such information.

Product returns are also a big problem in ecommerce. The problem is even more complicated because customers have various reasons to return. In direct mail marketing, customers return products due to the poor transaction fit. In digital marketing, customers may ‘default’ in the form of returning a product. Although customers are not able to make a default
choice as in this paper because they need to leave their payment information when making orders, they may return satisfactory products after using them. For example, a customer buys a dress for a special event, and return it after the event. She returns the product not because the transaction fit is poor, but because she does not want to pay. Such fraudulent product returns cause considerable costs for retailers. Besides, customers might order some products only to qualify for free shipping. They are going to return these products anyway, which is not related to transaction fit.

When we study product returns in ecommerce, we need to be clear about the different reasons about customers’ return behaviors. It is also necessary to consider default cost in customer’s return option. The method of studying default behaviors in this paper helps study fraudulent product returns in digital marketing. My paper also studies the extent to how lenient a firm’s return policy should be by simulating profits under different return costs. In ecommerce, firms change return costs mainly through three aspects: return shipping fee, restocking fee, how easy the return process is. In the future, it may be interesting to study the importance of each of the three aspects for customers. For example, customers may prefer to pay no return shipping fee rather than have an easy return process.

In summary, this paper contributes to direct marketing by studying defaults together with product returns. It suggests firms consider customers’ various purchase behaviors in direct mail targeting, which may also apply to targeting in ecommerce. In addition, the paper studies firms’ optimal return policies in direct mail industry, providing a first step in studying the complicated return behaviors in ecommerce.