

ESSAYS ON CONSUMER RETURNS AND RETAIL OPERATIONS

A Dissertation

by

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ABSTRACT

This dissertation offers two essays that together represent a deep investigation into consumer returns, channel integration via ship-to-store service, and omnichannel retailing practices. The results provide strong managerial insights regarding some of the widely implemented industry practices associated with consumer return abuse and omnichannel retailing. The first essay investigates return abuse with respect to both fraudulent and opportunistic consumer returns and two potential technology-enabled countermeasures to deal with them: customer profiling and product tracking. A customer profiling system identifies opportunistic customers by using their personal identification and transaction history. In contrast, a product tracking system identifies fraudulent returns by recording each transaction of a product through the use of unique identifiers. We demonstrate how these countermeasures impact a retailer's profitability, demand structure, and policy parameters with respect to price and refund.

The second essay looks into channel integration via ship-to-store service and investigates the impact of this omnichannel retailing practice on sales and returns across both online and brick-and-mortar channels. The advent of omnichannel retailing technologies enable integration of both physical and electronic marketplaces that is designed to deliver a seamless shopping experience to customers. For a retailer, these capabilities require significant investment, yet hold the promise of enhancing the revenue streams from both online and brick and mortar channels. We assess this promise by using transactional data from a national retailer to analyze the impact of introducing ship-to-store capability on a retailer's performance. Contrary to expectations, our findings show that online sales decrease after ship-to-store is implemented, although store sales increase. Some customers switch from the online channel to the brick-and-mortar channel. This occurs mainly for high-value purchases. The customers who actually use the ship-to-store service are those that typically buy low-value items. Our results also show that implementing ship-to-store increases returns of online purchases to physical stores. At the same time, these types of returns generate additional selling opportunities. About 28 percent of the online purchases

returned to a store are associated with a new purchase, amounting to more than \$7 million in additional revenue.

DEDICATION

I would like to dedicate this dissertation to my wife Elif Akturk, my precious daughter Ipek Akturk, my father Mehmet Akturk, my mother Ayse Akturk, my sister Sibel Gun, and to all members of Akturk family because of their unprecedented support both before and during my doctoral education at Texas A&M University. Without their support, my education would be much more agonizing.

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1. INTRODUCTION

This dissertation offers two essays that together represent a deep investigation into consumer returns and omnichannel retailing. The first essay investigates return abuse from a retailer’s perspective and evaluates the value of adopting customer profiling and product tracking technologies. The second essay looks into channel integration via ship-to-store service and investigates the impact of this omnichannel retailing practice on sales and returns across both online and brick-and-mortar (BM) channels. We will start our discussion with consumer return abuse and subsequently move our attention to omnichannel retailing.

According to the National Retail Federation (NRF), consumer returns have dramatically increased over the last couple of years from \$178 billion in 2007 to \$284 billion in 2014 (NRF 2007, 2014). Although part of the increase can be attributed to the increasing number of remote transactions, liberal return policies also play a notable role. Most retailers use liberal return policies to increase their demand by attracting more consumer traffic, but those policies may also motivate some customers to behave opportunistically by extracting some sort of physical, experiential, or financial benefit from the product at little to no cost. A recent return fraud survey by the NRF indicates that the dollar value of opportunism and fraud amounted to \$6.8 billion and \$10.8 billion in 2014, respectively (NRF 2014). Although return abuse and countermeasures to fight it have been significant retailer topics for decades (Jolson 1974), there is still limited research to address such behaviors.

We define an opportunistic return as a phenomenon in which the customer buys a product from a retailer with the full intention of returning it. By doing so, the customer extracts value either from the product or from the transaction itself and receives a refund or a store credit by returning the purchased item. In contrast, a fraudulent return occurs when a person engages in criminal activity such as returning a stolen item or committing receipt fraud (Speights and Hilinski 2005, NRF 2014).

Historically, tools for retailers to combat return abuse have been fairly limited. Some retailers implement restrictive return policies or impose shorter return windows while others create hassle costs or charge restocking fees to protect against fraudulent and opportunist-

tic returns. For example, Best Buy, Sears, and Recreational Equipment Inc. shortened their return window in 2013 to counteract a large growth in return abuse (Martinez 2013, Weisbaum 2013). Although previous studies indicate that such measures are effective to fight return abuse (Shulman et al. 2009, Chu et al. 1998), they may also lead to reduced demand as consumers value lenient return policies (Wood 2001, Ketzenberg and Zuidwijk 2009, Shulman et al. 2011).

In the first essay, we look into return abuse and evaluate the adoption of customer profiling and product tracking systems. The main objective is to address the question of how these technologies impact a retailer's policy decisions with respect to price and refund. For the analysis, we first introduce a model where the retailer faces both opportunism and fraud without the availability of countermeasures. Subsequently, we build upon the base model and introduce alternatives that allow for customer profiling and product tracking systems.

The contribution of the first essay arises from addressing *both* opportunism and fraud in the context of consumer returns, which is a problem many retailers face today. In addition, we introduce utility functions that capture key characteristics of return abuse behavior. From a managerial perspective, our findings demonstrate that a retailer can manipulate its price and refund policies to effectively prevent opportunism, but that such actions are only marginally effective to prevent return fraud. In general, a retailer should reduce both price and refund to prevent return abuse. Interestingly, when both fraud and opportunism are present, the optimal refund is actually higher than when only fraud is present. Our analysis also demonstrates conditions in which it is advantageous to invest in technology-enabled countermeasures and when such investments should be avoided.

In the second essay, we empirically investigate the impact of implementing an omnichannel retailing strategy, buy-online and ship-to-store (STS), on a retailer's operations by using a series of quasi-experiments. Given that consumer shopping habits have evolved to include multiple channels and different tasks or activities in each one of those channels, many retailers are looking for ways to adopt channel integration technologies and thereby offer omnichannel retailing practices. The main idea behind omnichannel retailing is the opportunity to offer consumers a seamless shopping experience and a consistent service

no matter which channel they use (Rigby 2011, Brynjolfsson et al. 2013, Bell et al. 2014). However, there has been little academic research on the efficacy of omnichannel retailing tactics to generate demand or increase store traffic. To fill this gap, we look into channel integration via ship-to-store service and investigate the impact of this omnichannel retailing practice on sales and returns across both online and BM channels. In particular, we use difference-in-differences (DID) econometrics methodology to examine both pre- and post-STS periods. For this analysis, we collected data from a national jewelry retailer that implemented STS. Overall, our data set includes more than 20 million transactions across both online and BM channels.

Building upon well-established theories like buyer behavior, risk in consumer choice, transaction costs economics, and production function, we make several important contributions to the literature. First, the theories that we employ to develop our hypotheses lead us to believe that both Internet and BM channel sales should increase after STS implementation. While we find that store sales do increase, online sales actually *decrease*. Note that STS requires store delivery from a centralized location that takes three business days. We find that although customers may be drawn to STS service to make their purchases, they decide not to wait for the store delivery, and instead opt to purchase stocked items at the store. We view this as a channel switching behavior and show that it primarily occurs for high-value items.

Second, we show that product returns at stores decrease, as does the time-to-return, while returns for online purchases remain unchanged. Because customers who switch from online to BM channel have conducted prior research online, they are then more knowledgeable about their purchases. As a result, they are less likely to return their merchandise. Similarly, those customers are able to make decisions regarding fit in a more timely manner because of their prior research, which in turn reduces time-to-return. Finally, we also show that the return rate of online purchases is *less* than that observed for BM purchases during both pre- and post-STS periods. This interesting finding arises because customers generally buy items online that are lower in value than those in stores and this observation is consistent with other studies that demonstrate low-value items are less likely to be returned than high-value items (Peterson and Kumar 2009, Anderson et al. 2009).

The rest of this research is organized as follows. In Section 2, we discuss customer profiling and product tracking countermeasures and compare those countermeasures in terms of price, refund, and profit. In Section 3, we introduce our data, methodology, and empirical models to analyze the impact of ship-to-store service on retail operations. Finally, we provide managerial insights, offer future research opportunities, and conclude in Section 4. Proofs of analytical results and robustness analyses for empirical models are provided in the Appendix.

2. MANAGING CONSUMER RETURN ABUSE AND AN ASSESSMENT OF TECHNOLOGY-ENABLED COUNTERMEASURES

2.1 Introduction

Consumer returns are increasing and in the U.S. alone reached a total volume of \$284 billion in 2014 (NRF 2014). A major driver of such a high return volume is the increasing number of remote transactions. Many retailers offer lenient return policies to reduce consumer risk and attract more customers since consumers are not able to fully evaluate the product prior to purchase (Su 2009). The most lenient return policies are often characterized by a full refund with no questions asked. However, lenient return policies are open to abuse and motivate some customers to behave opportunistically and even fraudulently. In this paper, we investigate return abuse and two potential countermeasures available to address it.

An opportunistic return occurs when a customer buys a product from a retailer with the full intention of returning it. By doing so, the opportunistic customer extracts some sort of physical, experiential, or financial benefit either from the product or from the transaction and receives a refund or a store credit by returning the item. Terms such as retailer borrowing, renting, wardrobing, and deshopping are often used to describe opportunistic return behavior. Two well known examples include buying a large screen TV for the super bowl game and returning it immediately afterwards and buying dresses or suits for special events and returning them once the event is over. In addition to the physical or experiential benefits, some people may also enjoy financial benefits by acting opportunistically. In such cases, opportunism can arise without any regard to the product itself, but rather, from the return policies that stores employ. For example, Costco, a major club warehouse, accepts only American Express (AMEX) credit cards at its physical stores while it accepts all major credit cards for online transactions. Some customers make purchases online using non-AMEX credit cards and return them at a physical store for a cash refund. Then, they use the cash refund to pay their credit card charge and enjoy the benefit of credit card rewards. Clearly, in such a case, the reward benefits have nothing to do with the intrinsic

value of the purchased product, but rather with its return. Note that opportunism is just one type of return abuse, fraud is yet another type.

Unlike an opportunistic return, a fraudulent return occurs when a person engages in criminal activity such as shoplifting, price switching, and receipt fraud, among others. (Speights and Hilinski 2005, NRF 2014). For example, with receipt fraud, a criminal looks for cash receipts in shopping carts or in discarded shopping bags. Upon finding a receipt, this individual enters the retailer, finds the same exact items on the receipt, and instead of purchasing them, simply returns them for a cash refund. According to a recent survey by the NRF, opportunism, referred to as friendly fraud, reached \$6.8 billion in 2014 (NRF 2014). In the same report, actual return fraud constitutes an even greater amount at \$10.8 billion.

Although retailers have been fighting return abuse for decades (Jolson 1974), there is limited research that addresses such behaviors. Tools for retailers to combat return abuse are fairly limited. Historically, retailers have fought return abuse through return policies by implementing restrictions and hassles such as short return windows and restocking fees. For example, Recreational Equipment Inc. (REI), which earned the moniker ‘Rental Equipment Inc.’ due to no time limits on returns, imposed a one year time limit on returns in 2013 (Martinez 2013). Prior studies that address opportunism demonstrate that return policy restrictions are effective in fighting return abuse (Davis et al. 1998, Chu et al. 1998). However, they may also reduce sales as consumers value liberal return policies (Wood 2001, Ketzenberg and Zuidwijk 2009, Shulman et al. 2011). A recent survey shows that 82% of consumers are likely to complete a sale with a free return policy whereas only 20% of consumers are willing to complete a sale when returns are not allowed (UPS 2014). Therein lies a dilemma for retailers: preventing return abuse by restricting return policies or attracting more customers with lenient return policies. In addition, there is no research in the literature that looks into how the retailers can address both return fraud *and* opportunism collectively.

The advent of new technologies has enabled two innovative countermeasures to fight return abuse: customer profiling and product tracking. To our knowledge, the value of such countermeasures to reduce return abuse has not been examined and our research also

aims to fill this gap. We now proceed to discuss each countermeasure with respect to the return abuse that it addresses.

2.1.1 Customer Profiling Technology

Customer profiling technology identifies opportunistic customers by recording the number, the frequency, and the dollar volume of returns made by each customer (Kang and Johnson 2009). An important requirement of this technology is to ask for customer IDs during the return process. When a customer wants to return merchandise, the retailer scans the original transaction receipt along with the individual's ID. Then, using the customer's identification and transaction history, third party service providers (TPSP) use statistical models to reject, warn, or accept the return from the customer. Another benefit for retailers is that they have an objective real-time decision during the return process. Some people might be concerned about the legality of restricting returns in this manner. According to the NRF, 70.9% of all retailers require customer IDs for returns without a receipt while 25.5% of all retailers require customer IDs for all returns (NRF 2014). For example, Best Buy (2015) explains its return policy and says:

“Like many retailers, we use a third party to help prevent losses by detecting improper returns, and, except where prohibited, require a valid ID for all store returns. Our third party processor may record your ID information when you return an item, and keep it in a secure database to help us validate future returns. If we caution you or deny your return, you may request a copy of your Return Activity Report by calling 1-800-XXX”.

The Retail Equation (TRE) and Fair Isaac Corporation (FICO) Retail Fraud Manager are two examples for customer profiling services. TRE is one of the biggest providers in the market and also offers a return activity report for individuals, which is similar to a credit score report. Major retailers like Home Depot, Best Buy, and Victoria's Secret use customer profiling technologies to manage their returns. Even so, other large retailers like Target, Apple, and Macy's do not use such technologies. Hence, we are interested in understanding the conditions that influence the adoption of customer profiling technology.

2.1.2 Product Tracking Technology

Product tracking technology is a solution to manage return fraud that works by recording each transaction of a product through the use of unique identifiers such as serial numbers. For example, this technology is able to detect a receipt fraud or a stolen merchandise return as the system alerts the return clerk that there is no prior purchase transaction for those products. The system can also detect most other common return fraud schemes.

Several TPSPs that offer product tracking and returns management solutions include InComm Product Control OmniChannel ReturnFlex Solutions, Cornell-Mayo Omniwatch Authorization System, and ACI Retail Commerce Servers for Refunds, among others. Several major retailers and manufacturers that use this service include Walmart, Target, Hewlett Packard, and General Electric. Similar to our inquiry into customer profiling, we are interested in understanding the conditions that influence the adoption of product tracking technology.

In sum, our contribution arises from addressing *both* opportunism and fraud in the context of consumer returns, which is a problem many retailers face today. We also introduce utility functions that capture key characteristics of return abuse behavior. From a managerial perspective, our findings demonstrate that a retailer can manipulate its price and refund policies to effectively prevent opportunism, but that such actions are only marginally effective to prevent return fraud. In general, a retailer should both reduce price and reduce the refund to prevent return abuse. Interestingly, when both fraud and opportunism are present, the refund is actually higher than when only fraud is present. Our analysis also demonstrates conditions in which it is advantageous to invest in technology-enabled countermeasures and when such investments should be avoided.

The rest of this paper is organized as follows. In §3.2, we review literature. In §3.4, we discuss the characteristics of the return abuse model and investigate three variations of that basic model. In §2.4, we introduce a customer profiling model that addresses opportunism. Similarly, we introduce a product tracking model in §2.5, which addresses return fraud. Finally, we provide managerial insights, offer future research opportunities, and conclude in §3.6. Proofs of analytical results are given in the Appendix.

2.2 Literature Review

In this study, we investigate the impact of return abuse on a retailer's profit, evaluate the use of price and refund decisions to mitigate such abuse, and explore two innovative countermeasures to address it. Overall, there are two streams of literature that are related to our work: analytical models that offer various techniques to manage return abuse and empirical studies that investigate the drivers of engaging in such behavior.

In the analytical domain, the most closely related research to our study in terms of modeling approach is Chu et al. (1998), who compare three refund policies: no-refund policy, no questions asked policy, and verifiable problems only policy. They show that a no questions asked policy with a partial refund is more profitable than the other two policies. However, that finding depends on the assumption that a returned product's salvage value is sufficiently high. Hess et al. (1996) argue that firms can profitably manage opportunistic returns by imposing non-refundable charges depending on the value of the product. Davis et al. (1995) shows that offering a return policy may increase a firm's profit if the salvage value of a returned item is high. Unlike studies where the refund is a decision variable, Ulku et al. (2013) assume a full refund policy and model the time window as a decision variable.

The literature to date defines opportunistic behavior as the act of buying a product to extract some value from it during the trial period and then either return or keep that product depending on the refund and the product's residual value (Davis et al. 1995, Hess et al. 1996, Chu et al. 1998, Ulku et al. 2013). In some cases, this comparison may also occur between the utility of keeping a product and the realized product valuation (Guangzhi et al. 2015). However, we find this definition too narrow as it only captures a small portion of opportunism. In fact, opportunism may have nothing to do with the product's value, but rather the transaction itself. Therefore, we adopt a broader definition of opportunism that includes customers who buy the product with the full intention of returning it (Speights and Hilinski 2005, Macintosh and Stevens 2013). In addition, although these prior studies analyze the impact of opportunistic returns on a retailer's profitability, they do not take into account return fraud.

Che (1996) compares offering a return policy to a no return allowed policy and shows

that firms may offer return policies when customers are risk averse. Although this research does not specifically address opportunism or fraud, it argues that return policies must have the potential to mitigate return abuse. Another closely related work to our research is Altug (2014), who studies a retailer facing both legitimate and opportunistic customers and shows that using a customer profiling system increases profitability by mitigating opportunism. Altug (2014) proposes a two-period model in which a customer's shopping decision in the second period depends only on the refund offered in the first period. However, ignoring privacy concerns of customers may lead to overestimating the demand (Conitzer et al. 2012), which could potentially change the insights of that study. We address this issue by incorporating a privacy cost for consumers. Moreover, Altug (2014) assumes that a fixed fraction of the market acts opportunistically although empirical evidence shows that legitimate customers may also behave in an opportunistic manner (Rosenbaum et al. 2011). In our model, we allow legitimate customers to act opportunistically.

In the empirical domain, a body of literature examines the drivers and motivations of opportunistic returners. King and Dennis (2003) use the theory of planned behavior to explain such unethical practices. Piron and Young (2000) identify the reasons that drive opportunistic behavior as social, economic, personal satisfaction, professional, and altruistic needs. Kang and Johnson (2009) show that buying impulsiveness and consideration of return policies before a purchase are associated with apparel return behavior. Harris (2010) study the factors that allow consumers to abuse lenient return policies and notes that most retailers are underestimating the costs of opportunistic returns. Wachter et al. (2012) build a measurement scale to capture a customer's orientation to return merchandise and analyze the relationship between return behavior and ethical issues. Rosenbaum and Kuntze (2005) depart from the traditional literature and explore the psychological and sociological drivers that lead to opportunistic returns. They note that fashion media and the urge of keeping-up with celebrities intensify compulsive buying behavior and by extension opportunism. In a later contribution, Rosenbaum et al. (2011) study the techniques used by opportunistic returners to justify their actions. Bower and Maxham-III (2012) show that although retailers may be tempted to prevent return abuse in the short run by imposing return fees on customers, they may face decreased future demand by doing so.

All the empirical studies above analyze the behavioral aspect of opportunistic returns, but none of them develops prescriptive models on how to manage return abuse.

2.3 Model

To begin, we consider a retailer that offers a product to satisfy customer demand over the course of a selling season. There are three different classes of customers: legitimate, opportunistic, and fraudulent. By legitimate, we mean customers who purchase a product with the intention to keep it. The retailer is able to influence the size of these segments by adjusting its pricing and refund policies. Figure 2.1 lays out from left to right each of the three stages of the decision-making process with respect to a purchase and a subsequent return. In stage one, the retailer sets the price and the refund. In stage two, customers decide whether to purchase the product or not and, in the final stage, customers decide whether to return the product or keep it. Note that we draw a box around legitimate and opportunistic customers to highlight that these segments are drawn from the same population. Depending on a customer's valuation for the product and the benefit they perceive from opportunism, they may behave in an opportunistic way or in a legitimate way (Hess et al. 1996). Fraudulent customers, however, are distinctly separate from legitimate and opportunistic customers.

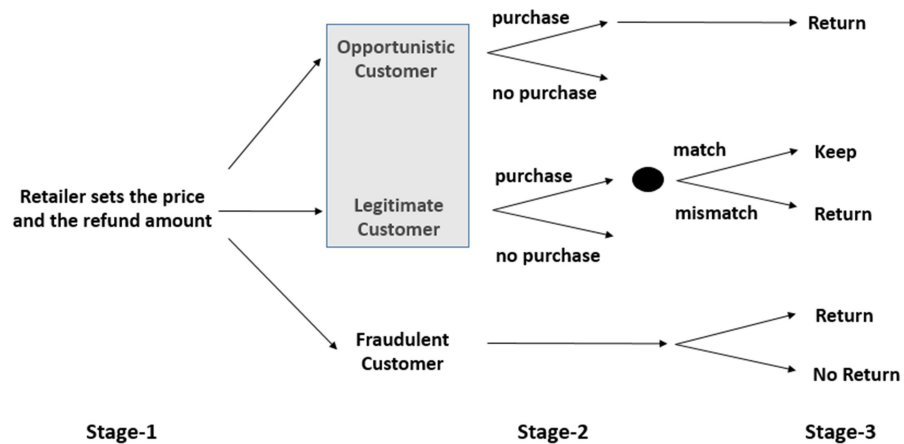


Figure 2.1: Sequence of Events

We analyze three different models to manage return abuse. For $j = 1$, we analyze the basic return abuse model (RAM), in which the retailer faces both opportunistic and fraudulent customers. This is the model that we develop in this section. For $j = 2$, we look into the customer profiling model, an extension of the basic RAM, in which the retailer uses certain technologies to address opportunism. Finally, for $j = 3$, we investigate the product tracking model, another model extension, in which the retailer uses technologies to address return fraud. For each model, we first compute the sizes of the legitimate (L_j) and opportunistic (O_j) customer segments that buy the product given a price p_j and a refund r_j . Concurrently, we compute the size of the fraudulent segment (F_j) given a refund r_j . Then, we analyze the first stage of the game and derive the optimal price and refund. We now proceed to develop the basic RAM model. Going forward, we suppress the subscript j when the context is clear.

In our settings, legitimate and opportunistic customers are differentiated by their intrinsic valuation v for a unit of the product, and we assume it to be uniformly distributed on the standard Hotelling line between zero and one. The procurement cost is given by c and the retailer salvages returned products for s . We assume that $c > s$, otherwise the problem would be trivial. The retailer's cost of handling each return is denoted by k . The retailer reserves the right to charge a restocking fee on returned items, which we reflect in a refund r where r is a fraction of the selling price p and $0 \leq r \leq p$. The operational decisions of interest are the product price p and the refund r . The optimal order quantity q^* can be derived once the other decisions are made.

The sequence of decisions for legitimate customers is as follows. First, they decide whether or not to purchase the product and then after purchase, they decide whether to keep the product or return it for a refund. Consistent with the previous literature, a legitimate customer obtains zero utility if the product does not fit (mismatch) expectations (Hess et al. 1996, Chu et al. 1998, Davis et al. 1998). Legitimate customers with a product mismatch return their merchandise and we refer to these returns as legitimate returns. Otherwise, legitimate customers with a product match keep their merchandise and we refer to them as net sales. We use λ to denote the probability of a mismatch and $1 - \lambda$ to denote the probability of a match.

Legitimate customers (L) make their purchase decision using their expected utility. Let \bar{v} denote the boundary legitimate customer who is indifferent between purchasing and not purchasing the product. Let $EU[\bar{v}]$ denote the expected utility of this customer. In the case of a match, the boundary customer extracts valuation \bar{v} and incurs a purchasing cost p . In the case of a mismatch, the boundary customer derives zero utility from the product, receives a refund r , and incurs a purchasing cost p . Hence, the expected utility for the boundary customer is given by

$$EU[\bar{v}] = (1 - \lambda) [\bar{v} - p] + \lambda [-p + r].$$

Because the boundary customer is indifferent about purchasing the product, the utility for this customer is zero. Setting $EU[\bar{v}] = 0$ and solving for \bar{v} , we get $\bar{v} = \frac{p - r\lambda}{1 - \lambda}$.

Opportunistic customers (O) make a single decision, which is whether or not to purchase the product. If they purchase the product, they do so with the full intention of returning it. The value that opportunistic customers are able to extract, either from the product during the trial period or from the transaction itself, plays a crucial role in their decision making process. We refer to these returns as opportunistic returns.

Let \hat{v} denote the boundary opportunistic customer who is indifferent between making a purchase and then returning it or not making the purchase in the first place. The utility for this boundary customer is given by $U[\hat{v}] = m\hat{v} - p + r$, where m is a scalar that denotes the benefit of opportunism. With such behavior, opportunistic customers extract $m\hat{v}$ utility from the product, receive refund r , and incur the purchase price p . Note that m may reflect a benefit that is only tangentially related to the product itself and otherwise might reflect utility gained from the transaction such as obtaining reward points by using a credit card. A common modeling approach in the literature is to assume that the value opportunistic customers extract from the product is proportional to the length of the trial period (Hess et al. 1996, Chu et al. 1998, Ulku et al. 2013). However, that modeling approach does not capture the disproportionate value that many customers extract by acting opportunistically. Hence, we put no bounds on m other than $m > 0$. Because the boundary opportunistic customer is indifferent between purchasing the product or not, the

utility for this customer is zero. Setting $U[\hat{v}] = 0$ and solving for \hat{v} , we get $\hat{v} = \frac{p - r}{m}$.

The only decision for fraudulent customers is whether or not to return the product. Let γ denote the size of the fraudulent segment, where $\gamma > 0$. We do not endogenize a utility function for fraudulent customers, although we conjecture that a representative utility function would look something like $r - \eta g$, where g denotes the cost of getting caught and η denotes the sensitivity to g . Clearly, the utility that a fraudster derives from the return transaction depends on the refund and the cost of getting caught, but there are also some moral, ethical, and psychological considerations that are not being captured and are beyond the scope of this research. Consequently, we take as given that a certain segment of the population is inclined to act fraudulently and simply consider that the proportion of the segment that is attracted to a retailer is influenced by the refund that is offered. The higher the refund, the greater the proportion of fraudulent customers making a return (Mellor 2013, Moraca 2014, Speights and Rittman 2015). We refer to these returns as fraudulent returns. Note that we normalize the size of the total market to $1 + \gamma$.

There are no corresponding sales transactions for the fraudulent return of products that are essentially stolen. In fact, the retailer incurs an additional cost (procurement cost of the item) if the item that is being returned is shoplifted from its own store, a practice that lies at the heart of receipt fraud and other criminal activities. We assume that the retailer replaces stolen items in order to satisfy demand rather than incur lost sales. As such, let ρ denote the proportion of the returned items that are stolen from the retailer's own store, which implies that the retailer incurs a total cost of $r + \rho c + k - s$ for each fraudulent return. Note that the order quantity is $q = L + O + \rho F$. Table 2.1 summarizes the principal notation in our model.

2.3.1 Model Analysis

We predicate our analysis on a model adapted from Hess et al. (1996) that we illustrate in Figure 2.2. Note that Chu et al. (1998) and Ulku et al. (2013) also draw upon the model introduced by Hess et al. (1996) in their analysis of opportunistic customers. We adapt the model here by adding the fraudulent segment. The area to the right of \bar{v} in Figure 2.2 identifies the segment of legitimate customers. Depending on the match $(1 - \lambda)$

Table 2.1: Parameters and Decision Variables

Symbol	Definition
p	Price (decision)
r	Refund amount (decision)
q	Ordering quantity (decision)
v	Customer valuation
s	Salvage value
c	Procurement cost
λ	Mismatch probability
m	Benefit of opportunism
γ	Fraudulent segment size
h	Hassle cost
ρ	Fraudulent return cost scalar
θ	Sensitivity of fraudulent customers to hassle cost
k	Return handling cost

and mismatch (λ) probabilities, legitimate customers are classified as net sales (S) or legitimate returns (R). The area between \hat{v} and \bar{v} represents opportunistic customers. Figure 2.2 makes clear that as \bar{v} shifts to the right (left), the opportunistic segment increases (decreases) relative to the legitimate customer segment. Similarly, as \hat{v} shifts to the right (left), the no purchase segment increases (decreases) relative to the opportunistic segment. Note that opportunistic customers have a lower valuation for the product than legitimate customers. If opportunistic customers had a higher valuation, they would instead want to purchase the product with the intention of keeping it: the very definition of a legitimate customer. Finally, the area above one on the vertical axis represents the overall size of the fraudulent segment. Because fraudulent customers are influenced by the refund, the area denoted by γr displays the number of fraudulent returns that the retailer realizes.

Note that opportunistic and legitimate returns might be a cost or a profit center depending on the margin ($p - r + s - c - k$). However, even when the opportunistic segment is profitable, they will still undermine the retailer's profit compared to a RAM without opportunism if the salvage value s is below a certain threshold. The derivation of this threshold is trivial so we omit it here. Typically, opportunism is costly to retailers and it is for this reason that they look for ways to reduce or eliminate it. However, as the benefit of opportunism m increases, more customers are attracted to renting or wardrobing type behavior. Indeed, in such cases, it may make sense for a retailer to switch from a selling model to a renting model in order to capture some of the rents from these customers. That

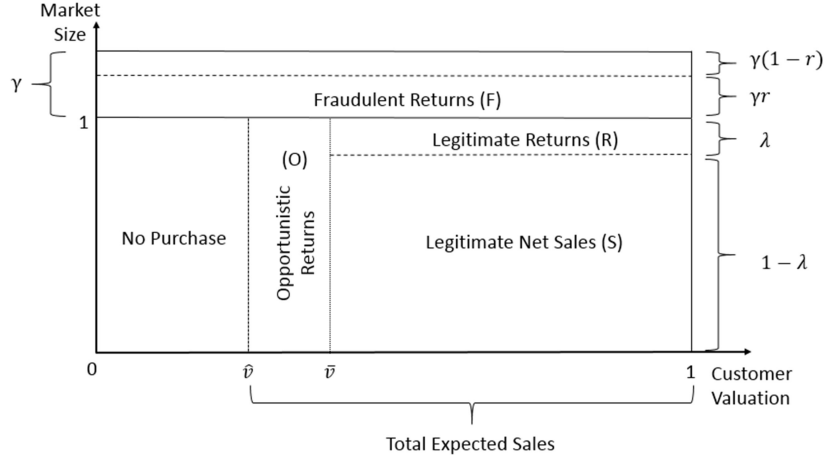


Figure 2.2: Customer Segments

is, if the opportunistic segment is large enough and the value extraction these customers are able to obtain by purchasing and returning the product is also large enough, then renting products may enable a retailer to profit from these customers. As for fraudulent returns, those returns may result in a loss if $s < r + k + \rho c$ and a profit otherwise. Note that the former is to be expected, while the latter would be perverse. In this study, we restrict our attention to the case where a return is not profitable. Clearly, if returns were profitable, there would be no need to restrict them.

Combining the results for the cutoff valuation points, we present the size of net sales ($S = L - R$) and each type of customer return below.

1. The size of legitimate customers (L) $\equiv \left(1 - \frac{p - r\lambda}{1 - \lambda}\right)$
2. The size of legitimate returns (R) $\equiv \left(1 - \frac{p - r\lambda}{1 - \lambda}\right) \lambda$
3. The size of opportunistic returns (O) $\equiv \left(\frac{p - r\lambda}{1 - \lambda} - \frac{p - r}{m}\right)$
4. The size of net sales (S) $\equiv \left(1 - \frac{p - r\lambda}{1 - \lambda}\right) (1 - \lambda)$
5. The size of fraudulent returns (F) $\equiv (\gamma r)$

The retailer's objective function for the RAM is given by

$$\max_{p,r} \pi = S(p - c) + (R + O)(p - r + s - c - k) + F(s - r - k - \rho c) \quad (2.1)$$

The first term in equation (2.1) represents net sales. The second term corresponds to opportunistic and legitimate returns. Finally, the last term refers to fraudulent returns. Maximizing this objective function with respect to p and r gives the optimal solution for the retailer's problem.

Proposition 1. *The retailer's optimal decisions for price p^* and refund r^* for the RAM are given by*

$$p^* = \frac{(k - s - 2)(1 + m\gamma) + (2 + m(1 - k + s))\lambda - c(1 - 2\lambda + \gamma(2 + (m - 2)\rho))}{4(\lambda - \gamma - 1) + m}$$

$$r^* = \frac{c + m - 2 - s(3 + 2\gamma - m) + 2(1 + s)\lambda - k(m + 2\lambda - 2\gamma - 3) + 2c\gamma\rho}{4(\lambda - \gamma - 1) + m}$$

The proof for Proposition 1 and all the other Propositions are provided in the Appendix. The sensitivity analysis for the RAM is provided in Table 2.2. To generate the table, we take partial derivatives of the decision variables (represented by columns) with respect to each parameter (represented by rows), where the signs (+) and (−) show whether these partial derivatives are positive or negative. Although most relationships between the parameters and the decision variables are generally intuitive, there are five observations that provide managerial insights that are worth highlighting.

Table 2.2: Sensitivity Analysis

Parameters	Price	Refund	Order Quantity	Profit
Salvage Value (s)	+	+	+	+
Procurement Cost (c)	+	−	−	−
Mismatch Probability (λ)	−	−	−	−
Benefit of Opportunism (m)	+	−	\cap	+
Fraudulent Segment Size (γ)	−	−	−	−
Fraudulent Return Cost Scalar (ρ)	−	−	+	−
Return Handling Cost (k)	−	−	−	−

Observation-1: *Price p increases with respect to the salvage value s .*

When the retailer has more profitable product disposition alternatives, it can afford a higher refund r . Note that the size of the opportunistic segment increases in m and r and decreases in p . Because a higher refund r increases the number of opportunistic returns, the retailer sets a higher price p to limit them.

Observation-2: *Refund r decreases with respect to the procurement cost c , even though price p increases.*

Because the cost of a return increases as the procurement cost c increases, the retailer offers a lower refund r to discourage their occurrence. As such, the retailer uses both price p and refund r to recover the additional cost arising from the increase in the procurement cost c .

Observation-3: *The relationship between the benefit of opportunism m and the order quantity q is concave.*

As opportunism increases when m increases, the retailer fights the opportunistic segment by increasing the price p and decreasing the refund r . As a consequence of the higher price and the lower refund, legitimate customer demand is smaller. Up to a point, as m increases, aggregate demand increases because the increase in opportunism due to an increase in m is greater than the decrease in legitimate customer demand. Beyond that point, however, aggregate demand decreases because the decrease in the legitimate customer demand is in excess of the increase in opportunism.

Observation-4: *Refund r decreases with respect to the mismatch probability λ .*

Normally, one would expect the retailer to compensate its customers in the case of a mismatch by offering a higher refund. However, opportunistic and fraudulent customers are also influenced by the refund, which constrains the retailer's decision-making. Instead, the retailer compensates its legitimate customers by setting a lower price p . A lower price, however, also increases the size of the opportunistic segment. Therefore, the retailer offers a lower refund r to discourage opportunism.

Observation-5: *Price p decreases with respect to the size of the fraudulent segment γ , the proportion of items stolen from the retailer's own store ρ , and the return handling cost k .*

The explanation for the behavior of price with respect to each parameter in Observation-

5 is similar so we clarify using γ as an example. As γ increases, the retailer will naturally set a lower refund r . However, a lower refund reduces legitimate customer demand, which then motivates the retailer to set a lower price in order to stimulate demand from them. Hence, both price p and refund r decrease with respect to the fraudulent segment size γ . We now employ a numerical study to generate additional insights.

2.3.2 Numerical Study

We conduct a numerical study to illustrate the effectiveness of the pricing and refund decisions to mitigate return abuse and to model behavior that is unavailable analytically. We use three variations of the basic RAM: fraud only, opportunism only, and no return abuse. Using these three variations, we assess the effectiveness of price and refund to address each type of return abuse separately and collectively. Our numerical study corresponds to a factorial experimental design and uses the parameter values displayed in Table 2.3. We chose these values to demonstrate a wide variety of operating environments that enables us to readily assess model behavior. We investigate a total of 2,187 scenarios.

Table 2.3: Parameter Values

Parameters	Low	Medium	High
c	0.20	0.25	0.30
s	0.50c	0.70c	0.90c
λ	0.30	0.35	0.40
k	0.10	0.15	0.20
m	0.10	0.20	0.30
γ	0.03	0.05	0.07
ρ	0.25	0.50	0.75

As we would expect, our results show that return abuse reduces profitability and that return fraud reduces profitability more than opportunism does. Table 2.4 presents our aggregate results and shows for each model variation the size of the different segments, the decision variables, and the profit. The values reported reflect averages across all of the numerical cases. For example, the quantity of legitimate returns in the opportunism only variation is 0.122. Note that the values in the table are small since we normalize the

market size to $1 + \gamma$. We also note that our discussion here is predicated on an aggregate analysis of averages across all experiments. However, we observe the same behavior across the individual numerical cases.

Table 2.4: Results

Cases	Net Sales	Leg.Ret.	Opport.	Fraud	Price	Refund	Profit
No Return Abuse	0.204	0.109	-	-	\$ 0.686	\$ 0.686	\$ 0.065
Only Opport.	0.228	0.122	0.010	-	\$ 0.553	\$ 0.375	\$ 0.063
Only Fraud	0.222	0.119	-	0.015	\$ 0.536	\$ 0.311	\$ 0.058
Fraud & Opport.	0.245	0.132	0.004	0.017	\$ 0.524	\$ 0.342	\$ 0.054

Note that the no return abuse case in Table 2.4 serves as a point of reference when evaluating the other cases. We find that when opportunism is the only type of return abuse, both the refund and the price are lower than when there is no return abuse. The lower price stimulates legitimate demand that is undermined due to the lower refund that is used to fight opportunism. When fraud is the only form of return abuse, the retailer charges a lower price and offers a lower refund; the same behavior that we observe with opportunism. Interestingly, when both fraud and opportunism are present (RAM), the refund is actually higher than when only fraud is present. This condition arises because the retailer sets the refund to attract more legitimate customers when both types of return abuse are present. We summarize these insights in Figure 2.3 and show the price and refund for each case. On a separate line, we also show the restocking fee. We define the restocking fee as the ratio of the nonrefunded dollar amount to the price, namely $\left(\frac{p-r}{p}\right)$. This metric is not a fee per se, but we refer to it as such to be consistent with the common retailer terminology. It is clear that the differences in bars, which reflects the restocking fee, is greatest where the line is highest and that corresponds to the fraud only case.

We also analyze segment sizes to examine how the price and refund decisions impact legitimate customer demand and return abuse behavior across the different cases. Figure 2.4 presents the sizes of no purchase, opportunism, legitimate returns, net sales, and fraud segments across different cases. Overall, we find that legitimate sales (net sales plus legiti-

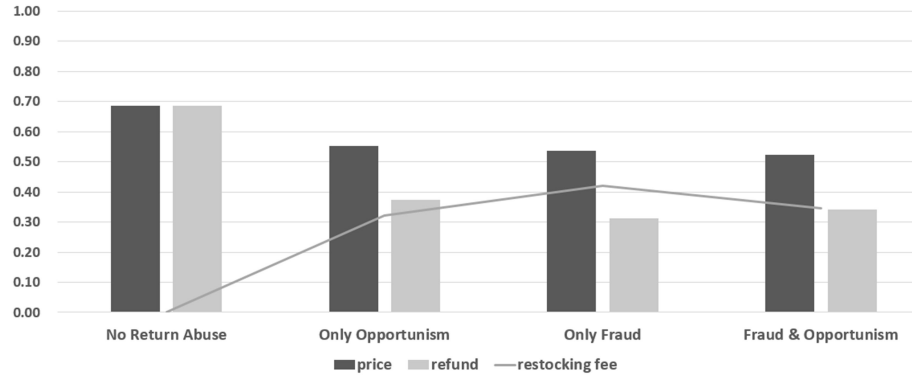


Figure 2.3: Price, Refund, and Restocking Fee Comparisons

mate returns) in the case of no return abuse are lower than those when any type of return abuse is present. This arises because without any return abuse, the retailer is able to set a price that extracts maximum rents from consumers. In contrast, when return abuse exists, the retailer is unable to set such a high price. Again, we use averages as a convenient way to illustrate how the market segments shift between the different cases.

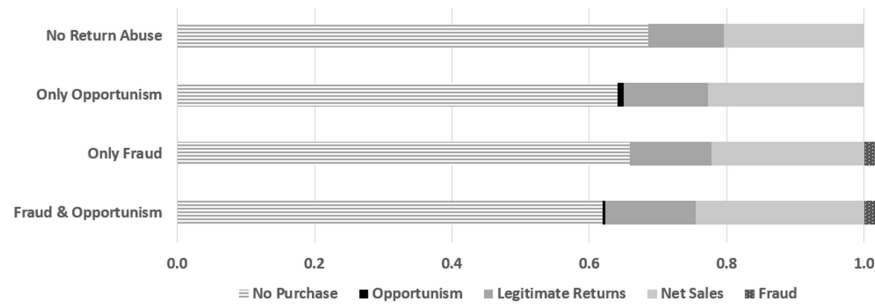


Figure 2.4: Segment Sizes Across Cases

As Figure 2.4 shows, when opportunism is the only type of return abuse, net sales are higher than when there is no return abuse. This arises because the price decrease compensates for the low refund that is used by the retailer to fight opportunism. When fraud is the only type of return abuse, net sales are slightly less than that in the opportunism only case because of the lower refund that is used by the retailer to fight fraud. When fraud

and opportunism are both present, net sales are higher than when there is no return abuse because of the reduced price. Furthermore, the price and the refund combination when both opportunism and fraud are present converts a smaller fraction of the no purchase segment into opportunistic customers relative to when only opportunism is present.

Finally, we examine the effectiveness of the retailer’s price and refund decisions for reducing return abuse (Table 2.5). Note that the first row serves as a benchmark by showing the magnitude of the two types of return abuse if they were ignored when setting the price and the refund. By way of reference, we can see the amount of return abuse that can be reduced by manipulating price and refund in the different variations of the RAM.

Table 2.5: Effectiveness of Price and Refund to Fight Return Abuse

Cases	Opportunism	Reduction	Fraud	Reduction	Profit
Benchmark	0.686	-	0.069	-	-\$ 0.182
Only Opportunism	0.010	98.6%	-	-	\$ 0.063
Only Fraud	-	-	0.020	55.0%	\$ 0.058
Fraud & Opportunism	0.004	99.4%	0.020	50.6%	\$ 0.054

The results in Table 2.5 show that, on average, the retailer’s price and refund policies are very effective at reducing opportunism, but they are only marginally effective at reducing fraud. We observe the same level of effectiveness across the individual numerical cases. For opportunism, the reduction across those cases ranges from 78.6% to 100.0% while for fraud the effectiveness ranges from 26.9% to 80.5%. Through a sensitivity analysis, we find that the effectiveness of the policies to reduce opportunism increases with respect to c , λ , k , and γ , and decreases with respect to s . Similarly, the effectiveness of the policies to reduce fraud increases with respect to c , k , and γ and decreases with respect to s and λ .

We now proceed to analyze the technology enabled countermeasures and their impact on retailer profitability. Technologies available for opportunism are customer profiling systems, while technologies for fraud are product tracking systems. In the following sections, we analyze managing return abuse with these technologies. One of our main objectives is to determine the value of such investments to fight return abuse.

2.4 Customer Profiling Model (CPM)

In the CPM, the retailer contracts with a TPSP to identify opportunistic returns. Returns are denied to those customers who are flagged as opportunistic by the system. We first assume that the technology is 100% accurate in order to obtain broad insights into the impact of the technology on the retailer. As such, we assume that the customers who are inclined towards acting opportunistically are effectively deterred and, therefore, the opportunistic segment is eliminated. However, it is clear that the technologies available in the marketplace are not 100% accurate. Hence, we explore the impact of inaccuracy in §2.4.1.

A principal disadvantage of this technology is that it increases the hassle cost to customers. Increased hassle arises because retailers require customers to provide their personal IDs at the point of return. Many customers view this as a hassle and as an invasion of privacy. In fact, customers incorporate a privacy cost into their decision making process (Masanell and Drane 2015). We use h to denote this *additional* hassle cost to customers arising from using this technology. Of course there are other forms of hassle that customers perceive when conducting a transaction. From this perspective, the base level of hassle cost inherent to the RAM is normalized to zero.

In order to analyze the CPM, we need to adjust the utility functions. The point \bar{v} which defines the boundary legitimate customer in the basic RAM is adjusted to incorporate the hassle cost and now we have $\bar{v} = \frac{p - r\lambda + h\lambda}{1 - \lambda}$. Although customer profiling is mostly used to fight opportunism, the sheer act of requiring IDs during the return process will deter some fraud. As such, the size of the fraudulent segment decreases in the hassle cost and we use θ as a scalar to represent the sensitivity of fraudulent customers to the hassle cost. We put no bounds on θ other than $\theta \geq 0$ because it is clear that privacy is more significant to individuals that partake in criminal activities. Then again, it should also be clear that there is nothing to prevent a criminal from using a fake or even a stolen ID. Below, we present the size of each segment for the CPM. Note that the order quantity q in the CPM is given by $L + \rho F$.

1. The size of legitimate customers (L) $\equiv \left(1 - \frac{p - r\lambda + h\lambda}{1 - \lambda}\right)$

2. The size of legitimate returns (R) $\equiv \left(1 - \frac{p - r\lambda + h\lambda}{1 - \lambda}\right) \lambda$
3. The size of net sales (S) $\equiv \left(1 - \frac{p - r\lambda + h\lambda}{1 - \lambda}\right) (1 - \lambda)$
4. The size of fraudulent returns (F) $\equiv \gamma (r - \theta h)$

The retailer's objective function for the CPM is given by

$$\max_{p,r} \pi = S(p - c) + R(p - r + s - c - k) + F(s - r - k - \rho c) \quad (2.2)$$

The first term in equation (2.2) represents the profit from net sales. Since the opportunistic segment is eliminated, the second term includes only legitimate returns. Finally, the last term represents fraudulent returns. Maximizing this objective function with respect to p and r gives the optimal solution for the CPM.

Proposition 2. *The retailer's optimal decisions for price p^* and refund r^* for the CPM are given by*

$$p^* = \frac{1}{2} (1 + c - (1 + h(1 - \theta))\lambda - c\lambda\rho) \quad r^* = \frac{1}{2} (s + h\theta - k - c\rho)$$

Table 2.6 presents the sensitivity analysis for the CPM. While most relationships are self-explanatory, there are a few surprising results. First, the relationship between the proportion of items stolen from the retailer's own store ρ and the order quantity q is concave. Within a certain range of ρ , the order quantity q increases because of the increasing proportion that fraudulent returns are shoplifted from the retailer's store. Beyond that point, however, the order quantity q decreases since the retailer reduces the refund r to limit fraud, which also reduces legitimate customer demand. Second, the refund r is insensitive to the mismatch probability λ . Because the retailer is limited in increasing the refund r due to fraudulent customers, it instead reduces price p to compensate its legitimate customers when the mismatch probability λ increases.

Third, unlike the RAM in which the retailer increases the price to discourage opportunistic returns as the salvage value increases, here the salvage value s does not have any

Table 2.6: Sensitivity Analysis

Parameters	Price	Refund	Order Quantity	Profit
Salvage Value (s)		+	+	+
Procurement Cost (c)	+	-	-	-
Mismatch Probability (λ)	-		-	-
Hassle Cost (h)	-	+	-	-
Fraudulent Return Cost Scalar (ρ)	-	-	\cap	-
Hassle Cost Scalar for Fraud (θ)	+	+	-	-
Return Handling Cost (k)		-	-	-

influence on price p since there is no opportunism. Fourth, we find that price p is also insensitive to the return handling cost k . When k increases, the retailer has two alternatives to recover that additional cost: increase price p or reduce refund r . In this case, it is more profitable for the retailer to only adjust the refund r so that just those who return pay for the return handling cost k .

Next, we compare the optimal prices, refunds, and corresponding restocking fees between the RAM and the CPM. In fact, while there are a number of thresholds one can derive to highlight model sensitivity to the policy decisions, we provide two as an example here. We choose the benefit of opportunism m and the hassle cost h since they represent the key differential parameters in the CPM relative to the RAM.

Proposition 3. 1. *If the benefit of opportunism is greater than a certain threshold, $m > \bar{m}$, where*

$$\bar{m} = \frac{2(c+k-s+2(\gamma+(1+\gamma)(h(\theta-1)-1)\lambda+(1+h-h\theta)\lambda^2))}{1+2(2-k+s)\gamma+(2k-3-2s+h(\theta-1))\lambda+c(1+2\gamma\rho-\lambda\rho)} - \frac{4c(\gamma-\lambda)(\lambda-1)\rho}{1+2(2-k+s)\gamma+(2k-3-2s+h(\theta-1))\lambda+c(1+2\gamma\rho-\lambda\rho)}$$

then the optimal price in the CPM is lower than the optimal price in the RAM.

2. *If the hassle cost is less than a certain threshold, $h < \hat{h}$, where*

$$\hat{h} = \frac{(2-m)(k-s-2)+4\lambda+c(2+(m+4\lambda-4)\rho)}{\theta(m+4\lambda-4\gamma-4)}$$

then the optimal refund in the CPM is lower than the optimal refund in the RAM.

The first part of Proposition 3 shows that the retailer charges a higher price in the RAM to discourage some of the opportunistic customers if the benefit of opportunism m is above a certain threshold. Because the opportunistic segment is eliminated in the CPM, the retailer now has the flexibility to set a lower price p in order to attract more legitimate customers. The second part of Proposition 3 is interesting because, intuitively, the retailer should be expected to offer a higher refund r when it eliminates one of the two customer segments that engage in return abuse. Note that in the RAM when both fraud and opportunism are present, the retailer accepts a slightly higher level of fraud in exchange for a more considerable reduction in opportunism. In the CPM, since opportunism is eliminated, the retailer actually lowers the refund relative to the RAM to further reduce fraud. This condition arises so long as the hassle cost is below the threshold \hat{h} , signifying that the benefit of eliminating opportunism is worth the added hassle cost to legitimate customer demand.

Despite Proposition 3, it is not clear if the retailer charges a higher or lower restocking fee in the CPM relative to the RAM. Although we omit it here, one can establish another threshold for the hassle cost h and show that if h goes beyond a certain point, then the restocking fee in the CPM is greater than the restocking fee in the RAM. That arises because the decrease in the refund to further reduce fraud in the CPM is greater than the decrease in the price enabled by eliminating opportunism. Note that the condition prevails due to the fact that restocking fee in the CPM decreases in the hassle cost h .

In what follows, we compare the CPM to the RAM in terms of net benefit ($\pi_2 - \pi_1$). Note that for the CPM service to be a viable option, the net benefit must be greater than the TPSP service cost. In this way, we can evaluate the value of adopting the CPM and the conditions in which it is the most beneficial. The parameters that we use for our analysis are the salvage value s and hassle cost h . The salvage value s influences the cost of opportunism. The hassle cost h is a tradeoff for the retailer such that it has to choose between eliminating opportunism and reducing legitimate customer demand.

Proposition 4. *For a given TPSP service cost b , if the hassle cost and the salvage value are less than certain thresholds, $h < \bar{h}$ and $s < \underline{s}$, then the net benefit of adopting the CPM over the RAM, $\pi_2 - \pi_1$, is positive. If, however, $h \geq \bar{h}$, then the net benefit is negative.*

Analyzing the relative profitability between the CPM and the RAM, we find that the retailer is better off adopting a profiling system if both the salvage value s and hassle cost h are low. Clearly, when the salvage value s is low, the cost of a returned item is high. As such, the retailer may increase its profit by eliminating opportunism. However, if the hassle cost is too high, the CPM is less favorable than the basic RAM due to reduced legitimate customer demand. Hence, there exist two dimensions for the retailer's decision of adopting a profiling system. By employing a sensitivity analysis, we also find that the net benefit of adopting a customer profiling system increases with respect to c , γ , ρ , θ , and k and decreases with respect to s , λ , m , and h .

2.4.1 Imperfect Customer Profiling Model (ICPM)

Our analysis so far assumes that customer profiling technology is perfectly accurate. Although there is considerable evidence on the existence and occurrence of opportunism, it is nevertheless challenging to identify any given individual or specific transaction as opportunistic. This arises because opportunism is largely defined by customer intentions and intentions are virtually impossible to predict with perfect accuracy. Hence, we now look into less than perfect accuracy to test model robustness. As such, we use α to denote the probability that the system rejects a return from an opportunistic customer and $1 - \alpha$ to denote the probability that an opportunistic customer is able to remain undetected and receive a refund.

The model for the ICPM is identical to the one in §2.4, with the exception of the utility expression for the opportunistic customers. Let v denote the boundary opportunistic customer who is indifferent between making or not making the purchase. The utility for this customer is given by $U[v] = mv - p + \alpha s_c + (1 - \alpha)r$, where s_c denotes the salvage value of the product from a customer's perspective. Note that s_c is not necessarily equal to s . In our setting, s_c represents the monetary value that opportunistic customers may receive by selling items that they were not allowed to return (e.g., selling through classified ads or electronic marketplaces such as Craigslist or eBay). With such behavior, opportunistic customers extract mv utility from the product, incur the purchase price p , and receive refund r with probability $1 - \alpha$ or receive salvage value s_c with probability α . Setting $U[v] = 0$ and solving for v , we get $v = \frac{p - r + r\alpha - \alpha s_c}{m}$. For the ICPM, the retailer's

objective function is given by

$$\max_{p,r} \pi = (S + \alpha O)(p - c) + (R + O(1 - \alpha))(p - r + s - c - k) + F(s - r - k - \rho c) \quad (2.3)$$

The first term in equation (2.3) represents the profit from net sales and sales to opportunistic customers whose returns are rejected. The second term refers to the legitimate returns and the returns from opportunistic customers whose returns are accepted. Finally, the last term refers to fraudulent returns. We report the solution for the ICPM in the Appendix. When $\alpha < 1$, the retailer still realizes some opportunistic returns. Therefore, relative to the CPM, the retailer's profit in the ICPM is lower. We also find that both price p and refund r decrease with respect to α . Note that as α increases, the size of the opportunistic segment decreases and, therefore, the performance of the ICPM approaches to that of the CPM, where the retailer reduces the refund to fight the fraudulent segment and compensates legitimate customers by setting a lower price. Furthermore, there still exist critical thresholds for the salvage value s and hassle cost h that delineate differences in the policies decisions between the ICPM and the RAM. Therefore, relative to the CPM, our analytical insights remain the same in the ICPM, although the retailer's profit will be less as long as $\alpha < 1$. Note that just as Proposition 4 does, one can also investigate the net benefit of adopting a customer profiling system relative to the basic RAM by deriving an accuracy threshold depending on α , which we omit here.

2.5 Product Tracking Model (PTM)

In the PTM, the retailer is able to eliminate fraudulent returns. As with the CPM, we first assume that the technology is 100% effective in its detection and prevention of fraud and then explore less than perfect effectiveness in §2.5.1. In addition to detecting fraud, product tracking technology may also help retailers eliminate or reduce hassle costs as well. Several examples of hassle include the privacy concerns related to requiring personal identification that we already discussed with respect to the CPM, but also extend to include rejecting returns without proof of purchase, requiring original packaging, shortening the return time window, and imposing restrictions on cross-channel returns. Because product tracking technology can eliminate the need for many of these hassles, retailers may do

away with them. Hence, customers may benefit from a lower level of hassle arising from the adoption of a product tracking service. Lower hassle itself translates into a more lenient return policy.

With a more lenient return policy, however, opportunistic behavior may increase (Davis et al. 1995). Hence, the adoption of product tracking technology to some extent involves a tradeoff between fighting return fraud, dealing with increased opportunistic behavior, and having more legitimate customer demand. We now use h to denote this extra benefit arising from reduced hassle cost. Just as the CPM incorporated an *increase* in the level of hassle, the PTM addresses a *decrease* in the level of hassle, relative to the RAM. We need to adjust the utility functions to do so. Specifically, we adjust the point \bar{v} which defines the boundary legitimate customer in the RAM so that now we have $\bar{v} = \frac{p - r\lambda - h\lambda}{1 - \lambda}$. Similarly, the point \hat{v} which defines the boundary opportunistic customer in the RAM is now adjusted to $\hat{v} = \frac{p - r - h}{m}$. Below, we present the size of each segment for the PTM. Note that the order quantity q is equal to $L + O$.

1. The size of legitimate customers (L) $\equiv \left(1 - \frac{p - (r + h)\lambda}{1 - \lambda}\right)$
2. The size of legitimate returns (R) $\equiv \left(1 - \frac{p - (r + h)\lambda}{1 - \lambda}\right)\lambda$
3. The size of net sales (S) $\equiv \left(1 - \frac{p - (r + h)\lambda}{1 - \lambda}\right)(1 - \lambda)$
4. The size of opportunistic returns (O) $\equiv \left(\frac{p - (r + h)\lambda}{1 - \lambda} - \frac{p - r - h}{m}\right)$

The retailer's objective function for the PTM is given by

$$\max_{p,r} \pi = S(p - c) + (R + O)(p - r + s - c - k) \quad (2.4)$$

Note that the objective function in equation (2.4) is the same as the one presented in equation (2.1) except that the last term, $F(s - r - k - \rho c)$, is eliminated. Maximizing this objective function with respect to p and r gives the optimal solution for the retailer's problem.

Proposition 5. *The retailer's optimal decisions for price p^* and refund r^* for the PTM are given by*

$$p^* = \frac{k + c\lambda - s - h + m(1 - k + s + h)\lambda + (\lambda - 1)(2 + c)}{m + 4\lambda - 4}$$

$$r^* = \frac{c + (1 + s - k)(m + 2\lambda) - 2 + 3(k - s) + h(1 - 2\lambda)}{m + 4\lambda - 4}$$

The sensitivity analysis for the PTM is the same as the one expressed in Table 2.2 for the RAM. Hence, we will not repeat it here. Next, we compare the PTM to the RAM in terms of price, refund, and profit. Although there are a number of thresholds one can derive to establish the behavior of the system in terms of the optimal decisions, here we focus on γ as an illustrative example.

Proposition 6. *1. If the fraudulent segment size is greater than a certain threshold, $\gamma > \bar{\gamma}$, where*

$$\bar{\gamma} = \frac{h(m + 4\lambda - 4)(m\lambda - 1)}{k(m - 2)^2(k - 2 - s) - 4h + 8\lambda + 4m(h - 1)\lambda + c(2 - m)(2 + (m + 4\lambda - 4)\rho)}$$

then the optimal price in the PTM is higher than the optimal price in the RAM.

2. If the fraudulent segment size is greater than a certain threshold, $\gamma > \hat{\gamma}$, where

$$\hat{\gamma} = \frac{h(1 - 2\lambda)(m + 4\lambda - 4)}{2(k(2 - m) + m(2 + s) - 2(2 + s - h - c + 2(h - 1)\lambda) + (m + 4\lambda - 4)c\rho)}$$

then the optimal refund in the PTM is higher than the optimal refund in the RAM.

The first part of Proposition 6 shows that the retailer charges a higher price in the PTM to discourage some of the opportunistic customers if the size of the fraudulent segment γ is above a certain threshold. Because the opportunistic segment remains in the PTM, the retailer sets a higher price p in order to discourage opportunistic customers. The second part of Proposition 6 shows that the retailer offers a higher refund in the PTM to attract more legitimate customers if the size of the fraudulent segment γ is above a certain threshold. This arises because the retailer has the flexibility to offer a higher refund to legitimate customers once the fraudulent segment is eliminated.

In what follows, we compare the PTM to the RAM in terms of net benefit ($\pi_3 - \pi_1$) just as we did for the CPM. In this way, we can evaluate the value of adopting the PTM and the conditions in which it is the most beneficial. The parameter that we use for our analysis is the service fee b that the TPSP charges for the product tracking service.

Proposition 7. *If the product tracking service fee is less than a certain threshold, $b < \bar{b}$, then the net benefit of adopting the PTM over the RAM, $\pi_3 - \pi_1$, is positive. If, however, $b \geq \bar{b}$, then the net benefit is negative.*

Proposition 7 provides a threshold at which the retailer is better off by adopting a product tracking system. A careful evaluation of the expression for \bar{b} demonstrates that the net benefit of adopting a product tracking system increases with respect to λ , γ , h , ρ , and k and decreases with respect to c . For s , k and m , the net benefit is convex: first decreasing and then increasing.

2.5.1 Imperfect Product Tracking Model (IPTM)

Our analysis so far assumes that product tracking technology is 100% effective. We now consider that the tracking system is not 100% effective in its detection of fraudulent returns to validate the robustness of our assumptions. As the product tracking technology uses product specific identifiers, effective detection of return fraud requires manufacturer participation since they are the only party that can place unique identifiers, such as serial numbers, on the product. Hence, the level of effectiveness, to some extent, depends on the participation level of manufacturers: the higher the level of participation, the higher the level of effectiveness. We use β to denote the effectiveness of the PTM in which effectiveness corresponds to the probability that the system rejects a return from a fraudulent customer. As such, $1 - \beta$ denotes the probability that a fraudulent customer is able remain undetected and receive a refund. For the IPTM, the retailer's objective function is given by

$$\max_{p,r} \pi = S(p - c) + (R + O)(p - r + s - c - k) + (1 - \beta)F(s - r - k - \rho c) \quad (2.5)$$

Note that the last term in equation (2.5) represents the fraction of fraudulent returns that avoid detection and are accepted by the retailer. Maximizing this objective function with respect to p and r gives the optimal solution for the retailer's problem.

Proposition 8. *The retailer's optimal decisions for price p^* and refund r^* for the IPTM are given by*

$$\begin{aligned}
p^* &= \frac{(k - s - 1)(1 - m\lambda) + (1 - \beta)\gamma(mk - ms - 2(m + h + c) - c\rho(2 - m))}{m + 4(\lambda + \gamma(\beta - 1) - 1)} \\
&\quad + \frac{2\lambda(1 + c) + mh\lambda}{m + 4(\lambda + \gamma(\beta - 1) - 1)} \\
r^* &= \frac{c + (2\lambda + m)(1 + s) - s(3 + 2\gamma - 2\beta\gamma) + h(1 - 2\lambda) - k(m - 3 + 2\lambda)}{m + 4(\lambda + \gamma(\beta - 1) - 1)} \\
&\quad - \frac{2\gamma(\beta - 1)(k - c\rho)}{m + 4(\lambda + \gamma(\beta - 1) - 1)}
\end{aligned}$$

When $\beta < 1$, the retailer still realizes some fraudulent returns. Therefore, relative to the PTM, the retailer's profit in the IPTM is lower. We also find that both price p and refund r increase with respect to β . Note that as β increases, the size of the fraudulent segment decreases and, therefore, the performance of the IPTM approaches to that of the PTM, where the retailer increases the price to fight the opportunistic segment and compensates legitimate customers by offering a higher refund. Furthermore, there still exists a service fee threshold between the IPTM and the RAM although it is lower for the IPTM. Therefore, relative to the PTM, our analytical insights remain the same in the IPTM, although the retailer's profit will be less. Note that just as Proposition 7 does, one can also investigate the net benefit of adopting a product tracking system relative to the basic RAM by deriving a threshold depending on β , which we omit here.

2.6 Conclusion

This paper examines return abuse with respect to both opportunistic and fraudulent consumer returns and two technologies to deal with them. Without technology-enabled countermeasures, the retailer can only fight return abuse by manipulating its policies with respect to price and refund. Our analysis of the basic RAM highlights the effectiveness of the retailer's pricing and refund decisions to fight each type of return abuse separately and collectively. Consistent with our intuition, the results show that return abuse reduces profitability and that return fraud reduces profitability more than opportunism. We further

show that while the price and the refund do a good job at mitigating opportunism, they are only marginally effective at fighting return fraud. It is also interesting to note that the deterioration in profitability that arises from fraud and opportunism when experienced together is greater than the combined reduction in profit from each type of return abuse separately. Analyzing the segment sizes across different cases, our results also show that legitimate sales in the case of no return abuse are lower than when any type of return abuse is present. This arises because without any return abuse, the retailer is able to set a price that extracts maximum rents from consumers. In contrast, when return abuse exists, the retailer is unable to set such a high price.

Although previous literature suggests using a customer profiling system to reduce opportunistic returns (Davis et al. 1995, Harris 2010, Rosenbaum et al. 2011), we establish conditions in which adoption is not recommended. There exists a clear tradeoff in adoption because eliminating opportunism comes at the expense of facing reduced legitimate customer demand due to a higher level of hassle. Figure 2.5a presents the managerial insights on the relative profitability between the CPM and the RAM. Here, we show that if both the salvage value and the hassle cost are high, adopting a customer profiling system is less favorable than the RAM. This finding helps us explain the motivation why retailers such as Victoria's Secret, ToysRUs, and Finish Line use customer profiling technologies to fight opportunistic behavior, since the salvage value of returned items for those retailers is low due to hygienic concerns. Furthermore, effective 8 November 2015, Best Buy changed its four-year-old policy of requiring IDs for all returns to requiring IDs only for returns that lack proof of purchase. We conjecture that Best Buy might have changed its "ID-required for returns" policy due to sensitivity of customers to disclosing their personal information.

Our analysis of the PTM shows that relative to the RAM, opportunistic behavior increases in the PTM since those customers enjoy an additional benefit arising from the reduced hassle cost. The reduction in the hassle cost stems from the fact that product tracking technology eliminates the need for hassles such as proof of purchase or restrictions on cross-channel returns. Similar to opportunism, legitimate customer demand also increases due to reduced hassle cost. Overall, we find that the retailer's profit increases with respect to the additional benefit term (reduced hassle) since the increased legitimate

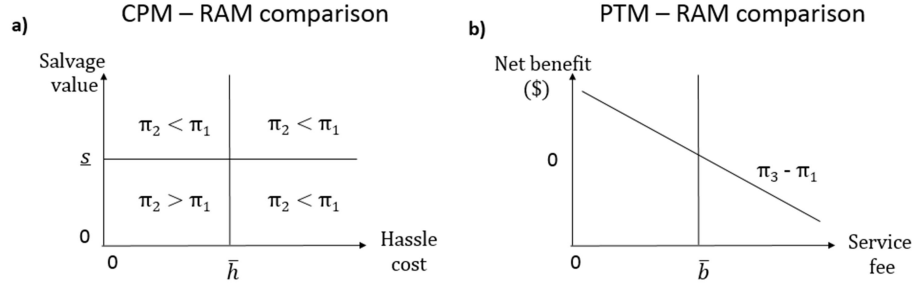


Figure 2.5: (a) Profit Comparison of CPM to RAM (b) Profit Comparison of PTM to RAM

sales more than compensate for the loss arising from increased opportunistic behavior. Comparing the profits between the PTM and the RAM, we also show that the net benefit of adopting a product tracking system is positive as long as the service fee is less than a certain threshold, which is presented in Figure 2.5b. We also note that the net benefit of choosing one countermeasure over the other depends on the hassle cost and the relative sizes of the fraudulent and opportunistic segments.

To the best of our knowledge, this research is the first to provide a prescriptive analytical treatment of fraud and opportunism along with technology enabled countermeasures to address them. As such, there are numerous opportunities for future research. The most promising avenues for extending our research are to investigate return abuse in a multi-period setting, to explore the impact of heterogeneous opportunism, and to observe return abuse in a competitive environment. With a multi-period setting, it would also be possible to examine the impact of each countermeasure on the future shopping intentions of legitimate customers. Second, our models assumed homogeneous value extraction for all opportunistic customers. In reality, however, opportunistic customers may differ in terms of how much value they can extract during a trial period. Actually, we have conducted a limited analysis with regard to heterogeneous hassle cost and provide it in the Appendix for the interested reader. Third, while our setting captures return abuse for a monopolist retailer, future research may examine return abuse in a competitive environment. Finally, it is also possible to extend our study by incorporating stochastic customer demand.

3. ASSESSING THE IMPACT OF SHIP-TO-STORE SERVICE ON SALES AND RETURNS IN OMNICHANNEL RETAILING: A DATA ANALYTICS STUDY

3.1 Introduction

With the advent of technology-enabled shopping alternatives, retailers have augmented their channel offerings with new service processes that have evolved into what is known today as omnichannel retailing. The main idea behind omnichannel retailing is the opportunity to offer consumers a seamless shopping experience no matter which channel they use (Rigby 2011, Brynjolfsson et al. 2013, Bell et al. 2014). With omnichannel retailing, customers can buy online, buy in stores, or choose from a hybrid purchase process. For example, major retailers offer buy-online and pick-up-in-store, ship-to-store, ship-from-store, or even reserve-online and pick-up-in-store omnichannel services to meet customer expectations.

Many omnichannel services are designed to draw customers into physical stores (RIS 2012, MA 2014) and thereby increase store traffic (Yantra 2005, Lieb 2015). Retailers do this with purchase options such as buy-online and pick-up-in-store and ship-to-store services, as well as with return options such as buy-online-return-to-store service (Zhang et al. 2010). Store traffic is essential to increase sales (Gulati and Garino 2000, Bell et al. 2014), either through impulse purchases or through the assistance of store employees (Fisher and Raman 2010, Mani et al. 2015). For example, at the national retailer that we study, employee guidelines and training materials make it clear that both ship-to-store and buy-online-return-to-store services are important selling occasions. For ship-to-store, sales associates are directed to use the occasion for selling accessories and attendant items, along with other more highly profitable services like warranties. For returns, the retailer's selling prescription for the salesperson is to convert the return into an exchange or up-sell to a more expensive item.

From a customer's perspective, the benefit of channel integration is an increase in the value proposition offered by retailers (Gallino and Moreno 2014, Gao and Su 2016) arising from lower transaction costs (e.g lower shipping fee, expedited delivery), higher

service quality, and lower perceived risk (Herhausen et al. 2015). With ship-to-store service, another benefit for customers is a perceived increase in product variety because retailers can augment the physical inventory of stores with virtual inventory on the Internet (Radial 2016). Hence, hybrid service offerings should directly stimulate demand for a retailer's products and services. Clearly, the benefits of omnichannel retailing have not been lost on practitioners as evidenced by the sheer number of retailers pursuing this strategy. Even so, there has been little academic research on the efficacy of omnichannel retailing tactics to generate demand or increase store traffic.

While omnichannel retailing provides benefits to customers, and ostensibly, to retailers, implementation involves the adoption of innovative and often costly information technologies that generate new operational challenges (Davis 2008, Zhang et al. 2010). Omnichannel retailing requires integrating inventory systems, warehouses, promotion campaigns, and assortment planning for online and offline channels (Gallino and Moreno 2014). Historically, retailers have had inventory record accuracy issues and have had a hard enough time tracking their store inventory in the first place (DeHoratius and Raman 2008), let alone having the capability to offer inventory visibility across numerous channels in a real-time way on the Internet. As a case in point, while 60% of retailers in a recent survey claim they have implemented inventory visibility across channels, 80% of them report that their systems need improvement due to implementation issues (BRP 2016).

There is a clear tradeoff between the cost and challenges associated with implementing omnichannel retailing and the benefits that arise from such an implementation. Complicating matters is that there is a variety of omnichannel services, each having different operational complexities and value propositions for customers. Although many people use the terms STS and buy-online and pick-up-in-store (BOPS) interchangeably, they are in fact two different service processes with different fulfillment tradeoffs (Acomvic and Graves 2015). Essentially, BOPS provides customers with product availability information and lets customers complete transactions online and later pick-up the item in a store at their convenience (Gao and Su 2016). BOPS also reduces the transaction cost for customers since items are prepared by store employees prior to pick-up. With STS service, however, customers complete their purchase transactions online and wait for delivery of items to their

local stores, free of charge. Shipping will generally occur even if the item is already available at the store, as is the case with the retailer we study. Hence, STS requires centralized fulfillment, while BOPS uses in-store inventory to fulfill customer demand. Furthermore, relative to BOPS, STS generally brings an additional shipping cost for retailers unless STS delivery is somehow synchronized with store replenishment, and even so, enabling such synchronization is generally costly in and of itself.

In practice, we observe many variations of BOPS and STS services. In Table 3.1, we compare eight national retailers in terms of the omnichannel features that they offer to their customers. Clearly, there is no single strategy that retailers are pursuing. Hence, we are left to wonder why a retailer chooses to offer a certain set of services. Academic research currently adds little clarity. We are aware of only two published research contributions that address BOPS (Gallino and Moreno 2014, Gao and Su 2016) and only one forthcoming paper that addresses STS (Gallino et al. 2016). Clearly, this gap in the literature, considered along with the extensive offering of these omnichannel services in the marketplace, signals a significant research opportunity.

Table 3.1: BOPS vs. STS

Firms	Offers BOPS	BOPS lead time	Offers STS	STS lead time
Walmart	Yes	4 hours	Yes	7-10 business days
Best Buy	Yes	45 min	Yes	3-7 business days
Lowe's	Yes	20 min	No	-
Kohl's	Yes	4 hours	No	-
Macy's	Yes	4 hours	No	-
REI	No	-	Yes	7-10 business days
Michaels	No	-	Yes	5-7 business days
Kirkland's	No	-	Yes	7-10 business days

In this paper, we empirically investigate the impact of implementing STS service on a retailer's operations by using a series of quasi-experiments. In particular, we use DID econometrics methodology to examine the pre and post periods of STS implementation. To do so, we have collected a proprietary data set from a national jewelry retailer that implemented STS service. Our data set spans two years and consists of more than 20 million purchase and return transactions. Furthermore, the retailer that we study operates

more than 600 stores in the U.S. and Canada. Using this data set, we are able to observe how purchase and return behaviors of customers change as a result of the new service and how these changes affect retailer performance.

Given the nascent state of research, we are positioned to make several important contributions to the literature. We build upon well-established theories like buyer behavior, risk in consumer choice, transaction costs economics, and production function, to develop and test a set of hypotheses that explain how STS implementation affects customer behavior. Leading theoretical arguments, drawn from the theories we employ lead us to believe that both Internet and BM channel sales should increase. Although we find that store sales do increase, online sales actually *decline*. Moreover, the increase in BM sales is larger than the decrease in online sales. Plainly, there is more to the story than a simple channel shift of demand. A key point to note as well is that the theoretical underpinning for an increase in BM sales resides with an increase in online sales. Ostensibly, STS directly stimulates online demand and through the process of store pick-ups, generates store traffic and hence store sales. Yet, we find that online sales *decline*. We are not proposing that well-established theories like buyer behavior and risk in consumer choice are incorrect, but clearly their application in the context of STS requires a more nuanced explanation.

In short, we find that while customers may be drawn to STS service to make their purchases, they decide not to wait for store delivery, and instead opt to go directly to the store and get their merchandise. This behavior occurs mainly for high-value items. What is striking here is that there is no way for customers to know that the items they are interested in are available at the store since such information is not made available online. In fact, there are a significant number of items available via STS that are not even stocked in stores. Evidently, the research that customers conduct online must make them comfortable enough to believe that the selection offered in stores will satisfy their needs, whether or not the online item is immediately available. The online customers that do end up using STS are customers that mainly purchase the lowest valued items, corresponding to cases in which the savings in shipping cost offered by the STS service is disproportionately greater.

Another facet of the story regarding the implementation of STS is its affect on product

returns. We find that product returns at stores decrease, as does the time-to-return, while returns for online purchases remain unchanged. Evidently, because customers who switch from online to BM channel have conducted prior research online, they are then more knowledgeable about their purchases. This is known as a reverse showrooming (webrooming) effect (Bell et al. 2014, Verhoef et al. 2015) and is the stimulus for the increase in BM sales that we observe in the first place. Yet, the same phenomenon applies to product returns as well. Customers are more knowledgeable about their own likes and preferences as well as that of a product’s ability to meet their needs. Consequently, they are able to make decisions regarding fit in a more timely manner - less learning is required after purchase, since more learning about fit occurs prior to purchase.

An interesting side-note is that for the retailer we study, the return rate of online purchases is *less* than that observed for BM purchases during both pre- and post-STS periods. Generally, we find in practice that the converse is true (Ryan 2015, JDA 2016) since less information about products, such as fit, is available for online purchases. For the retailer that we study, however, customers generally buy items online that are lower in value than in stores and this observation is consistent with other studies that demonstrate low-value items are less likely to be returned than high-value items (Peterson and Kumar 2009, Anderson et al. 2009). This finding contributes by showing that product value can have a greater influence on return decisions than product fit uncertainty (i.e. lack of touch and feel experience) that are inherent to online shopping.

We present a more complete and rigorous discussion of our findings in the main body of our paper. The rest of this manuscript is organized as follows. In §3.2, we review literature. In §3.3, we develop the theory that guides our research and introduce our hypotheses. In §3.4, we introduce and test our models. Given our initial results, we then provide an extended analysis in §3.5. Finally, we provide managerial insights, offer future research suggests, and conclude in §3.6.

3.2 Literature Review

There are three streams of literature related to our work. The first stream investigates channel integration and omnichannel retailing. The second stream examines the channel switching behavior of customers. The third stream addresses consumer returns in the

context of omnichannel retailing. We proceed to discuss each stream and position our work with respect to them.

Research on channel integration and omnichannel retailing only began to attract scholarly attention recently. Herhausen et al. (2015) study the impact of channel integration on customer behavior and find that it increases the perceived service quality and decreases the perceived risk inherent to online shopping. Cao and Li (2015) investigate the association between channel integration and firm performance and find that it stimulates sales growth depending on the firm's previous online experience and physical store presence. Brynjolfsson et al. (2009) examine cross-channel competition and find that online retailers face a higher level of competition from BM retailers for mainstream products relative to niche products. Huang and Van Mieghem (2014) empirically examine a setting where a firm operates the online channel as a showroom (catalog) and accepts orders at the BM channel. For such a case, they evaluate the value of using online channel clickstream information to improve the BM channel operations and show that clickstream data can be used to predict the ordering probability, amount, and timing of BM channel orders. Bendoly et al. (2005) explore the association between product availability and consumer retention and show that in the case of an availability failure (out-of-stock), perceived channel integration can prevent customers from shopping at competing firms by attracting them to the alternate channel. Gallino et al. (2016) study the impact of introducing omnichannel functionalities on a retailer's inventory decisions and show that STS service increases the contribution of the lowest-selling products to total sales (sales dispersion). Although these papers explore the overall performance impact of channel integration and cross-channel competition, none of them separately evaluates the impact of channel integration on the online and BM channels in terms of both sales and returns as we do in this study. Furthermore, we also contribute to the literature by exploring how channel integration influences cross-channel returns.

In the second stream, the following studies focus on the channel switching behavior of customers after the existing channels are integrated. Ansari et al. (2008) explore customer channel migration and show that marketing efforts influence customers to shift to the online channel and increase their sales volume. Chintagunta et al. (2012) investigate the process

of choosing a channel for grocery purchases and empirically show that relative transaction costs play important roles when consumers select between online and offline channels. Jareth et al. (2015) study the behavior of customers in a multichannel service environment and show that customers use different channels with different objectives. The authors find that customers use a telephone for important health-related concerns while they prefer the Internet for more structured information needs. Forman et al. (2009) study the competition between the online and offline channels and find that customers switch from online to BM channel after a store opens in a local community. In a related work, Avery et al. (2012) investigate the impact of store openings on direct channels like the Internet and catalog sales. They show that the presence of a physical store decreases catalog sales, but does not affect Internet sales in the short run. In the long run, both catalog and Internet channel sales increase.

In another study, Bell et al. (2017) explore the impact of information provision on the shopping behavior of consumers and show that some customers switch from online to BM channel with the introduction of a display only showroom. Gao and Su (2016) investigate the impact of BOPS service on store operations and find that offering BOPS may increase a retailer's customer base while making some existing customers shift from online channel to physical stores. Similarly, Gallino and Moreno (2014) empirically explore the impact of offering BOPS service on a retailer's online and physical store sales and show that BOPS increases store sales and reduces online sales. Note that these papers identify channel switching behavior as a result of providing availability information to online customers. With STS service, however, such information is not available to online customers. Hence, we contribute to the literature by exploring how online and BM customers respond to channel integration via STS service wherein store product availability information is not provided.

The third stream focuses on consumer returns which are another inseparable aspect of retailing and reached a total volume of \$284 billion in 2014 (NRF 2014). In this stream, Wood (2001) examines consumer returns in a remote purchase environment and shows that a lenient return policy increases the probability of an order. De et al. (2013) empirically investigate the impact of implementing certain web technologies on online product

returns and show that zoom technology is associated with fewer returns. Studying consumer returns in a multichannel context, Ofek et al. (2011) show how store assistance and pricing decisions change after introducing the online channel. Gao and Su (2017) analyze three omnichannel information mechanisms—physical showrooms, virtual showrooms, and information availability—and find that virtual showrooms may increase online returns if they lead to excessive customer migration from BM to online channel. Griffis et al. (2012) empirically explore the return behavior of consumers on the Internet and find that prior experience with returning positively affects future repurchase behavior. Rabinovich et al. (2011) explore the virtual assortment offered on the Internet and show that retailers may benefit from increasing their online assortment if they can successfully manage the increase in product returns arising from execution errors and product mismatches.

Given that consumer shopping habits have evolved to include multiple channels and different tasks or activities in each one of those channels, Peterson and Kumar (2009) examine the impact of cross-channel purchases on product returns and find that when customers buy familiar products from new channels, they return fewer items whereas when they buy unfamiliar products from new channels, they return more. The authors also show that the number of product returns is positively associated with a customer’s future purchase behavior. In a related work, Bower and Maxham-III (2012) compare fee-based and free return shipping alternatives in online retailing and show that customers who pay for return shipping decrease their future spending while customers who enjoy free return shipping increase their future purchase behavior. Ertekin et al. (2016) study the relationship between product returns and the in-store customer shopping experience. Combining transaction data with customer survey responses, the authors show that retailers can mitigate the impact of unpleasant store ambience on returns by improving the competence levels of sales associates. We, too, predicate our analysis on customer transaction data. Unlike the existing contributions in the literature, however, we investigate the change in return behavior that arises from introducing a free shipping option on purchases that simultaneously reduces the hassles associated with returning online purchases. As we will discuss in in §3.1, implementing STS is tantamount to increasing return policy leniency, which in turn provides us with an opportunity to investigate the effect that leniency has on return

behavior.

3.3 Theory Building

In this section, we draw upon theory to develop a set of hypotheses to direct our research. To begin, we explain how STS is expected to affect the online channel by using arguments associated with cost savings, risk reduction, and perceived leniency of a return policy with STS implementation. Next, we develop how STS should have a positive impact on the BM channel sales because of the expected increase in the physical store traffic arising from store pick-ups. Finally, we express the convenience of returning an online purchase to a physical store from a customer's perspective and develop arguments about how STS should increase consumer returns of online purchases to physical stores.

3.3.1 Impact of STS on the Online Channel

To investigate how STS affects online sales, we follow and extend the theory of buyer behavior (Howard and Sheth 1969) to the online context to argue that a high shipping fee is one of the major inhibitors to online purchasing. For example, Lewis et al. (2006) and Gumus et al. (2013) show that compared to shopping in a physical store, there exist additional surcharges in online shopping, such as shipping and handling fees, which have a significant influence on the purchase intentions of customers. Similarly, Lewis (2006) empirically shows that shipping fees reduce online customer traffic and order sizes. According to some surveys, one of the major reasons why most customers abandon online shopping carts is due to high shipping fees (Ernst and Young 2001, UPS 2015). Consistent with Bower and Maxham-III (2012), 71 percent of the consumers in the Earnst and Young survey consider that free shipping and delivery is a top reason for their brand loyalty intentions (Ernst and Young 2015). In another study, about 90 percent of consumers report that free shipping would make them shop online more frequently (Walker Sands 2016). Hence, consistent with Kukar-Kinney and Close (2010), who suggest retailers offer free shipping options to reduce online cart abandonment, we hypothesize that implementing STS will increase online sales due to cost savings arising from free shipping.

From a consumer's perspective, online shopping involves risks that include product performance risk, financial risk, and time/inconvenience risk (Danaher et al. 2003, Peck and

Childers 2003, Griffis et al. 2012). The financial risk denotes concerns and additional expenses about returning an online purchase (Hassan et al. 2006) while the time/inconvenience risk arises from the delivery process (Forsythe et al. 2006). Ofek et al. (2011) note that the likelihood of a product mismatch for a purchase is higher in an online channel than in a BM channel. The authors also note that in the case of a mismatch, consumers incur additional costs to return merchandise. Given that some consumers may see online shopping as a risky decision due to the difficulty of returns, it is reasonable to expect that risk-averse customers are less likely to shop online (Forman et al. 2009). Furthermore, according to the theory of risk in consumer choice (Taylor 1974), any uncertainty about the transaction will act as a risk for the consumer, which will in turn affect the purchase decision. There are two components of the theory, which include uncertainty about the outcome and uncertainty about the consequences. Uncertainty about the outcome may be considered as the ambiguity about the outcome (i.e. lack of touch and feel experience) of a transaction while uncertainty about the consequences may be considered as the potential damage that is incurred by the customer in case the consequences are not favorable.

Once STS is implemented, however, the risks arising from the difficulty of returning an item decreases since customers may immediately make a hassle-free return at the time they pick-up their merchandise at stores. Hence, we propose that STS reduces the uncertainty about the consequences for consumers, given the confidence and the comfort that they can return an item during the pick-up process. Subsequently, we expect that the reduction in overall purchase risk will result in increased online shopping. It is also true that the perceived risk arising from a return policy is greater for high-value items, since consumers pay more for these items and bear a higher risk of returning, as it has been clearly demonstrated in the literature that higher-value items are more likely to be returned (Peterson and Kumar 2009, Anderson et al. 2009). Moreover, the retailer that we study requires a signature for the delivery of high-value ($>$ \$100) products, which increases inconvenience risk because the customer must wait at home for delivery. Implementing STS alleviates this inconvenience by allowing customers to pick-up merchandise at their own discretion. Hence, we expect that any reduction in perceived risk will impact high-value items more than low-value items.

- **Hypothesis-1a (H1A):** Implementing STS will increase online sales.
- **Hypothesis-1b (H1B):** The increase in online sales due to STS will be greater for high-value products relative to low-value products.

Another element of omnichannel retailing is the flexibility offered by allowing cross-channel returns through services like buy-online-return-to-store (RTS). According to a recent survey, 65 percent of consumers consider the ability to return an online purchase to a store as a positive feature of a hassle-free return experience (UPS 2015). Although customers of the retailer that we study had the RTS option before STS was implemented, we believe that STS also influences RTS behavior among online customers. According to transaction cost economics (TCE) theory, buyers and sellers incur costs during marketplace transactions (Williamson 1975). In an online shopping environment TCE costs include price-type costs (travel costs, credit charges etc.), time-type costs (overall shopping time, delivery time etc.), and psychological-type costs (inconvenience, perceived ease of use, frustration etc.) (Chircu and Mahajan 2006).

Note that when STS customers pick up their merchandise in stores, they can immediately perform a physical test and resolve any uncertainty arising from the lack of touch and feel experience with online shopping. Upon inspection, if customers find that an item does not match their expectations, they can immediately make a simple, easy, and costless return. In effect, STS increases the perceived leniency of a return policy because customers do not need to repack the item, locate the receipt, create a return label for shipping, ship it to the online center or drive to the nearest store. Those hassles are eliminated for the customer. As a result of the perceived leniency of a return policy arising from STS, customers will feel more comfortable about the return process, which in turn will reduce price-type and psychological-type costs. Therefore, consistent with TCE theory, we propose that RTS incidents will increase after STS is implemented. Furthermore, since RTS incidents and online channel sales are both expected to increase, we also expect that overall consumer returns for online purchases will increase. Similarly, because returning an online item to a store can take place during the pick-up process and customers consider this experience hassle-free and more convenient, we also expect that time-to-return (TTR) for online purchases will decrease after STS is implemented.

- **Hypothesis-2a (H2A):** Implementing STS will increase RTS incidents.
- **Hypothesis-2b (H2B):** Implementing STS will increase returns of online purchases.
- **Hypothesis-2c (H2C):** Implementing STS will decrease TTR for online purchases.

3.3.2 *Impact of STS on the BM Channel*

To investigate how STS affects BM sales, we employ the production function theory, which explains the transformation process of inputs into outputs and expresses the maximum attainable amount of output with a given set of inputs (Aigner et al. 1977). Extending the theory to physical stores, we consider that store traffic is the input while store sales are the outputs. Perdikaki et al. (2012) note that increasing store traffic and converting the increased traffic into new sales are vital to the retail industry. Previous empirical studies clearly show that sales generated in stores (sales response function) depend on both store traffic and labor (Lam et al. 1998, Mani et al. 2015, Chuang et al. 2016). By definition of STS, online customers will visit physical stores to pick up their merchandise. Store traffic is critical for generating retail sales from several perspectives including impulse buying (unplanned purchasing) and directed sales initiatives. Impulse purchases account for between 27%-62% percent of total sales at department stores (Wirtz 2010, Bae et al. 2011), while 47 percent of BM channel customers engage in impulse purchases (eMarketer 2015). Similarly, customers that engage in BOPS or STS services end up spending more on additional items while they are visiting physical stores to pick up their online merchandise (eMarketer 2015). According to the STS operating procedures of the retailer that we study, sales associates are instructed to try to sell additional merchandise and warranty services at the time of pick-up. Thus, we expect sales associates will convert increased store traffic into additional revenue by cross-selling additional products and services to STS customers.

- **Hypothesis-3 (H3):** Implementing STS will increase BM channel sales.

We expect BM channel sales will also increase due to an increase in RTS incidents. Note that one of the main objectives of STS is to increase BM store traffic by bringing online customers into physical stores and thereby to sell additional products and warranty services to those customers. Interestingly, the same phenomenon also applies to consumer

returns. If a return takes place at one of the physical stores, then the retailer acquires another opportunity to sell additional products and warranty services to those customers. Given H2A, we expect store sales to increase. During a return, the operating procedures of the retailer that we study instruct sales associates to try to convert returns into exchanges or purchases of other items. Applying production function theory to store traffic that arises from returns of online purchases to physical stores, we expect that STS implementation will not only increase sales due to increased store traffic at the time of pick-up, but also due to increased store traffic at the time of return.

- **Hypothesis-4 (H4):** Implementing STS will increase BM channels sales indirectly through an increase in RTS incidents.

3.4 Analyzing the Impact of STS

A simple approach to investigate the impact of STS would examine the differences between the variables of interest before and after STS is introduced. However, this approach may not generate accurate results, since other factors may also have influenced the changes. For example, changing trends in the variables of interest (e.g. increasing online sales or decreasing store sales) or a contemporaneous shock to the economy may drive such changes. To account for such challenges and to help protect against problems associated with endogeneity in general, we employ a DID approach to answer our research questions. Note that ignoring endogeneity may lead to biased inferences (Ketoviki and Guide 2015). DID is used to estimate the impact of policy interventions and requires two separate subpopulations: treatment and control groups (Donald and Lang 2007). Furthermore, in DID, the change in the treatment group, which is subject to intervention, is adjusted by the change in the control group, which is not affected by the intervention. With both groups, this approach accommodates trends in data that may otherwise confound the analysis (Athey and Imbens 2006). Once the treatment and control groups are identified, one can apply DID and measure the impact of the treatment by comparing the differences between the treatment and control groups both before and after STS is implemented. DID has been the preferred methodology to evaluate a policy change when the data set is structured as a quasi-experiment and where control and treatment groups can be clearly identified. We

note too that DID methodology has been previously used in the operations management literature (e.g., Caro and Gallien 2010, Gallino and Moreno 2014, Song et al. 2015).

For this study, we collected data from a national jewelry retailer that implemented STS. The retailer offers a wide variety of brand-name jewelry, watches, accessories, and service plans to its customers and has more than 1,000 BM stores in the U.S. and Canada. In addition to BM stores, the retailer also operates online channels. Our data set includes all purchase and return transactions for customers at both online and BM channels from from 01 August 2009 to 31 July 2013, which extends four fiscal years. We note that the retailer we study operates several different brands that include flagship, secondary, and outlet stores in the U.S. To simplify our analysis, we focus our attention on the flagship brand, which constitutes about 70% of stores and 73% of sales in the U.S. We do however provide additional analyses on non-flagship brands in the appendix to further validate our findings.

The first STS transaction took place on 01 August 2011. Apparently, STS was first introduced in California prior to a national rollout as evidenced by only 535 STS transactions in August 2011 with nearly 90% of them from California. It is not until September 2011 that we observe a meaningful number of STS transactions (3,629 STS transactions) indicative of a nationwide rollout of the service. Hence, we use September 2011 as our start date for the STS service. Nevertheless, we have done an analysis using August 2011 as the start date as well and the results are consistent with what we report here. With September 2011 as our start date, we use data one year prior and one year after September 2011 to evaluate the impact of STS on customer behavior and retail operations (from September 2010 to September 2012). Consistent with Song et al. (2015), we consider that customers need a warm-up (acclimation) period to be familiarized with the new service. Therefore, we specify September 2011 as the warm-up period and do not use the data for this month in our analyses.

Before STS was implemented, the retailer offered its customers different fee-based shipping options. After STS, customers have the option to select between a free ship-to-store option and the same fee-based shipping alternatives previously offered. If customers choose STS, their orders are shipped from a central warehouse to their preferred store location

within three business days.

We understand that it is typical to organize and present research in a sequence that first describes the data and defines the variables of interest, second introduces and defines all of the requisite models used for estimation, and third, presents all of the estimation results and statistical tests. That, however, is not the approach we take here. Our research addresses two different populations that involve models with different units of analysis and different control variables. There are also multiple models with different dependent variables. Therefore, we feel that discussing all the data, then all the models, and finally all of the results, would be a disservice to the reader. Instead, we choose to separate our analysis for the online and BM channels and believe doing so will simplify the exposition and enable a more focused narrative of the research. Hence, for each channel, we will describe the associated data set, models, and results separately. Furthermore, within our analysis of the online channel, we separate our discussion on the impact of STS on sales from our discussion on the impact of STS on returns. In the rest of this section, we first report our analysis on the impact of STS with respect to the online channel in §4.1 and then with respect to the BM channel in §4.2.

3.4.1 Analysis of the Online Channel

Our main objective is to understand how STS impacts sales and returns in the retailer’s online channel. To do so, we will need to establish control and treatment groups for our DID analysis. A natural way to define these groups is by taking into account the distance between online customers and their closest stores. Basically, STS is only viable for a customer if a store is nearby since customers will need to travel to the store to pickup their purchase. Hence, the treatment group consists of geographic areas with stores that are in close proximity. Similarly, the control group corresponds to geographic areas that are not in close proximity to stores and therefore, are not affected by STS. A convenient way to establish these groups is to use a designated-market-area (DMA)¹ as the unit of analysis. This approach is also consistent with Gallino and Moreno (2014), which investigates BOPS.

¹A DMA is a group of counties that form an exclusive geographic area in which the home market television stations hold a dominance of total hours viewed. There are 210 DMA regions, covering the entire continental United States, Hawaii, and parts of Alaska. The DMA boundaries and DMA data are owned solely and exclusively by the Nielsen Company (Nielsen Media Research 2013).

There are 210 DMAs. We choose 50 miles as the cut-off threshold for classifying DMAs as either treatment or control. While 50 miles is somewhat arbitrary, it is large enough to make the STS inconvenient and unattractive to customers. Hence, a DMA is in the treatment group if the median distance between customers and their closest stores in the DMA is less than 50 miles, otherwise the DMA is in the control group. Using this approach, we have 185 DMAs in the treatment group and 25 DMAs in the control group. For robustness analysis, we investigate different distances (30, 35, 40, 45 or 60 miles) and show that there are no significant differences at these distances. We also create treatment and control groups using another approach and our findings remain consistent, as we demonstrate in the Appendix.

3.4.1.1 Variables and Summary Statistics

To investigate the impact of STS on sales and returns, we use total dollar sales, total dollar returns, total number of purchase transactions, total number of return transactions, and TTR for each month and DMA in the U.S. We also include two DMA specific control variables that may influence the dependent variables in our models. Unemployment rate (UNEMPLOYMENT) indicates the fraction of eligible population that is unemployed in each DMA and controls for economic differences between DMAs. Total retail sales (RETAIL SALES) denotes the total amount of retail sales in each DMA and controls for relative sizes of DMAs. The two DMA level controls are taken from annual reports published by Nielsen Media Research. Although we have access to other potential control variables such as total adult population, average income, and buying power index, these variables are highly correlated with UNEMPLOYMENT and RETAIL SALES. Hence, we do not include them in our models. Table 3.2 reports the summary statistics (mean and standard deviation) for key variables of interest for all DMAs both before and after the STS implementation.

We also employ monthly indicator variables as seasonal controls. These variables include whether a transaction occurred during the holiday season (HOLIDAY) or during the summer discount period (SUMMER). HOLIDAY spans the entire month of December. SUMMER covers the months of June and July, which correspond to the time-period for summer clearance events. In addition, the transaction data also provides an opportunity to

Table 3.2: Summary Statistics for the Online Channel by DMA

Time-Variant Variables	Treatment (affected DMAs)				Control (Unaffected DMAs)			
	pre-STS		post-STS		pre-STS		post-STS	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD
ONLINE SALES (000)	30.84	60.89	35.02	68.88	4.68	6.33	5.79	7.41
ONLINE RETURNS (000)	4.79	9.35	5.59	11.47	0.72	1.21	0.85	1.30
NUMBER OF PURCHASES	176.11	374.54	193.66	415.07	23.62	33.02	27.79	39.23
NUMBER OF RETURNS	19.15	39.46	20.94	46.09	2.48	3.21	2.78	3.80
TIME-TO-RETURN (days)	25.40	20.76	27.62	17.00	24.11	16.76	31.29	25.40
Time-Invariant Variables	Mean		SD		Mean		SD	
UNEMPLOYMENT (%)	5.01		1.82		4.59		1.36	
RETAIL SALES (000)	28,595.37		40,084.17		5,818.83		4,673.34	

observe whether a transaction occurred with a discount offer or promotional event. These offers include marketing coupons, store coupons, military discounts, gift certificates, and promotional events, among others. Using this information, we employ PROMOTION at DMA d during month t to denote the fraction of purchases that take place with a discount offer. This variable helps control for differences in the retailer’s marketing efforts across DMAs. We report the correlations between these variables in Table 3.3.

Table 3.3: Correlations of Variables for the Online Channel

	1	2	3	4	5	6	7	8
1. TIME-TO-RETURN	1.00							
2. ONLINE SALES	0.13	1.00						
3. ONLINE RETURNS	0.11	0.86	1.00					
4. HOLIDAY	0.11	0.28	0.18	1.00				
5. UNEMPLOYMENT	-0.05	-0.03	-0.03	0.00 [†]	1.00			
6. RETAIL SALES	0.06	0.68	0.62	-0.01 [†]	-0.06	1.00		
7. SUMMER	-0.17	-0.09	-0.04	-0.14	0.00 [†]	0.01 [†]	1.00	
8. PROMOTION	0.09	0.21	0.12	0.36	0.00 [†]	0.01 [†]	-0.22	1.00

Note: Except for cells with †, all coefficients are significant at $p < 0.05$ level.

Note that none of the correlations between independent variables have levels close to or higher than 0.80, which minimizes concerns about multicollinearity (Song et al. 2015). We also check for multicollinearity by computing variance inflation factors (VIF). Results show that the largest VIF is 5.19 and the mean VIF is 2.10. Looking solely at the suggested cut-off level of ten (Wooldridge 2012), we do not expect multicollinearity to be an issue. Even so, blindly using a pure cut-off level without further consideration of the sample size and

context of the data analysis is not recommended (Ketoviki and Guide 2015). Considering all elements, however, we feel comfortable dismissing multicollinearity as a concern.

Our explanatory variables include indicator variables that denote whether DMA d is within a store’s area of influence ($GROUP_d$) and if the observation belongs to the time period after STS implementation ($POLICY_t$). These indicator variables are given by

$$GROUP_d = \begin{cases} 1 & \text{if median customer distance to closest BM stores in } DMA_d < 50 \text{ miles} \\ 0 & \text{otherwise} \end{cases}$$

$$POLICY_t = \begin{cases} 1 & \text{if } t > \text{September 2011} \\ 0 & \text{otherwise} \end{cases}$$

We capture the adoption of STS with a binary interaction term, $GROUP_d * POLICY_t$, which is equal to one for the affected DMAs after the implementation of STS and is zero otherwise. The estimation of a coefficient for this variable measures the impact of STS on the dependent variable in our models. Hence, $GROUP_d * POLICY_t$, is the key variable in our models used to test hypotheses.

One potential concern is that store openings and closings might affect the median distance of customers to the closest stores within a DMA. First off, we note that there are no store openings or closings in the control group DMAs. As for the treatment group DMAs, we calculate the median distance of customers to all of the stores that are open by month and by DMA. We find there is no treatment DMA in which the median distance changes a DMA’s classification between control group and treatment group. In effect, store openings and closings have no affect on the designation of treatment versus control groups in the data set.

3.4.1.2 Models, Estimation, and Results for Online Sales

To examine H1A, we use the following model specification

$$\begin{aligned} \log(ONLINE SALES_{dt}) = & \mu_d + \alpha_1 GROUP_d + \alpha_2 POLICY_t + \alpha_3 GROUP_d * POLICY_t \\ & + \alpha_m CONTROLS_{m dt} + \epsilon_{dt} \end{aligned} \tag{3.1}$$

where the dependent variable denotes the log of total online product sales at DMA d during month t . We log transform our dependent variables in this section. $CONTROLS_{mdt}$ denotes the vector of control variables including HOLIDAY, SUMMER, PROMOTION, RETAIL SALES, and UNEMPLOYMENT while α_m is a vector of coefficients that correspond to control variables. Note that m represents the size of the vector for control variables.

Although our DMA level controls are time-invariant, we consider that RETAIL SALES and UNEMPLOYMENT can explain cross-DMA variation in dependent variables. Hence, we use a random effects models for estimation. We also conduct a Hausman test, which rejects the fixed-effects model in favor of the random-effects model ($\chi^2 = 2.23, p > 0.05$). Nonetheless, for robustness, we examine fixed-effects models in the Appendix and find that our results are consistent across both types of models.

To investigate the impact of STS on sales of high-value and low-value online products, we use \$98.69 as a threshold to create the two groups. This value represents the median for online sales and it is also close to what the retailer considers to be the threshold for high-value items (\$100) as indicated by their shipping policy. To test H1B, we apply equation 3.1 separately to both the high-value sales group and the low-value sales group.

Our main results are reported in Table 3.4. Each column (separated by vertical lines) in Table 3.4 represents a test of the hypothesis specified in the second to last row of the table. The first row of each column identifies the dependent variable for the corresponding regression model. For each column, we report the results for the variable of interest ($GROUP_d * POLICY_t$) in the fourth row. Note that the number of observations, N , is different for each column. This arises because there may be no high/low-value product purchases for a DMA in a specific month, which affects the number of observations for each corresponding model.

The results for H1A using the estimation of equation 3.1 are reported in the second column of Table 3.4. We observe that after STS implementation, there is a negative and significant effect ($\alpha_3 = -0.14, p < 0.001$) on the retailer's online sales in affected DMAs ($GROUP_d * POLICY_t == 1$) relative to those DMAs that are not within the influence area of a physical store ($GROUP_d * POLICY_t == 0$). This result shows that implementing

Table 3.4: Impact of STS on Online Channel Sales

Variables	ONLINE SALES	HIGH SALES	LOW SALES
GROUP	0.45*** (0.084)	0.40*** (0.082)	0.47*** (0.085)
POLICY	0.24*** (0.036)	0.23*** (0.038)	0.12 ** (0.041)
GROUP*POLICY	-0.14*** (0.038)	-0.15*** (0.040)	-0.02 (0.044)
HOLIDAY	1.14*** (0.023)	1.13*** (0.025)	1.38*** (0.024)
SUMMER	-0.22*** (0.017)	-0.20*** (0.018)	-0.37*** (0.018)
PROMOTION	1.06*** (0.059)	1.01*** (0.057)	0.74*** (0.047)
RETAIL SALES	0.99*** (0.024)	0.98*** (0.023)	1.00*** (0.023)
UNEMPLOYMENT	0.02 (0.014)	0.02 (0.013)	0.01 (0.013)
N	5,024	5,009	4,966
R^2	0.56	0.53	0.60
HYPOTHESIS	H1A	H1B	H1B
SUPPORT	No	No	No

Note: Standard errors are reported in parentheses.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

STS reduces online channel sales. Hence, H1A is not supported. While DID methodology is intended to account for potential confounding due to endogeneity, a remaining concern for this analysis is the potential existence of different trends for the control and treatment groups before STS is implemented. To address this issue, we conduct a robustness analysis in the Appendix. The results support the validity of our findings.

The results for H1B are reported in the third and fourth columns of Table 3.4. We find that the effect of STS on the retailer's online sales of high-value products in affected DMAs is negative and significant ($\alpha_3 = -0.15$, $p < 0.001$) relative to DMAs that are not affected. Our results also show that STS implementation does not have any impact ($\alpha_3 = -0.02$, $p > 0.05$) on the retailer's online sales of low-value products in affected DMAs relative to unaffected DMAs. Hence, we do not have any support for H1B.

It is surprising to find that our first two main hypotheses are not supported since they are firmly grounded in theory. Clearly, there is something unexplained and unaccounted for going on in the online channel, which leads us to investigate further in §3.5. For now, we proceed to look at the impact of STS on consumer returns.

3.4.1.3 Models, Estimation, and Results for Online Returns

Here, we analyze the impact of STS on product returns. We first introduce models to examine hypotheses related to online returns (H2B) and TTR (H2C). Subsequently, we introduce our model to evaluate online product returns that are returned to stores (H2A).

We present in this order since the model for H2A adds a complication not present in the other two models.

For H2B, which describes the relationship between STS implementation and online product returns, we use the following model specification

$$\begin{aligned} \log(\text{ONLINE RETURNS}_{dt}) = & \mu_d + \beta_1 \text{GROUP}_d + \beta_2 \text{POLICY}_t + \beta_3 \text{GROUP}_d * \text{POLICY}_t \\ & + \beta_4 \log(\text{ONLINE SALES}_{dt}) + \beta_m \text{CONTROLS}_{mdt} + \epsilon_{dt} \end{aligned} \quad (3.2)$$

where our dependent variable represents the log of online product returns at DMA d during month t . We also include $\log(\text{ONLINE SALES}_{dt})$ as a control variable since sales influence the amount of returns.

For H2C, which describes the relationship between STS and TTR, we use the following model ² specification

$$\begin{aligned} \log(\text{TTR}_{dt}) = & \mu_d + \beta_1 \text{GROUP}_d + \beta_2 \text{POLICY}_t + \beta_3 \text{GROUP}_d * \text{POLICY}_t \\ & + \beta_m * \text{CONTROLS}_{mdt} + \epsilon_{dt} \end{aligned} \quad (3.3)$$

where our dependent variable represents the log of average TTR at DMA d during month t . Because there are observations with average TTR of zero days (same day return), we perform a common transformation by adding one more day for each observation to avoid undefined values such as $\log(0)$.

We next analyze the impact of STS on online purchases that are returned to stores (H2A). We find over 60,000 online transactions in our data that have been returned to a BM store. Because the DID analysis requires a large number of observations, we use state-month as our unit of analysis in this model, rather than DMA-month. Since we have 210 DMAs, DID methodology will have, on average, 12 purchase transaction per month for each DMA ($60,000/(210 * 24) = 11.9$). With a state-level analysis, however, our model will

²Technically, the coefficients in equation 3.3 should be different from those in equation 3.2 (and 3.4) because they are coefficients in different equations. However, we believe this would unnecessarily complicate the formulations because we hardly ever refer to the coefficients. Furthermore, when we do refer to them, we make the context very clear. To be rigorous, we would either need an additional subscript for the coefficients or different symbols for each of the equations.

have on average 50 purchase transaction per month for each state ($60,000/(50 * 24) = 50$) and will provide enough statistical power to detect differences if they exist. Therefore, we use state-level analysis. A difficulty here is that state populations are more densely located in large metropolitan areas, precisely where most stores are also located. As a result, our ability to separate out populations that are unaffected by STS is constrained. If we use 50 miles as our threshold distance for classification of states, as we did for DMAs, we would have only one state in the control group. Instead, we choose 35 miles. Note that choosing a shorter distance threshold provides a more conservative test of hypotheses since the influence of STS diminishes with distance. Hence the shorter the distance, the more one should expect the control group to behave like the treatment group and consequently the more difficult it will be to observe statistically significant differences. With 35 miles, there are 4 states in the control group. We also repeat the same analysis with a threshold distance as short as 30 miles. Our findings remain consistent with those that we report here.

For H2A, which describes the relationship between STS and RTS incidents, we use the following model specification

$$\begin{aligned} \log(CROSS\ RETURNS_{kt}) = & \mu_k + \beta_1 GROUP_k + \beta_2 POLICY_t + \beta_3 GROUP_k * POLICY_t \\ & + \beta_4 \log(ONLINE\ SALES_{kt}) + \beta_m CONTROLS_{mkt} + \epsilon_{kt} \end{aligned} \tag{3.4}$$

where our dependent variable represents the log of online product sales that are returned to a store in state k during month t . As in equation 3.2, we include $\log(ONLINE\ SALES_{kt})$ as a control variable, which allows us to evaluate the effect of STS on consumer returns at DMAs that do not arise from a change in online product sales.

Results are reported in Table 3.5. The results for H2A using the estimation of equation 3.4 are reported in the second column of Table 3.5. We observe the effect of STS on the RTS behavior in the affected states is positive and significant ($\beta_3 = 0.52, p < 0.001$) compared to unaffected states. This finding supports H2A. We find it interesting that RTS incidents increase when actually online sales decrease. We believe this result arises because of a perceived increase in return policy leniency. STS makes returning online purchases

easier for customers. Alternatively, this result may indicate STS in and of itself is simply informing more online customers about stores that are nearby.

Table 3.5: Impact of STS on Online Channel Returns

Variables	CROSS RETURNS		ONLINE RETURNS		TTR	
GROUP	0.20	(0.174)	-0.23***	(0.063)	0.05	(0.053)
POLICY	-0.29	(0.148)	-0.13	(0.071)	0.28***	(0.059)
GROUP*POLICY	0.52***	(0.151)	0.10	(0.074)	-0.16*	(0.061)
ONLINE SALES	1.05***	(0.039)	1.05***	(0.023)	-	-
HOLIDAY	-0.23 **	(0.080)	-0.22***	(0.046)	0.19***	(0.032)
SUMMER	0.05	(0.051)	0.11***	(0.029)	-0.30***	(0.024)
PROMOTION	0.38***	(0.110)	-0.50***	(0.114)	0.14	(0.092)
RETAIL SALES	-	-	0.04	(0.026)	0.09	(0.012)
UNEMPLOYMENT	0.05 **	(0.020)	-0.00	(0.007)	-0.01	(0.006)
<i>N</i>	1,160		4,667		4,667	
<i>R</i> ²	0.53		0.64		0.07	
HYPOTHESIS	H2A		H2B		H2C	
SUPPORT	Yes		No		Yes	

Note: Standard errors are reported in parentheses.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

The results for H2B, using equation 3.2, are reported in the third column of Table 3.5. We observe that the effect of STS on the retailer’s consumer returns in the affected DMAs is not significant ($\beta_3 = 0.10$, $p > 0.05$) compared to DMAs that are not affected. Hence, we do not have any support for H2B. Again, we find this a bit surprising given that RTS incidents are significantly increasing. There are two possible explanations why online returns are not changing after STS implementation. We surmise that either the observed increase in RTS incidents is not measurable, with respect to the totality of returns, since RTS incidents represent a small portion of overall returns, or other types of online returns are decreasing.

The results for H2C, using equation 3.3, are reported in the fourth column of Table 3.5. We observe the effect of STS on TTR in the affected DMAs is negative and significant ($\beta_3 = -0.16$, $p < 0.05$) compared to DMAs that are not affected. Hence, H2C is supported.

3.4.2 Analysis of the Brick-and-Mortar Channel

Next, we investigate the impact of STS on BM stores. We again employ a DID approach, but here the treatment group consists of U.S. stores while the control group consists of

Canadian stores. This convenient classification arises because STS was implemented in the U.S. but not in Canada. A concern might be raised that any observed differences might be explained by cultural or economic differences between the two countries, rather than the impact of STS. To address this concern, we repeat our analysis using a different treatment group from Canada. This alternative treatment group consists of stores that the retailer operates under a different brand name and for which STS was also implemented, but at a date that is a full year later than that was in the U.S. (September 2012). The results from that analysis are reported in the Appendix. Moreover, this second comparison also enables us to check a potential confounding effect arising from the introduction of a new credit card program for the U.S. brand that was introduced concurrently with STS service in August 2011. Since both sets of comparisons lead to the same, consistent results, we find additional support that the change in behavior we report arises from the implementation of STS rather than from any sort of economic, cultural, or other market differences between the treatment and control groups.

Note that there are 18 store openings and 61 store closings throughout the period of analysis that could potentially distort our results. To alleviate this concern, we only include stores that are open both pre-STS and post-STS. Doing so leaves 602 stores from the U.S. and 51 stores from Canada.

3.4.2.1 Variables and Summary Statistics

To investigate the impact of STS on BM sales and returns, we use total dollar sales, total dollar returns, total number of purchase transactions, and total number of return transactions for each month and store in the U.S. and Canada. Table 3.6 reports the summary statistics (mean and standard deviation) for these variables of interest.

We also include store level and state/province level control variables into our analysis. We control for store characteristics using six variables. Number of pads (PAD COUNT) and number of cases (CASE COUNT) are inventory display devices used by stores. Inventory turnover (INVENTORY TURNS) denotes the number of times inventory is sold and replaced in a year for each store. Inventory volume group (VOLUME GROUP) is an ordinal variable that the retailer uses to classify its stores based on the annual sales revenue (e.g. \$1-\$1.5 million corresponds to B). VOLUME GROUP has four levels, which include

Table 3.6: Summary Statistics for the BM Channel by Store

Time-Variant Variables	Treatment (U.S. stores)				Control (Canada stores)			
	pre-STS		post-STS		pre-STS		post-STS	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD
STORE SALES (000)	113.58	88.04	127.07	98.52	102.75	72.96	104.32	74.75
STORE RETURNS (000)	20.60	19.09	22.67	20.42	16.62	13.58	17.46	14.61
NUMBER OF PURCHASES	277.59	231.95	310.28	266.83	368.79	251.32	389.46	299.35
NUMBER OF RETURNS	34.36	26.82	38.35	31.72	38.57	27.31	39.55	30.35
UNEMPLOYMENT (%)	8.97	1.95	8.08	1.73	7.72	1.25	7.31	1.39
Time-Invariant Variables	Mean		SD		Mean		SD	
CASE COUNT	33.02		4.96		30.14		4.38	
PAD COUNT	87.16		10.77		87.39		11.57	
STORE SIZE (sqft)	1,682.53		418.19		1,544.94		228.71	
INVENTORY TURNS	0.90		0.15		0.83		0.16	

ordinal values such as A+, B+, B, and C. Store size (STORE SIZE) denotes the physical square footage of each store. Mall grade (MALL GRADE) is a categorical variable used by the retailer to classify the location of stores based on a mall's total sales area, number of stores, customer traffic, and annual sales revenue. MALL GRADE has nine levels, which include community centers, regional centers, power centers, lifestyle centers, metro centers, village locations, and a set of ordinal values such as A+, B, C, and F. We obtained MALL GRADE information both from the retailer that we study and from the Directory of Major Malls.

Finally, we include an economic control variable, UNEMPLOYMENT, which indicates the monthly unemployment rate for U.S. states and Canada provinces. We obtained UNEMPLOYMENT information from the U.S. Bureau of Labor Statistics and Canada Census. Just as we do for the online channel analysis, we also employ monthly indicator variables, which include HOLIDAY, SUMMER, and PROMOTION. We report the correlations between variables in Table 3.7. As we did for the online channel, we check for multicollinearity and remove PAD COUNT from our analyses since it is highly correlated with both CASE COUNT and STORE SIZE. For the remaining variables, we find that multicollinearity is not a likely concern for our analysis of the BM channel.

Table 3.7: Correlations of Variables for the BM Channel

	1	2	3	4	5	6	7	8	9	10
1. STORE SALES	1.00									
2. STORE RETURNS	0.86	1.00								
3. HOLIDAY	0.58	0.38	1.00							
4. CASE COUNT	0.12	0.13	0.00 [†]	1.00						
5. PAD COUNT	0.23	0.25	0.00 [†]	0.60	1.00					
6. STORE SIZE	0.20	0.22	0.00 [†]	0.24	0.60	1.00				
7. INVENTORY TURNS	0.37	0.32	0.00 [†]	0.02	0.13	0.10	1.00			
8. UNEMPLOYMENT	-0.03	0.03	0.03	0.09	0.10	0.10	-0.10	1.00		
9. SUMMER	-0.13	-0.10	-0.13	0.00 [†]	0.00 [†]	0.00 [†]	0.00 [†]	-0.04	1.00	
10.PROMOTION	0.14	0.13	0.16	0.07	0.00 [†]	0.05	0.06	0.21	-0.14	1.00

Note: Except for cells with †, all coefficients are significant at $p < 0.05$ level.

3.4.2.2 Models, Estimation, and Results for BM Sales

To examine H3 and evaluate the impact of STS on store sales, we use the following model specification

$$\begin{aligned} \log(STORE\ SALES_{jt}) = & \mu_j + \delta_1 GROUP_j + \delta_2 POLICY_t + \delta_3 GROUP_j * POLICY_t \\ & + \delta_s CONTROLS_{s jt} + \epsilon_{jt} \end{aligned} \quad (3.5)$$

where our dependent variable represents the log of total sales at store j during month t . The explanatory variables include indicator variables that denote if store j is located in the U.S. ($GROUP_j$), if the observation belongs to the time period after the STS implementation ($POLICY_t$), and an interaction term between these indicator variables. We capture the adoption of STS with a binary interaction term ($GROUP_j * POLICY_t$) which is equal to one for the U.S. stores after the implementation of STS and zero otherwise. $CONTROLS_{s jt}$ denotes the vector of control variables while δ_s is a vector of coefficients that correspond to control variables. Note that s represents the size of the vector for control variables.

Although store level control variables are time-invariant, these variables may explain cross-store variation in the dependent variables. Hence, we use random effects models for estimation. Note that the Hausman test rejects the fixed-effects model in favor of the random-effects model ($\chi^2 = 10.67, p > 0.05$). In the Appendix, we conduct fixed-effects models for robustness and show that our findings are consistent across both types of models.

The results for H3, using equation 3.5, are reported in the second column of Table 3.8

that is organized and presented the same as Table 3.4. We find that the impact of STS on the retailer's post-STS sales in the U.S. stores ($GROUP_j * POLICY_t == 1$) is positive and significant ($\delta_3 = 0.15$, $p < 0.001$) relative to Canadian stores. This finding shows that implementing STS increases store sales. Hence, H3 is supported.

Table 3.8: Impact of STS on BM Channel

Variables	STORE SALES	
GROUP	-0.17***	(0.031)
POLICY	0.02	(0.016)
GROUP*POLICY	0.15***	(0.017)
HOLIDAY	1.05***	(0.008)
SUMMER	-0.09***	(0.006)
PROMOTION	0.83***	(0.039)
MALL GR. A+	0.00	(0.036)
MALL GR. B	-0.06*	(0.022)
MALL GR. C	-0.12***	(0.022)
MALL GR. F	-0.20***	(0.029)
MALL GR.-COM	-0.24*	(0.095)
MALL GR.-LIF	-0.16***	(0.045)
MALL GR.-MET	0.11	(0.108)
MALL GR.-POW	-0.18	(0.131)
MALL GR.-VIL	-0.12	(0.096)
VOL. GR. A+	0.24***	(0.049)
VOL. GR. B	-0.64***	(0.028)
VOL. GR. B+	-0.34***	(0.029)
VOL. GR. C	-0.98***	(0.030)
STORE SIZE	0.00*	(0.000)
CASE COUNT	0.00 * *	(0.002)
INVEN. TURNS	0.53***	(0.054)
UNEMPLOYMENT	0.00	(0.003)
<i>N</i>	15,672	
<i>R</i> ²	0.61	
HYPOTHESIS	H3	
SUPPORT	YES	

Note: Standard errors are reported in parentheses.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

We now proceed to investigate sales generated after RTS incidents. Given the results of our test for H2A, which shows that RTS incidents increase, to demonstrate support for H4, all we need to show is that RTS incidents lead to new purchases in stores. Looking into our data set, we find about 17,000 instances in which there are one or more store purchase transaction on the same day as when an RTS incident occurs. This finding shows that 28%

of all RTS incidents are converted into new sales, which corresponds to \$7.17 million in additional sales revenue. Hence, H4 is supported.

So far our research has demonstrated a link between the implementation of STS and an increase in BM channel sales, but the explanation for it remains elusive. With one channel demonstrating an increase in sales and another demonstrating a decrease, there appears to be a channel shift in customer purchase behavior through the implementation of STS. This finding is unexpected. The production function theory indicates that the increase in BM sales should be driven by an increase in store traffic that arises from customer pickups and returns of online purchases. Yet, that cannot be the explanation since online sales actually decrease. Moreover, our hypothesis (H1B) that the increase in online sales should be greater for high value items than for low-value items is clearly not supported. After implementation of STS, the *decrease* in online sales can mainly be attributed to high-value items. To clarify our understanding of what is happening both within and between channels, we conduct an extended analysis in the next section.

3.5 Extended Analysis

The simple fact that our results do not support our primary theory-driven hypotheses raises a number of fundamental questions we intend to answer in this section. STS is designed to increase online sales. Through that increase, store sales should increase as well. Yet, that is not what we observe. Online sales decrease, although store sales do increase. There must be mechanisms at work here that are not explained by our theories. Does the increase in BM channel sales and the decrease in online sales simply represent a channel shift in buyer behavior? When considering the channels in aggregate, does the retailer observe a net increase or decrease in sales due to STS? What differentiates the customers that end up using STS from those that continue to use home delivery and those that buy in stores? Our analysis here is directed towards answering these and similar questions. First, we dig deeper into the BM channel to better explain the increase in sales that we observe with STS implementation. Then, we perform an aggregate analysis to determine the overall effect of STS on sales. Finally, we conduct a comprehensive cross-channel analysis to gain a better understanding of how customers differentiate between channels.

3.5.1 Digging Deeper into the BM Channel

To begin, we want to clarify our understanding of the change that occurs in the BM channel due to STS implementation. We know, statistically, that online sales of high-value items decrease and low-value items remain unchanged. Can the increase in BM sales be attributed to the decline in the online sale of high-value items? Similarly, we would like to know how BM returns are affected since high-value items are typically more likely to be returned than low-value items (Peterson and Kumar 2009, Anderson et al. 2009).

To proceed with this analysis, we once again employ DID methodology to take a closer look at both sales and returns for the BM channel before and after STS implementation, differentiating between low and high-value items. To be consistent with §3.4.1, we first use \$98.69 as a threshold to create the two groups of items. Subsequently, we also use \$150 since the median of BM channel sales is near \$150 (\$149.99). We note the results are the same for the two approaches. Our dependent variables for the analysis of BM sales are the log of BM channel sales of high- and low-value products at store j during month t . We again use the model specification in equation 3.5 and estimate it separately for both the high-value sales group and the low-value sales group.

Similarly, we also evaluate returns of high-value and low-value items at the BM channel. To do so, we use the following model. Note that we include $STORE SALES_{jt}$ as a control variable.

$$\begin{aligned} \log(RETURNS_{jt}) = & \mu_j + \delta_1 GROUP_d + \delta_2 POLICY_t + \delta_3 GROUP_d * POLICY_t \\ & + \delta_4 \log(STORE SALES_{jt}) + \beta_s CONTROLS_{s jt} + \epsilon_{jt} \end{aligned} \quad (3.6)$$

We report the results of our models in Table 3.9. We find the effect of STS on the retailer's BM channel sales of high-value products in the U.S. stores is positive and significant ($\delta_3 = 0.22$, $p < 0.001$) relative to Canadian stores that are not affected. We also show that STS does not have any statistically significant affect ($\delta_3 = -0.03$, $p > 0.05$) on the retailer's BM channel sales of low-value products in the U.S. stores relative to Canadian stores. These results, in light of what we observe for the online channel, provide strong evidence that customers have switched from the online channel to the BM channel to pur-

chase high-value products, while they have continued using the online channel to purchase low-value products. It is interesting to note that the channel shift for high-value items occurs even though in-store product availability is not provided to online customers and that many of the products offered online are not available in stores.

Table 3.9: Impact of STS on BM Channel Sales and Returns of High- and Low-Value Items

Variables	SALES		RETURNS			
	HIGH	LOW	HIGH	LOW	HIGH	LOW
GROUP	-0.26*** (0.032)	-0.89*** (0.041)	0.13*** (0.034)	0.09* (0.036)		
POLICY	-0.12*** (0.016)	0.16*** (0.026)	0.07 * * (0.025)	0.00 (0.036)		
GROUP*POLICY	0.22*** (0.017)	-0.03 (0.028)	-0.07 * * (0.026)	0.07 (0.038)		
HOLIDAY	1.00*** (0.008)	1.55*** (0.013)	-0.36*** (0.017)	0.11*** (0.025)		
SUMMER	-0.08*** (0.006)	-0.39*** (0.010)	-0.03*** (0.009)	0.04 * * (0.015)		
PROMOTION	1.52*** (0.052)	-0.15*** (0.028)	-0.39*** (0.078)	-0.10* (0.039)		
MALL GR. A+	-0.00 (0.036)	0.02 (0.048)	-0.01 (0.033)	-0.02 (0.035)		
MALL GR. B	-0.06* (0.022)	0.00 (0.030)	-0.02 (0.020)	-0.01 (0.022)		
MALL GR. C	-0.12*** (0.023)	0.05 (0.030)	-0.05* (0.021)	-0.05* (0.022)		
MALL GR. F	-0.21*** (0.030)	0.10* (0.039)	-0.09 * * (0.027)	-0.07* (0.029)		
MALL GR.-COM	-0.25* (0.097)	0.21 (0.128)	-0.12 (0.088)	-0.22* (0.095)		
MALL GR.-LIF	-0.15 * * (0.046)	-0.06 (0.061)	-0.03 (0.042)	-0.04 (0.045)		
MALL GR.-MET	0.13 (0.110)	0.29* (0.146)	-0.03 (0.101)	0.06 (0.106)		
MALL GR.-POW	-0.17 (0.133)	0.02 (0.176)	-0.18 (0.121)	-0.17 (0.135)		
MALL GR.-VIL	-0.15 (0.097)	0.34 * * (0.130)	-0.03 (0.088)	-0.16 (0.093)		
VOL. GR. A+	0.24*** (0.050)	0.24*** (0.066)	0.01 (0.045)	0.08 (0.047)		
VOL. GR. B	-0.64*** (0.028)	-0.36*** (0.038)	0.06* (0.027)	-0.01 (0.028)		
VOL. GR. B+	-0.34*** (0.030)	-0.18*** (0.039)	0.00 (0.027)	-0.01 (0.029)		
VOL. GR. C	-0.98*** (0.031)	-0.56*** (0.041)	0.12*** (0.030)	0.00 (0.030)		
STORE SIZE	0.00 (0.000)	0.00 * * (0.000)	0.00 (0.000)	0.00*** (0.000)		
CASE COUNT	0.00* (0.002)	0.00 (0.002)	-0.00 (0.001)	-0.00 (0.002)		
INVEN. TURNS	0.53*** (0.055)	0.47*** (0.073)	-0.31*** (0.051)	0.01 (0.054)		
UNEMP. RATE	-0.00 (0.003)	0.00 (0.005)	0.03*** (0.004)	0.02*** (0.004)		
STORE SALES	-	-	1.25*** (0.012)	0.90*** (0.011)		
N	15,672	15,672	15,672	15,672		
R ²	0.60	0.54	0.61	0.52		

Note: Standard errors are reported in parentheses.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Furthermore, we also find that the effect of STS on the retailer's BM channel returns of high-value products in the U.S. stores is negative and significant ($\delta_3 = -0.07$, $p < 0.01$) relative to Canadian stores that are not affected. A potential explanation for this finding arises from the channel switching behavior of customers. After STS implementation, when online customers elect the shipping option for STS they may learn that a store is located near them and decide that they prefer to make a purchase in-person. Customers may also decide they would rather not wait the three business-days for store delivery that STS requires. Either way, it is clear that customer switching behavior occurs after they conduct

online research about the products, prices, assortment, and other product characteristics of the item(s) they are interested in purchasing. This behavior typifies what is known as *reverse showrooming* or *webrooming*, in which customers gather information online and once they make their purchase decision, go to a physical store to make the purchase. Since customers are more informed, they make better decisions and consequently are less likely to return purchases. Lending credence to this explanation is that the average purchase price post-STS implementation actually increases in stores. Prior to STS implementation, the average purchase price is \$348.40 and afterwards it is \$352.05. Generally, we observe higher return rates for more expensive items (Peterson and Kumar 2009, Anderson et al. 2009), but here we observe the reverse. More informed customers is the likely explanation.

3.5.2 Aggregate Analysis

Since sales in one channel decline and increase in the other, it remains unclear what happens at the aggregate level. Based on the results in Table 3.4, we know that online channel sales decreased by 14% in affected DMAs after STS implementation, relative to unaffected DMAs. Furthermore, we also know that BM channel sales in the U.S. stores increased by 15% after STS implementation relative to Canadian stores, which were not affected (Table 3.8). Note that online channel sales represent a small portion (7.5%) of total sales. Hence, the increase in BM channel sales dominates, increasing overall sales by about 13%.

Although this approach helps us evaluate the aggregate impact on the retailer's total sales, we also employ a DID approach to conduct a more rigorous investigation. Our unit of analysis for the aggregate impact is state-month. The treatment group includes states that are located in the U.S. and the control group includes provinces in Canada. Our dependent variable is the log of total sales at state s during month t ($TOTAL SALES_{st}$). The model specification for total sales is given by

$$\begin{aligned} \log(TOTAL SALES_{st}) = & \mu_s + \gamma_1 GROUP_s + \gamma_2 POLICY_t + \gamma_3 GROUP_s * POLICY_t \\ & + \gamma_a CONTROLS_{ast} + \epsilon_{st} \end{aligned} \quad (3.7)$$

We observe that after STS implementation, there is a positive and significant effect ($\gamma_3 =$

0.13, $p < 0.001$, $R^2 = 0.73$) on the retailer’s total sales in the U.S. states relative to Canadian provinces. Hence, this result further supports our finding that implementing STS increased the retailer’s total sales. We also conduct a robustness analysis in the Appendix to investigate the potential existence of different preintervention trends for the control and treatment groups and show that they follow the same trend in the pre-STIS period.

3.5.3 Cross-Channel Analysis of STS

To further validate our findings, we conduct cross-channel analyses for average purchase price, return rate, and TTR during both pre- and post-STIS periods. First, we use within-channel paired t-tests. Subsequently, we conduct cross-channel paired t-tests for both pre-STIS and post-STIS periods. Consistent with prior sections, we use 12 months before and 12 months after STIS implementation. For this analysis, we classify STIS transactions separately in order to tease out differences in customer behavior between regular online purchases and STIS purchases. We report results in Table 3.10. Note that the fifth column in Table 3.10 reports the p-value for a paired t-test between online and BM channels while the seventh column reports the p-value for a paired t-test between STIS transactions and the online channel.

Table 3.10: Cross-Channel Analysis

		BM Channel	Online Channel	P-value	STS	P-value
AVG PRICE	Pre-STIS	\$348.40	\$168.10	0.000		
	Post-STIS	\$352.05	\$176.99	0.000	\$166.75	0.000
	P-value	0.000	0.000			
RETURN RATE	Pre-STIS	0.187	0.167	0.038		
	Post-STIS	0.183	0.162	0.004	0.183	0.015
	P-value	0.491	0.585			
TIME-TO-RETURN	Pre-STIS	28.15	24.09	0.003		
	Post-STIS	24.40	26.62	0.016	26.84	0.780
	P-value	0.000	0.058			

We first investigate the average purchase price across channels before and after STIS is implemented. Note we do not have any STIS transactions in the pre-STIS period. We show the average purchase price in both the BM and online channels increases after STIS.

Furthermore, our results also show the average purchase price for STS transactions is lower than for the online channel at large. These findings indicate that after STS is implemented, customers switch from online to the BM channel to purchase high-value items while they switch from home delivery to STS to purchase low-value items.

Next, we analyze whether the return rate changes across channels after STS implementation. We compute return rate as the ratio of total refunds to total sales for each month and channel. We find within-channel return rates do not change from pre-STS to post-STS period. Interestingly, however, the results also show that the online channel return rate is lower than the BM channel return rate, which runs counter to what is generally reported (Rogers and Tibben-Lembke 1999, Dunn 2015, Winkler 2016). This interesting finding arises because customers use the BM channel to purchase higher-valued items, which are more likely to be returned due to financial risks (Peterson and Kumar 2009, Anderson et al. 2009).

Evaluating the average TTR between channels, we find that TTR for the BM channel decreases after STS is implemented. We conjecture that this arises because customers who switch from online to BM channel to purchase high-value items are knowledgeable about the products and product assortment because of their previous online research. Hence their decision of a match/mismatch is quicker than other customers. As for the apparent increase in TTR for online channel returns, we note that it is not statistically significant. Moreover, this result should not be confused with those reported in §4 that indicate TTR for treatment group DMAs is lower than that for control group DMAs.

3.6 Conclusion

In this research, we explore how STS service, that allows customers to buy items online and later pick them up at a nearby store, affects both retail sales and returns. Our results are extensive and somewhat surprising, providing a fairly comprehensive analysis on the impact of STS service on a large, national retailer. We find that STS decreases online sales, increases BM sales, increases cross channel returns, and reduces store returns. The fundamental understanding guiding management thinking about offering STS service is that STS would generate foot traffic at stores in the form of customer pick-ups and therefore provide secondary, additional selling opportunities for store employees. Indeed, our theory

development initially led us to expect the same behavior. Yet, our results disconfirm this view. The main effect of STS is not from generating ancillary store sales opportunities indirectly through online purchases. Rather, STS appears to directly increase store traffic and generate sales because some customers switch from online to BM channel to purchase high-value items. Moreover, STS draws new customers online that end-up making their purchases in stores. The increase in BM sales dwarfs the decrease we observe in online sales.

The direct increase in store sales due to STS is somewhat perplexing. The only direct impact that STS can make should be limited to the online channel, since a major inhibitor to online shopping, shipping fee, is removed via the free ship-to-store option. So, the message must be reaching online customers to use STS service. However, instead of buying online and later picking up their purchases at a store, many customers go directly to the store to buy their items. Interestingly, this channel switching behavior occurs mainly for high-value items. Furthermore, it occurs even though there is no store product availability information provided online and many of the items that are available for purchase online are not even stocked in stores. One of the key propositions offered to retailers through the implementation of STS is that it enables them to augment the physical inventory of their stores with the virtual inventory they provide on the Internet. So, unless a customer calls ahead to the store prior to making a store visit, there is no way to know if the product is available at the store. We agree this is possible, but probably not the likely reason, given the scale of the effect of STS that we observe in practice.

A more rigorous explanation is that the research customers conduct online makes them more comfortable with their own preferences and with the assortment offered by the retailer in general. In addition, since STS requires a visit to a store anyway, it probably makes sense to go directly and avoid the three business day wait for STS delivery. In fact, building on this latter argument is the notion of increasing the immediacy for purchase through successful search. That is, finding items online that they like, customers will then want those items more immediately (Kukar-Kinney and Close 2010). The most immediate way for them to purchase is by going to a store.

Another interesting part of the story is that the increase in BM sales is far more than

a simple channel shift from online to BM. Our results clearly indicate that the increase in BM is far more than the decrease in online. Store customers are also of higher-value than online shoppers and buy more expensive items and more profitable services like product warranties. Consider that the average purchase for a store transaction was \$348.40 prior to STS implementation and for online customers it was less than half that, at \$168.10. Yet the value of store customers after STS implementation actually increases, with an average store purchase of \$352.05. By all appearances, STS service generates foot traffic of high-value store customers, not low-value online customers.

Another outcome of STS service is related to its impact on product returns. We find that product returns of high-value items at BM channel decrease, as does the time-to-return, while overall returns for online purchases remain unchanged. As we discuss in §3.5, the decrease in return rate for BM channel arises because customers who switch from online to BM channel to purchase high-value items have conducted prior online research. As a result, they are more knowledgeable about the products and product assortment compared to other customers. In turn, more informed customers return less. This phenomenon is known as a reverse showrooming (webrooming) effect (Bell et al. 2014, Verhoef et al. 2015) and is the main factor for the increase in BM sales that we observe. The same argument also applies to consumer returns as well. Because customers are more knowledgeable about their own preferences along with a product's ability to meet their needs, they are able to make more informed and quicker (i.e. shorter TTR) decisions regarding a product's fit.

The only ancillary sales opportunities provided by STS are those that arise from a) the small subset of customers that actually end up using the STS service and also from b) an increase in RTS incidents. By definition, returning an item to a store increases store traffic and presents additional selling opportunities. It is very interesting to note that the average STS return rate is nearly identical to the average store return rate of 18.3% which is substantially higher than the average online return rate of 16.2%. This arises even though STS purchases are less expensive than other online purchases and considerably less expensive than typical store purchases. We believe there are two persuasive explanations. First, STS makes returning an item simple and easy since a customer is already at the store to pick up the item. In effect, the return policy is more lenient since it eliminates

all the hassles and costs typically associated with returning online purchases. We have argued that return rates for online items are lower than for store purchases because the items that are purchased online are less expensive. We have also cited other studies that have observed that return rates for less expensive items are lower than for more expensive items. Yet, in the case of the retailer we study, the lower return rate for online items may also be, at least partly, attributed to the greater inconvenience posed by making returns of online purchases as compared to making in-store returns. The second explanation for a higher return rate of STS purchases is that store sales associates are able to intervene at the point of pickup and steer customers to other higher-priced items. As our analysis has shown, 28% of RTS incidents result in new sales.

The least valuable customers are the ones that ultimately end up using the STS service. The average STS purchase is \$166.75. Overall, customers buy less expensive items online since there is less risk with these purchases. The most price sensitive customers use the STS service since it provides the greatest perceived benefit, in terms of a disproportionate savings provided by free store shipping. Hence, the lower average sales that we observe for these customers. Not only are these customers less valuable, but they are more costly since the retailer now absorbs the shipping cost for these customers with the advent of STS. With a decrease in online sales and an increase in the cost of servicing online customers, the implementation of STS service is a failure when viewed solely from an online channel perspective. Such a singular view, however, would ignore the impact on the BM channel and would run counter to the omnichannel retailing strategy that is enabled through STS.

As one of the first contributions on the impact of STS service on omnichannel retailing, there are, of course, plenty of opportunities for future research. A few promising avenues would include exploring the potential moderating impact of product category on STS. Here, we explore jewelry products, but these are luxury, highly experiential products in which search is quite important. Do the same effects hold for other product categories? We believe another significant opportunity lies in comparing and contrasting STS with BOPS. What are the operating conditions in which one service is preferred to another? For that matter, when should retailers avoid these services altogether? Finally, we think future research should explore the impact of lead time on customer behavior. In our research, we

cannot distinguish how lead time for store delivery affects customer switching behavior.
Would a shorter or longer lead time have the same effect?

4. SUMMARY AND CONCLUSION

In this dissertation, we present two essays that look into retail operations in terms of both consumer returns and omnichannel retailing practices. Given that consumer returns have reached a total volume of \$284 billion in 2014 (NRF 2014), most retailers are now looking for ways to more effectively manage returns and minimize their impact on the current operations. Furthermore, a recent survey by NRF also indicates that the total dollar value of return abuse (opportunism and return fraud together) reached \$17.6 billion in 2014 (NRF 2014).

In response to those return abuse practices, several major retailers turned to technology-enabled countermeasures to thwart them, such as customer profiling and product tracking systems. A customer profiling service is a solution to prevent or reduce opportunism by recording the number, the frequency, and the dollar volume of both purchases and returns made by each customer (Kang and Johnson 2009). Retailers benefit from this service by reducing the volume of opportunistic returns and by having an objective real-time decision for each return activity. Likewise, a product tracking service is a solution to fight return fraud and focuses on managing the product throughout its entire lifecycle by tracking each transaction involved with it through the use of unique identifiers such as serial numbers. With the help of this service, retailers are able to effectively deter return fraud.

In the first essay, we evaluate the impact of return abuse on retail operations and quantify the value of adopting customer profiling and product tracking technologies relative to a return abuse model in which the retailer does not use any technology to manage returns. We show that in the absence of technology-enabled countermeasures, the retailer is able to manipulate its pricing and refund policies to effectively mitigate opportunism but they are only marginally effective at dealing with return fraud. Furthermore, despite the fact that previous literature suggests using a customer profiling system to reduce opportunistic returns (Davis et al. 1995, Harris 2010, Rosenbaum et al. 2011), we establish conditions in which adoption is not recommended. This arises because eliminating opportunism comes at the expense of facing reduced legitimate customer demand due to a higher level of hassle.

From a modeling perspective, the first essay has several important contributions to the literature. First, we address *both* opportunism and return fraud in the context of consumer returns, which is a problem many retailers face today. Second, we develop utility functions that capture key characteristics of return abuse behavior. Finally, our analyses compare and contrast three technology adoption scenarios in terms of price, refund, and profit.

Our results from the second essay are extensive and provide strong managerial insights regarding the impact of STS service on a large, national retailer. First, we show that STS decreases online sales, increases BM sales, increases cross channel returns, and reduces store returns. Contrary to our expectations, online sales decrease after STS implementation because some customers switch from online to BM channel to purchase high-value items. It is also a bit surprising that the direct increase in store sales is not primarily due to store pick ups for STS transactions. Rather, the increase is due to customers who switch from online to BM channel after STS implementation. Note that channel switching behavior for high-value items occurs even though product availability information in stores is not provided to online customers and many of the items that are available for purchase online are not even stocked in stores. We also show that the increase in the BM channel in terms of sales is much greater than the decrease in the online channel, which shows that implementing STS service increased the retailer's total sales.

Another facet concerning STS implementation is related to product returns. Our results show that product returns at stores decrease, as does the time-to-return, while returns for online purchases remain unchanged after STS service. We believe that product returns at stores decrease because customers who switch from online to BM channel have conducted prior research online. As a result, they are more knowledgeable about their purchases and in turn less likely to return their merchandise. Note that this phenomenon is closely related to reverse showrooming (webrooming) effect in which browsing starts in the online channel and once customers make their decisions, they go to the BM channel to complete their transactions (Bell et al. 2014, Verhoef et al. 2015). The same argument also applies to consumer returns as well. Because customers are more knowledgeable about their own preferences along with a product's ability to meet their needs, they are able to make more informed and quicker (i.e. shorter TTR) decisions regarding a product's fit.

Finally, we also show that the return rate for the online channel is *less* than that observed for BM channel during both pre- and post-STS periods. Generally, both industry practice and academic literature suggest that the converse is true (Ryan 2015, JDA 2016) for two reasons. First, there is a lack of touch-and-feel experience in online shopping. Second, less information about products, such as fit, is available for online purchases. For the retailer that we study, however, our results show that customers generally prefer the online channel to buy lower-valued items while they prefer the BM channel to buy higher-valued items. Note that this observation is consistent with other studies which indicate that low-value items are less likely to be returned than high-value items because of their lower financial risk (Peterson and Kumar 2009, Anderson et al. 2009).

REFERENCES

- Acomvic, J., S.C. Graves. 2015. Making better fulfillment decisions on the fly in an online retail environment. *Manufacturing and Service Operations Management* **17**(1) 34–51.
- Aigner, D., C.A.K. Lovell, P. Schmidt. 1977. Formulation and estimation of stochastic frontier production function models. *Journal of Econometrics* **6**(1) 21–37.
- Altug, M.S. 2014. Effectiveness of targeted returns management in retailing. Working Paper, School of Business, George Washington University, Washington D.C.
- Anderson, E.T., K. Hansen, D. Simester. 2009. The option value of returns: Theory and empirical evidence. *Marketing Science* **28**(3) 405–423.
- Ansari, A., C.F. Fela, S.A. Neslin. 2008. Customer channel migration. *Journal of Marketing Research* **45**(1) 60–76.
- Athey, S., G.W. Imbens. 2006. Identification and inference in nonlinear difference-in-differences models. *Econometrica* **74**(2) 431–497.
- Avery, J., T.J. Steenburgh, J. Deighton, M. Caravella. 2012. Adding bricks to clicks: Predicting the patterns of cross-channel elasticities over time. *Journal of Marketing* **76**(3) 96–111.
- Bae, S.H., S. Nam, S.H. Kim. 2011. Empirical investigation of consumers’ impulse purchases from television home shopping channels: A case of order cancellation behavior. Working Paper, University of Chicago, Chicago, IL.
- Bell, D., S. Gallino, A. Moreno. 2017. Offline showrooms in omni-channel retail: Demand and operational benefits. Available at <https://ssrn.com/abstract=2370535>. (accessed date March 30, 2017).
- Bell, D.R., S. Gallino, A. Moreno. 2014. How to win in an omnichannel world. *MIT Sloan Management Review* **56**(1) 44–53.
- Bendoly, E., J.D. Blocher, K.M. Brethauer, S. Krisnan, M.A. Venkataramanan. 2005. Online/in-store integration and customer retention. *Journal of Service Research* **7**(4) 313–327.

- Best Buy. 2015. Returns and exchanges. Available at <http://www.bestbuy.com/site/help-topics/return-exchange-policy/pcmcat260800050014.c?id=pcmcat260800050014>. (accessed date October 16, 2015).
- Bower, A.B., J.G. Maxham-III. 2012. Return shipping policies of online retailers: Normative assumptions and the long-term consequences of fee and free returns. *Journal of Marketing* **76**(5) 110–124.
- BRP. 2016. Pos/customer engagement survey: 17th annual survey. Available at <https://bostonretailpartners.com/2016-pos-survey/>. (accessed date March 30, 2017).
- Brynjolfsson, E., Y.J. Hu, M.S. Rahman. 2009. Battle of retail channels: How product selection and geography drive cross-channel competition. *Management Science* **55**(11) 1755–1765.
- Brynjolfsson, E., Y.J. Hu, M.S. Rahman. 2013. Competing in the age of omnichannel retailing. *MIT Sloan Management Review* **54**(4) 22–29.
- Cao, L., L. Li. 2015. The impact of cross-channel integration on retailers' sales growth. *Journal of Retailing* **91**(2) 198–216.
- Caro, F., J. Gallien. 2010. Inventory management of a fast-fashion retail network. *Operations Research* **58**(2) 257–273.
- Che, Y-K. 1996. Customer return policies for experience goods. *The Journal of Industrial Economics* **44**(1) 17–24.
- Chintagunta, P.K., J. Chu, J. Cebollada. 2012. Quantifying transaction costs in online/off-line grocery channel choice. *Marketing Science* **31**(1) 96–114.
- Chircu, A.M., V. Mahajan. 2006. Managing electronic commerce retail transaction costs for customer value. *Decision Support Systems* **42**(2) 898–914.
- Chu, W., E. Gerstner, J.D. Hess. 1998. Managing dissatisfaction: How to decrease consumer opportunism by partial refunds. *Journal of Service Research* **1**(2) 140–155.
- Chuang, H.H., R. Oliva, O. Perdikaki. 2016. Traffic-based labor planning in retail stores. *Production and Operations Management* **25**(1) 96–113.
- Conitzer, V., C.R. Taylor, L. Wagman. 2012. Hide and seek: Costly consumer privacy in a market with repeat purchases. *Marketing Science* **31**(2) 277–292.

- Danaher, P.J., I.W. Wilson, R.A. Davis. 2003. A comparison of online and offline consumer brand loyalty. *Marketing Science* **22**(4) 461–476.
- Davis, D. 2008. Profits in pick-up? Available at <https://www.digitalcommerce360.com/2008/10/30/profits/-in/-pick/-up/>. (accessed date April 18, 2017).
- Davis, S., E. Gerstner, M. Hagerty. 1995. Money back guarantees in retailing: Matching products to consumer tastes. *Journal of Retailing* **71**(1) 7–22.
- Davis, S., M. Hagerty, E. Gerstner. 1998. Return policies and the optimal level of hassle. *Journal of Economics and Business* **50**(5) 445–460.
- De, P., Y.J. Hu, M.S. Rahman. 2013. Product-oriented web technologies and product returns: An exploratory study. *Information Systems Research* **24**(4) 998–1010.
- DeHoratius, N., A. Raman. 2008. Inventory record inaccuracy: An empirical analysis. *Management Science* **54**(4) 627–641.
- Donald, S.G., K. Lang. 2007. Inference with difference-in-differences and other panel data. *The Review of Economics and Statistics* **89**(2) 221–233.
- Dunn, C. 2015. Why it's time for retailers to embrace online returns. Available at www.entrepreneur.com/article/246421. (accessed date October 13, 2016).
- eMarketer. 2015. Retail roundup 2015. Available at http://www.emarketer.com/public_media/docs/eMarketer_Retail_Roundup.pdf. (accessed date March 30, 2017).
- Ernst and Young. 2001. Global online retailing report. Available at <https://www.indiadomain.com/pdf/globalonlineretailing2001.pdf>. (accessed date March 30, 2017).
- Ernst and Young. 2015. Americas retail report. Available at [http://www.ey.com/Publication/vwLUAssets/EY-americas-retail-report-june-2015//\\$FILE/EY-americas-retail-report-june-2015.pdf](http://www.ey.com/Publication/vwLUAssets/EY-americas-retail-report-june-2015//$FILE/EY-americas-retail-report-june-2015.pdf). (accessed date March 30, 2017).
- Ertekin, N., M. Ketzenberg, G. Heim. 2016. Assessing the impact of service quality on consumer returns: A data analytics study. Working Paper, Mays Business School, Texas A&M University, College Station, TX.
- Fisher, M.L., A. Raman. 2010. *The new science of retailing*. Harvard Business Press, Boston.

- Forman, C., A. Ghose, A. Goldfarb. 2009. Competition between local and electronic markets: How the benefit of buying online depends on where you live. *Management Science* **55**(1) 47–57.
- Forsythe, S., C.Liu, D. Shannon, L.C. Gardner. 2006. Development of a scale to measure the perceived benefits and risks of online shopping. *Journal of Interactive Marketing* **20**(2) 55–75.
- Gallino, S., A. Moreno. 2014. Integration of online and offline channels in retail: The impact of sharing reliable inventory availability information. *Management Science* **60**(6) 1434–1451.
- Gallino, S., A. Moreno, I. Stamatopoulos. 2016. Channel integration, sales dispersion, and inventory management. *Management Science* (Articles in Advance) 1–19.
- Gao, F., X. Su. 2016. Omnichannel retail operations with buy-online-and-pick-up-in-store. *Management Science* (Articles in Advance) 1–15.
- Gao, F., X. Su. 2017. Online and offline information for omnichannel retailing. *Manufacturing and Service Operations Management* **19**(1) 84–98.
- Griffis, S.E., S. Rao, T.J. Goldsby, T.T. Niranjan. 2012. The customer consequences of returns in online retailing: An empirical analysis. *Journal of Operations Management* **30**(4) 282–294.
- Guangzhi, S., B. Ghosh, M. Galbreth. 2015. Optimal retail return policies with consumer opportunism. Working Paper, College of Business, Florida State University, Tallahassee, FL.
- Gulati, R., J. Garino. 2000. Get the right mix of bricks and clicks. *Harvard Business Review* **78**(3) 107–114.
- Gumus, M., S. Li, W. Oh, S. Ray. 2013. Shipping fees or shipping free? A tale of two price partitioning strategies in online retailing. *Production and Operations Management* **22**(4) 758–776.
- Harris, L.C. 2010. Fraudulent consumer returns: Exploiting retailers’ return policies. *European Journal of Marketing* **44**(6) 730–747.
- Hassan, A.M., M.B. Kunz, A.W. Pearson, F.A.Mohamed. 2006. Conceptualization and

- measurement of perceived risk in online shopping. *The Marketing Management Journal* **16**(1) 138–147.
- Herhausen, D., J. Binder, M. Schoegel, A. Herrmann. 2015. Integrating bricks with clicks: Retailer-level and channel-level outcomes of online-offline channel integration. *Journal of Retailing* **91**(2) 309–325.
- Hess, J.D., W. Chu, E. Gerstner. 1996. Controlling product returns in direct marketing. *Marketing Letters* **7**(4) 307–317.
- Howard, J.A., J.N. Sheth. 1969. *The theory of buyer behavior*. Wiley, New York.
- Huang, T., J.A. Van Mieghem. 2014. Clickstream data and inventory management: Model and empirical analysis. *Production and Operations Management* **23**(3) 333–347.
- Jareth, K., A. Kumar, S. Netessine. 2015. An information stock model of customer behavior in multichannel customer support services. *Manufacturing and Service Operations Management* **17**(3) 368–383.
- JDA. 2016. Returns management and the intelligent store: Solving the omni-channel conundrum. Available at <https://jda.com/-/media/jda/knowledge-center/white-papers/returns-management-intelligent-store.ashx>. (accessed date March 30, 2017).
- Jolson, M.A. 1974. Consumers as offenders. *Journal of Business Research* **2**(1) 89–98.
- Kang, M., K. Johnson. 2009. Identifying characteristics of consumers who frequently return apparel. *Journal of Fashion Marketing and Management* **13**(1) 37–48.
- Ketoviki, M., V.D.R. Guide. 2015. Notes from the editors: Redefining some methodological criteria for the journal. *Journal of Operations Management* **37** v–viii.
- Ketzenberg, M.E., R.A. Zuidwijk. 2009. Optimal pricing, ordering, and return policies for consumer goods. *Production and Operations Management* **18**(3) 344–360.
- King, T., C. Dennis. 2003. Interviews of deshopping behavior: An analysis of theory of planned behavior. *International Journal of Retail and Distribution Management* **31**(3) 153–163.
- Kukar-Kinney, M., A.G. Close. 2010. The determinants of consumers' online shopping cart abandonment. *Journal of the Academy of Marketing Science* **38**(2) 240–250.

- Lam, S., M. Vandenbosch, M. Pearce. 1998. Retail sales force scheduling based on store traffic forecasting. *Journal of Retailing* **74**(1) 61–88.
- Lewis, M. 2006. The effect of shipping fees on customer acquisition, customer retention, and purchase quantities. *Journal of Retailing* **82**(1) 13–23.
- Lewis, M., V. Shng, S. Fay. 2006. An empirical study of the impact of nonlinear shipping and handling fees on purchase incidence and expenditure decisions. *Marketing Science* **25**(1) 51–64.
- Lieb, R. 2015. From web traffic to foot traffic: How brands and retailers can leverage digital content to power in-store sales. Available at <http://www.iab.com/wp-content/uploads/2015/09/Cofactor-Web-to-Foot-Report.pdf>. (accessed date March 30, 2017).
- MA. 2014. The flexible fulfillment playbook: Omni-channel strategies for retail supply chain executives. Available at <http://www.manh.com/sites/default/files/sys/en/document/manh-flexible-fulfillment-playbook-white-paper-en.pdf>. (accessed date March 30, 2017).
- Macintosh, G., C.D. Stevens. 2013. Individual differences in opportunistic claiming behavior. *Journal of Consumer Behavior* **12**(1) 10–19.
- Mani, V., S. Kesavan, J.M. Swaminathan. 2015. Estimating the impact of understaffing on sales and profitability in retail stores. *Production and Operations Management* **24**(2) 201–218.
- Maronick, T.J. 2007. Consumer perceptions of extended warranties. *Journal of Retailing and Consumer Services* **14**(3) 224–231.
- Martinez, A. 2013. Rei now limiting returns to one year. Available at <http://www.seattletimes.com/business/rei-now-limiting-returns-to-one-year/>. (accessed date March 23, 2015).
- Masanell, R.C., A.H. Drane. 2015. Competing with privacy. *Management Science* **61**(1) 229–246.
- Mellor, R. 2013. Retailers lose billions when crooks exploit return policies. Former Vice

- President of Loss Prevention, National Retail Federation. (Interview at mprnew.org, accessed date November 25, 2015).
- Moraca, B. 2014. Fraudulent returns of stolen presents cost us retailers more than \$3.5bn. Vice President of Loss Prevention, National Retail Federation. (Interview at the-guardian.com, accessed date November 24, 2015).
- Nielsen Media Research. 2013. Dma regions. Available at <http://www.nielsen.com/intl-campaigns/us/dma-maps.html>. (accessed date March 30, 2017).
- NRF. 2007. Return fraud survey 2007. Available at <https://lizwalk.files.wordpress.com/2009/11/national-retail-federation-return-fraud-survey.pdf>. (accessed date March 30, 2017).
- NRF. 2014. Return fraud survey 2014. Available at <https://nrf.com/who-we-are/annual-reports>. (accessed date January 12, 2015).
- Ofek, E., Z. Katona, M. Sarvary. 2011. Bricks and clicks: The impact of product returns on the strategies of multichannel retailers. *Marketing Science* **30**(1) 42–60.
- Peck, J., T.L. Childers. 2003. To have and to hold: The influence of haptic information on product judgements. *Journal of Marketing* **67**(2) 35–48.
- Perdikaki, O., S. Kesavan, J.M. Swaminathan. 2012. Effect of traffic on sales and conversion rates of retail stores. *Manufacturing and Service Operations Management* **14**(1) 145–162.
- Peterson, J.A., V. Kumar. 2009. Are product returns a necessary evil? Antecedents and consequences. *Journal of Marketing* **73**(3) 35–51.
- Piron, F., M. Young. 2000. Retail borrowing: Insights and implications on returning used merchandise. *International Journal of Retail and Distribution Management* **28**(1) 27–36.
- Rabinovich, E., R. Sinha, T. Laseter. 2011. Unlimited shelf space in internet supply chains: Treasure trove or wasteland? *Journal of Operations Management* **29**(4) 305–317.
- Radial. 2016. Simplified in-store ecommerce fulfillment. Available at www.radial.com/sites/default/files/. (accessed date September 21, 2016).
- Rigby, D. 2011. The future of shopping. *Harvard Business Review* **89**(12) 65–76.

- RIS. 2012. Enhancing the store shopping experience in an omnichannel world. Available at http://media.elotouch.com/pdfs/reviews/risnews_may-2012.pdf. (accessed date March 30, 2017).
- Rogers, D.S., R.S. Tibben-Lembke. 1999. *Going backwards: Reverse logistics trends and practices*. Reverse Logistics Executive Council, Pittsburgh, PA.
- Rosenbaum, M.S., R. Kuntze. 2005. Looking good at the retailer's expense: Investigating unethical retail disposition behavior among compulsive buyers. *Journal of Retailing and Consumer Services* **12**(3) 217–225.
- Rosenbaum, M.S., R. Kuntze, B.R. Wooldridge. 2011. Understanding unethical retail disposition practice and restraint from the consumer perspective. *Psychology and Marketing* **28**(1) 29–52.
- Ryan, T. 2015. Online shopping exacerbates return headaches for retailers. Available at www.retailwire.com/online/shopping/exacerbates/returnheadaches/for/retailers. (accessed date October 08, 2016).
- Shulman, J.D., A.T. Coughlan, R.C. Savaskan. 2009. Optimal restocking fees and information provision in an integrated demand-supply model of product returns. *Manufacturing and Service Operations Management* **11**(4) 577–594.
- Shulman, J.D., A.T. Coughlan, R.C. Savaskan. 2011. Managing consumer returns in a competitive environment. *Management Science* **57**(2) 347–362.
- Song, H., A.L. Tucker, K.L. Murrell. 2015. The diseconomies of queue pooling: An empirical investigation of emergency department length of stay. *Management Science* **61**(12) 3032–3053.
- Speights, D., M. Hilinski. 2005. Return fraud and abuse: How to protect profits. *Retailing Issues Letter, Texas A&M University, Mays Business School, Center for Retailing Studies* **17**(1) 1–6.
- Speights, D., T. Rittman. 2015. Fighting return fraud during the holiday season. White Paper, The Retail Equation. (accessed date November 25, 2015).
- Su, X. 2009. Consumer returns policies and supply chain performance. *Manufacturing and Service Operations Management* **11**(4) 595–612.

- Taylor, J.W. 1974. The role of risk in consumer behavior. *Journal of Marketing* **38**(2) 54–60.
- Ulku, M.A., L.C. Dailey, H.M. Yayla-Kullu. 2013. Serving fraudulent consumers? The impact of return policies on retailer's profitability. *Service Science* **5**(4) 296–309.
- UPS. 2014. 2014 UPS pulse of the online shopper. Available at <https://www.ups.com/media/en/2014-UPS-Pulse-of-the-Online-Shopper.pdf>. (accessed date March 30, 2017).
- UPS. 2015. 2015 UPS pulse of the online shopper. Available at https://solvers.ups.com/assets/UPS_Pulse_of_the_Online_Shopper.pdf. (accessed date March 30, 2017).
- Verhoef, P.C., P.K. Kannan, J.J. Inman. 2015. From multi-channel to omni-channel retailing: Introduction to special issue on multi-channel retailing. *Journal of Retailing* **91**(2) 174–181.
- Wachter, K., R.K. Shelton S.J. Vitell, K. Park. 2012. Exploring consumer orientation toward returns: Unethical dimensions. *Business Ethics: A European Review* **21**(1) 115–128.
- Walker Sands. 2016. Future of retail 2016. Available at <http://www.walkersands.com/Futureofretail>. (accessed date March 30, 2017).
- Weisbaum, H. 2013. Receive an awful gift? Return policies now tighter. Available at <http://www.cnn.com/2013/12/19/return-policies-now-tighter.html>. (accessed date September 15, 2015).
- Williamson, O.E. 1975. *Markets and hierarchies: Analysis and antitrust implications*. Free Press, New York.
- Winkler, N. 2016. How to reduce your return rate and predict exactly what customers want. Available at <https://www.shopify.com/enterprise/102947142>. (accessed date October 13, 2016).
- Wirtz, J. 2010. Art of triggering impulse buying. *The Business Times* 24–25.
- Wood, S.L. 2001. Remote purchase environments: The influence of return policy leniency on two-stage decision processes. *Journal of Marketing Research* **38**(2) 157–169.

- Wooldridge, J.M. 2012. *Introductory econometrics: A modern approach*. Cengage Learning, Mason, OH.
- Yantra. 2005. Buy online pick up in-store: A guide to implementing an in-store pickup initiative. Available at http://www-07.ibm.com/businesscenter/au/industry/pdf/White_Paper_-_In-store_PickUp.pdf. (accessed date March 30, 2017).
- Zhang, J., P.W. Farris, J.W. Irvin, T. Kushwaha, T.J. Steenburgh, B.A. Weitz. 2010. Crafting integrated multichannel retailing strategies. *Journal of Interactive Marketing* **24**(2) 168–180.

APPENDIX A

PROOFS FOR THE FIRST ESSAY

Optimal Price and Refund Decisions for RAM Variants

Table A.1 summarizes the optimal price and refund decisions for RAM variants.

Table A.1: Optimal Decisions for RAM Variants

Cases	Decisions	Values
Fraud Only	Price	$p^* = \frac{1}{2}(1 + c - \lambda - c\lambda\rho)$
	Refund	$r^* = \frac{1}{2}(s - k - c\rho)$
Opportunism Only	Price	$p^* = \frac{2+c+s-k-(2+2c+m(1-k+s))\lambda}{4-m-4\lambda}$
	Refund	$r^* = \frac{2+3(s-k)-c-(m+2\lambda)(1+s-k)}{4-m-4\lambda}$
No Return Abuse	Price	$p^* = \frac{1+c-(1-k+s)\lambda}{2(1-\lambda)}$
	Refund	$r^* = \frac{1+c-(1-k+s)\lambda}{2(1-\lambda)}$

Proof of Proposition 1 The first order conditions for the objective function in equation (2.1) are given by

$$\begin{aligned} \frac{\partial \pi}{\partial p} &= \frac{c + k + m - km - 2p + 2r - mr + (m - 1)s}{m} = 0 \\ \frac{\partial \pi}{\partial r} &= -\frac{c + (m - 2)p + (2r - s)(1 + m\gamma) + k(1 + m(\gamma - \lambda)) + m(1 - 2r + s)\lambda}{m} \\ &\quad + \frac{cm\gamma\rho}{m} = 0 \end{aligned}$$

Solving first order conditions simultaneously gives the unique solution for p and r , which are presented in Proposition 1. Substituting this solution into $q = L_1 + O_1 + \rho F_1$ yields q^* . Below, we use the hessian matrix to verify that the second order conditions are satisfied.

$$H(p, r) = \frac{\partial^2 \pi}{\partial p \partial r} = \begin{bmatrix} -\frac{2}{m}, & \frac{2}{m} - 1 \\ \frac{2}{m} - 1, & 2\lambda - \frac{2}{m} - 2\gamma \end{bmatrix}$$

The first leading principal minor $(-\frac{2}{m})$ is negative because the denominator is positive since $m > 0$. The second principal minor is given by $Det[H(p, r)] = \frac{4 - m + 4\gamma - 4\lambda}{m}$, which is positive so long as $m < 4(1 + \gamma - \lambda)$. This shows that $H(p, r)$ is negative definite and the objective function in equation (2.1) is strictly concave. Hence, the solution in Proposition 1 is optimal. ■

Proof of Proposition 2

The first order conditions for the objective function in equation (2.2) are given by

$$\begin{aligned}\frac{\partial \pi}{\partial p} &= \frac{1 + c - 2p - (1 + h - k - 2r + s)\lambda}{1 - \lambda} = 0 \\ \frac{\partial \pi}{\partial r} &= \frac{(1 - \lambda)(s + h\theta - c\rho)\gamma - \lambda(1 + c - 2p) + \lambda^2(1 + h + s) - (\gamma - \gamma\lambda + \lambda^2)(2r + k)}{1 - \lambda} = 0\end{aligned}$$

Solving first order conditions simultaneously gives the unique solution for p and r , which are presented in Proposition 2. Substituting this solution into $q = L_2 + \rho F_2$ yields q^* . Below, we use the hessian matrix to verify that the second order conditions are satisfied.

$$H(p, r) = \frac{\partial^2 \pi}{\partial p \partial r} = \begin{bmatrix} \frac{2}{\lambda - 1}, & \frac{2\lambda}{1 - \lambda} \\ \frac{2\lambda}{1 - \lambda}, & \frac{2\lambda^2}{\lambda - 1} - 2\gamma \end{bmatrix}$$

The first leading principal minor $\frac{2}{\lambda - 1}$ is negative because $\lambda < 1$. The second principal minor is given by $Det[H(p, r)] = \frac{4\gamma}{1 - \lambda}$, which is always positive because $\lambda < 1$ and $\gamma > 0$. This shows that $H(p, r)$ is negative definite and the objective function in equation (2.2) is strictly concave. Hence, the solution in Proposition 2 is optimal. ■

Proof of Proposition 3

From Propositions 1 and 2, we know that

$$\begin{aligned}p_1^* &= \frac{(k - s - 2)(1 + m\gamma) + (2 + m(1 - k + s))\lambda - c(1 - 2\lambda + \gamma(2 + (m - 2)\rho))}{4(\lambda - \gamma - 1) + m} \\ p_2^* &= \frac{1}{2}(1 + c - (1 + h(1 - \theta))\lambda - c\lambda\rho)\end{aligned}$$

Setting $p_1^* = p_2^*$ and solving for m produces the threshold \bar{m} value given in Proposition 3.

Similarly, from Propositions 1 and 2, we know that

$$r_1^* = \frac{c + m - 2 - s(3 + 2\gamma - m) + 2(1 + s)\lambda - k(m + 2\lambda - 2\gamma - 3) + 2c\gamma\rho}{4(\lambda - \gamma - 1) + m}$$

$$r_2^* = \frac{1}{2}(s + h\theta - k - c\rho)$$

Setting $r_1^* = r_2^*$ and solving for h produces the threshold \hat{h} value given in Proposition 3. ■

Proof of Proposition 4

We first derive the maximum hassle cost \bar{h} that makes it possible for the CPM to be more favorable than the RAM. To do so, we set $s = 0$ in π_1 and π_2 and solve for h . Note that the lower the salvage value s , the better for the retailer to adopt a profiling service. This analysis shows that even when the salvage value s is zero, the retailer is worse off adopting a profiling service if $h \geq \bar{h}$. If, however, $h < \bar{h}$, then we find the threshold salvage value \underline{s} which makes the CPM more favorable than the RAM. To do so, we set $\pi_1 = \pi_2$ and solve for s . The expressions for \bar{h} and \underline{s} are too complex and cumbersome to present here. However, they are available from the authors upon request. ■

Optimal Solution for the ICPM

The first order conditions for the objective function in equation (2.3) are given by

$$\frac{\partial \pi}{\partial p} = \frac{(2p - c)(1 - \lambda) + (\alpha - 1)(2r - s + k(1 - m) + m(s - r)) + (m(1 - r + s - k))\lambda}{m(\lambda - 1)}$$

$$+ \frac{(\alpha(s - k) + k + 2r(1 - \alpha))\lambda + \alpha(\lambda - 1)s_c}{m(\lambda - 1)} = 0$$

$$\frac{\partial \pi}{\partial r} = \gamma(h\theta - r) + \frac{(c - p)(\alpha + \alpha^2(\lambda - 1) - (1 + m)\alpha\lambda - m(\lambda - 1)\lambda)}{m(\lambda - 1)}$$

$$+ \frac{(c + k - p + r - s)\left((\alpha - 1)^2 + (1 + m - \alpha)(\alpha - 1)\lambda + m\lambda^2\right)}{m(\lambda - 1)} - \gamma(k + r - s + c\rho)$$

$$- (1 - \alpha)\left(\frac{p + h\lambda - r\lambda}{1 - \lambda} + \frac{r - p - r\alpha + \alpha s_c}{m}\right) - \frac{\lambda(p - 1 + (1 + h - r)\lambda)}{\lambda - 1} = 0.$$

Solving first order conditions simultaneously gives the unique solution for p and r , which are too complex and cumbersome to present here. Below, we use the hessian matrix to

verify that the second order conditions are satisfied.

$$H(p, r) = \frac{\partial^2 \pi}{\partial p \partial r} = \begin{bmatrix} -\frac{2}{m}, & -1 + \frac{2-2\alpha}{m} - \frac{\alpha}{\lambda-1} \\ -1 + \frac{2-2\alpha}{m} - \frac{\alpha}{\lambda-1}, & 2 \left(-\frac{(\alpha-1)^2}{m} - \gamma + \lambda + \frac{\alpha\lambda}{\lambda-1} \right) \end{bmatrix}$$

The first leading principal minor $-\frac{2}{m}$ is negative because $m > 0$, which makes the denominator negative. The second principal minor is given by

$$Det[H(p, r)] = -\frac{m(\alpha + \lambda - 1)^2 + 4(\lambda - 1)(1 + \alpha^2 + \gamma + 2\alpha(\lambda - 1) - (2 + \gamma)\lambda + \lambda^2)}{m(\lambda - 1)^2}$$

Note that the second principal minor is positive so long as $m < 4 \left(1 - \lambda + \frac{\gamma(\lambda - 1)^2}{(\alpha + \lambda - 1)^2} \right)$. Given the condition for m is satisfied, $H(p, r)$ is negative definite and the objective function in equation (2.3) is strictly concave. Hence, the solution is optimal. ■

Proof of Proposition 5

The first order conditions for the objective function in equation (2.4) are given by

$$\begin{aligned} \frac{\partial \pi}{\partial p} &= \frac{c + k + m - km - 2p + 2r - mr + (m - 1)s + h}{m} = 0 \\ \frac{\partial \pi}{\partial r} &= (k + 2r - s - 1 + h)\lambda - \frac{c + k + (m - 2)p + 2r - s + h}{m} = 0 \end{aligned}$$

Solving first order conditions simultaneously gives the unique solution for p and r , which are presented in Proposition 5. Substituting this solution into $q = L_3 + O_3$ yields q^* . Below, we use the hessian matrix to verify that the second order conditions are satisfied.

$$H(p, r) = \frac{\partial^2 \pi}{\partial p \partial r} = \begin{bmatrix} -\frac{2}{m}, & \frac{2}{m} - 1 \\ \frac{2}{m} - 1, & 2\lambda - \frac{2}{m} \end{bmatrix}$$

The first leading principal minor $(-\frac{2}{m})$ is negative because $m > 0$. The second principal minor is given by $Det[H(p, r)] = \frac{4 - m - 4\lambda}{m}$, which is positive so long as $m < 4(1 - \lambda)$. This shows that $H(p, r)$ is negative definite and the objective function in equation (2.4) is

strictly concave. Hence, the solution in Proposition 5 is optimal. \blacksquare

Proof of Proposition 6

From Propositions 1 and 5, we know that

$$p_1^* = \frac{(k-s-2)(1+m\gamma) + (2+m(1-k+s))\lambda - c(1-2\lambda + \gamma(2+(m-2)\rho))}{4(\lambda-\gamma-1)+m}$$

$$p_3^* = \frac{k+c\lambda-s-h+m(1-k+s+h)\lambda + (\lambda-1)(2+c)}{m+4\lambda-4}$$

Setting $p_1^* = p_3^*$ and solving for γ yields the threshold $\bar{\gamma}$ value that is presented in Propositions 6. Similarly, from Propositions 1 and 5, we know that

$$r_1^* = \frac{c+m-2-s(3+2\gamma-m) + 2(1+s)\lambda - k(m+2\lambda-2\gamma-3) + 2c\gamma\rho}{4(\lambda-\gamma-1)+m}$$

$$r_3^* = \frac{c+(1+s-k)(m+2\lambda) - 2+3(k-s) + h(1-2\lambda)}{m+4\lambda-4}$$

Setting $r_1^* = r_3^*$ and solving for γ yields the threshold $\hat{\gamma}$ value that is presented in Propositions 6. Furthermore,

$$\frac{\partial p_1^*}{\partial \gamma} = -\frac{(-2+m)(2-m)(k-s-2) + 4\lambda + c(2+(m+4\lambda-4)\rho)}{(m+4\lambda-4\gamma-4)^2} < 0$$

$$\frac{\partial r_1^*}{\partial \gamma} = \frac{2(2-m)(k-s-2) + 4\lambda + c(2+(m+4\lambda-4)\rho)}{(m+4\lambda-4\gamma-4)^2} < 0$$

Hence, we conclude that the optimal price and the refund in the presence of fraud are lower than those when fraud is eliminated. \blacksquare

Proof of Proposition 7

To compare the PTM and the RAM in terms of profit, we plug p_1^* and r_1^* into equation (2.1) and p_3^* and r_3^* into equation (2.4). Setting $\pi_1 = \pi_3$ and solving for the service fee b_3 yields the threshold service fee value \bar{b} . The expression for \bar{b} is too complex and cumbersome to present here. However, it is available from the authors upon request. \blacksquare

Proof of Proposition 8

The first order conditions for the objective function in equation (2.5) are given by

$$\begin{aligned}\frac{\partial \pi}{\partial p} &= \frac{c + k + m - km - 2p + 2r - m(r - s) - s + h}{m} = 0 \\ \frac{\partial \pi}{\partial r} &= \frac{(2 - m)p + m(2r - s)(\beta - 1)\gamma - h + m(2r + h - s - 1)\lambda}{m} \\ &\quad + \frac{k(m((\beta - 1)\gamma + \lambda - 1)) + c(m(\beta - 1)\gamma\rho - 1) - 2r + s}{m} = 0\end{aligned}$$

Solving first order conditions simultaneously gives the unique solution for p and r , which are presented in Proposition 8. Substituting this solution into $q = L_3 + O_3$ yields q^* . Below, we use the hessian matrix to verify that the second order conditions are satisfied.

$$H(p, r) = \frac{\partial^2 \pi}{\partial p \partial r} = \begin{bmatrix} -\frac{2}{m}, & \frac{2}{m} - 1 \\ \frac{2}{m} - 1, & 2\left(\gamma(\beta - 1) + \lambda - \frac{1}{m}\right) \end{bmatrix}$$

The first leading principal minor $(-\frac{2}{m})$ is negative because $m > 0$. The second principal minor is given by $Det[H(p, r)] = -\frac{m + 4(\gamma(\beta - 1) + \lambda - 1)}{m}$, which is positive so long as $m < 4(\gamma(\beta - 1) + \lambda - 1)$. This shows that $H(p, r)$ is negative definite and the objective function in equation (2.4) is strictly concave. Hence, the solution in Proposition 8 is optimal. \blacksquare

Analysis of Table 2

Below, we analyze the partial derivative of the price with respect to each parameter. Note that in Proposition 1, m needs to be less than $4(1 + \gamma - \lambda)$ for the second principal minor to be positive, which implies that $(m - 4(1 + \gamma - \lambda)) < 0$.

$$\begin{aligned}\frac{\partial p^*}{\partial s} &= \frac{m(\lambda - \gamma) - 1}{m - 4(1 + \gamma - \lambda)}, \text{ which is positive so long as } \lambda < \frac{1}{m} + \gamma. \\ \frac{\partial p^*}{\partial c} &= \frac{2\lambda - 1 - \gamma(2 + (m - 2)\rho)}{m - 4(1 + \gamma - \lambda)}, \text{ which is always positive so long as } \lambda < \frac{1}{2}. \\ \frac{\partial p^*}{\partial \lambda} &= \frac{(m - 2)(k(2 - m) + m - 2s + ms + 4\gamma + c(2 + 4\gamma\rho))}{(m - 4(1 + \gamma - \lambda))^2}, \text{ which is negative so long as } \\ &\quad m < 2. \\ \frac{\partial p^*}{\partial m} &= \frac{(1 + 2\gamma - 2\lambda)(c - (k - s - 2)(1 + 2\gamma) + 2(k - s - 1)\lambda + 2c\gamma\rho)}{(m - 4(1 + \gamma - \lambda))^2}, \text{ which is positive}\end{aligned}$$

so long as $(\lambda - \gamma) < \frac{1}{2}$.

$$\frac{\partial p^*}{\partial \gamma} = \frac{-(m-2)((2-m)(k-s-2) + 4\lambda + c(2 + (m+4\lambda-4)\rho))}{(m-4(1+\gamma-\lambda))^2}, \text{ which is negative so}$$

long as $m < 2$ and $\frac{4\lambda + c(2 + (m+4\lambda-4)\rho)}{(2-m)(k-s-2)} < 1$.

$$\frac{\partial p^*}{\partial \rho} = \frac{(2-m)c\gamma}{m-4(1+\gamma-\lambda)}, \text{ which is negative so long as } m < 2.$$

$$\frac{\partial p^*}{\partial k} = \frac{1+m(\gamma-\lambda)}{m-4(1+\gamma-\lambda)}, \text{ which is negative so long as } \lambda < \frac{1}{m} + \gamma.$$

Next, we analyze the partial derivative of the refund with respect to each parameter.

$$\frac{\partial r^*}{\partial s} = \frac{m-3-2(\gamma-\lambda)}{m-4(1+\gamma-\lambda)}, \text{ which is positive so long as } m < 3+2(\gamma-\lambda).$$

$$\frac{\partial r^*}{\partial c} = \frac{1+2\gamma\rho}{m-4(1+\gamma-\lambda)}, \text{ which is always negative.}$$

$$\frac{\partial r^*}{\partial m} = \frac{(k-s-2)(1+2\gamma) + 2(1-k+s)\lambda - c(1+2\gamma\rho)}{(m-4(1+\gamma-\lambda))^2}, \text{ which is negative so long as}$$

$\lambda < \gamma + \frac{1}{2}$.

$$\frac{\partial r^*}{\partial \gamma} = \frac{2(2-m)(k-s-2) + 4\lambda + c(2 + (m+4\lambda-4)\rho)}{(m-4(1+\gamma-\lambda))^2}, \text{ which is negative so long as}$$

$m < 2$.

$$\frac{\partial r^*}{\partial \rho} = \frac{2c\gamma}{m-4(1+\gamma-\lambda)}, \text{ which is always negative.}$$

$$\frac{\partial r^*}{\partial k} = \frac{3-m+2(\gamma-\lambda)}{m-4(1+\gamma-\lambda)}, \text{ which is negative so long as } m < 3+2(\gamma-\lambda).$$

The partial derivatives of q^* and π^* with respect to parameters are too complex and cumbersome to present here. But, they are available from the authors upon request. ■

Analysis of Table 6

Below, we analyze the partial derivative of the price with respect to each parameter.

$$\frac{\partial p^*}{\partial s} = 0. \quad \frac{\partial p^*}{\partial c} = \frac{1}{2}(1-\lambda\rho), \text{ which is always positive.} \quad \frac{\partial p^*}{\partial \rho} = -\frac{c\lambda}{2}, \text{ which is always}$$

negative.

$$\frac{\partial p^*}{\partial \lambda} = \frac{1}{2}((\theta-1)h - c\rho - 1), \text{ which is always negative.} \quad \frac{\partial p^*}{\partial \theta} = \frac{h\lambda}{2}, \text{ which is always}$$

positive.

$$\frac{\partial p^*}{\partial h} = \frac{1}{2}(\theta-1)\lambda, \text{ which is always negative.} \quad \frac{\partial p^*}{\partial k} = 0.$$

Next, we analyze the partial derivative of the refund with respect to each parameter.

$$\begin{aligned} \frac{\partial r^*}{\partial s} &= \frac{1}{2}, \text{ which is always positive.} & \frac{\partial r^*}{\partial c} &= -\frac{\rho}{2}, \text{ which is always negative.} \\ \frac{\partial \lambda}{\partial r^*} &= 0. & \frac{\partial r^*}{\partial h} &= \frac{\theta}{2}, \text{ which is always positive.} & \frac{\partial r^*}{\partial k} &= -\frac{1}{2}, \text{ which is always negative.} \\ \frac{\partial r^*}{\partial \rho} &= -\frac{c}{2}, \text{ which is always negative.} & \frac{\partial r^*}{\partial \theta} &= \frac{h}{2}, \text{ which is always positive.} \end{aligned}$$

Finally, we present the partial derivative of the order quantity with respect to each parameter.

$$\begin{aligned} \frac{\partial q^*}{\partial s} &= \frac{1}{2} \left(\frac{\lambda}{1-\lambda} + \gamma\rho \right), \text{ which is always positive.} & \frac{\partial q^*}{\partial c} &= \frac{1}{2} \left(\frac{1}{\lambda-1} - \gamma\rho^2 \right), \text{ which is} \\ & \text{always negative.} & & \\ \frac{\partial q^*}{\partial \lambda} &= -\frac{c+h+k-s}{2(\lambda-1)^2}, \text{ which is always negative.} & \frac{\partial q^*}{\partial h} &= \frac{1}{2} \left(\frac{\lambda}{\lambda-1} - \gamma\theta\rho \right), \text{ which is} \\ & \text{always negative.} & & \\ \frac{\partial q^*}{\partial \rho} &= -\frac{1}{2}\gamma(k-s+h\theta+2c\rho), \text{ which is positive if } \rho < \frac{s-h\theta-k}{2c} \text{ and negative otherwise.} & & \\ \frac{\partial q^*}{\partial \theta} &= -\frac{1}{2}h\gamma\rho, \text{ which is always negative.} & \frac{\partial q^*}{\partial k} &= \frac{1}{2} \left(\frac{\lambda}{\lambda-1} - \gamma\rho \right), \text{ which is always} \\ & \text{negative.} & & \end{aligned}$$

The partial derivatives of π^* with respect to parameters is too complex and cumbersome to present here. But, they are available from the authors upon request. ■

A.1 Model Extension

Customer Profiling Model with Heterogenous Hassle Cost

Here, we explore the impact of heterogenous hassle cost arising from privacy concerns. To do so, we assume the simplest case where there are two types of customers. One type, the “Lows”, has a low hassle cost whereas the other type, the “Highs”, has a high hassle cost. The proportions μ and $1-\mu$ denote the size of each type, respectively, in the market. We normalize the hassle costs for these two customer types and assume that the hassle costs of Lows is zero while the hassle cost of Highs is h_H . Hence, $\mu \left(1 - \frac{p-r\lambda}{1-\lambda} \right)$ and $(1-\mu) \left(1 - \frac{p+h_H\lambda-r\lambda}{1-\lambda} \right)$ represent the legitimate customers who purchase the product with low and high hassle costs, respectively. For simplicity, we assume that fraudulent customers are of high hassle cost type. Hence, the size of the fraudulent segment is equal

to $\gamma(r - \theta h_H)$. The retailer's objective function for this model is given by

$$\max_{p,r} \pi = S(p - c) + R(p - r + s - c - k) + F(s - r - k - \rho c) \quad (\text{A.1})$$

Maximizing this objective function with respect to p and r , we report the optimal decisions for price p^* and refund r^* for the model with heterogenous hassle cost in equation (A.2).

$$p^* = \frac{1}{2}(1 + c - (1 + h_H(1 - \theta - \mu))\lambda - c\lambda\rho) \quad r^* = \frac{1}{2}(s + h_H\theta - k - c\rho) \quad (\text{A.2})$$

Although the retailer's optimal decisions are different with homogenous and heterogenous hassle costs, our analytical insights from the CPM with homogenous hassle cost carry over to the CPM with heterogenous hassle cost so long as μ is not equal to one. It should be clear that legitimate customer demand (and profit) increases as μ increases, because the hassle cost only impacts the remaining $1 - \mu$ fraction of the population. We also find that while the price, the order quantity, and the profit increase, the refund is insensitive with respect to the proportion of population with low hassle cost μ . Despite these differences with the homogenous case, comparing the CPM with heterogenous hassle cost to the RAM shows that there still exist thresholds for salvage value s and hassle cost h_H such that the result is similar to the one discussed in Proposition 4. However, note that the values of these thresholds are both greater than their counterparts in Proposition 4. In light of those points, we conclude that the analytical insights from the two models are the same. ■

APPENDIX B

ROBUSTNESS ANALYSES FOR THE SECOND ESSAY

In this section, we report the results of additional robustness tests that we conduct in order to validate our findings. First, we perform the same analyses for the BM and online channels by using both the dollar value and the number of observations for each variable of interest (i.e. purchases, returns, and returns to stores). Although we report the results of the analyses using the dollar value of those variables in §3.4.2 and §3.4.1, our results are the same when we use the number of observations for each variable of interest.

Second, we repeat the analyses for the impact of STS on the BM channel by using a different treatment group. We conduct this analysis for two reasons. First, any observed differences might be explained by cultural or economic differences between the U.S. and Canada, rather than the impact of STS. Second, there may be concerns that the new credit card program, which was implemented in the U.S. concurrently with the STS service, may confound our results. To address these concerns, we employ an additional data set, which belongs to a different set of stores in Canada that the retailer owns and operates under a different brand name. It is also worth noting that the retailer started implementing STS at this brand in September 2012, about a year after the U.S. stores. Note that we use 10 months before and 10 months after STS implementation for this analysis since there are only 10 months in our data set after September 2012. Our data set for this robustness analysis includes a total of 194 stores from Canada. Of those 194 stores, 143 were affected by STS and 51 were not affected. Evidently, the control group is the same as the one that we used in §3.4.2 while the treatment group is different. We conduct the exact same analyses as the ones explained in §3.4.2 by using these 194 stores. We find that the coefficient for the variables of interest, $GROUP * POLICY$, for store sales is positive and significant ($p < 0.001$, $R^2 = 0.74$) with the point estimate being 0.20. Hence, we conclude that implementing STS increases store sales and address concerns that might arise from a potential economic difference between the U.S. and Canada or the new credit card program.

Third, we repeat the analyses for the impact of STS on the BM channel by using a different control group. We conduct this analysis to address concerns arising from potential differences between brands. To do so, we employ the same additional data set from Canada, which was explained in the previous paragraph. Our data set for this robustness analysis includes a total of 745 stores from both the U.S. and Canada. Of those 745 stores, 602 were affected by STS and 143 were not affected. Note that these 143 Canadian stores were not affected by STS service between September 2011 and September 2012. We conduct the exact same analyses as the ones explained in §3.4.2 by using these 745 stores. We find that the coefficient for the variables of interest, $GROUP * POLICY$, for store sales is positive and significant ($p < 0.001$, $R^2 = 0.62$) with the point estimate being 0.07. Hence, our results regarding the increase in the store sales are again corroborated.

Fourth, we repeat the analyses for the impact of STS on the BM channel by using non-flagship brands in the treatment group. By doing so, we address concerns that may arise from a potential economic difference between the flagship and non-flagship brands. Our data set for this robustness analysis includes a total of 294 stores from both the U.S. and Canada. Of those 294 stores, 123 belong to the secondary brand and 123 belong to the outlet brand in the U.S. Note that STS was implemented for these 246 stores concurrently with the flagship brand stores. As explained in §3.4.2, the remaining 51 Canadian stores constitute the control group in our analysis. We conduct the exact same analyses as the ones explained in §3.4.2 by using these 294 stores. We find that the coefficient for the variables of interest, $GROUP * POLICY$, for store sales is positive and significant ($p < 0.001$, $R^2 = 0.57$) with the point estimate being 0.06. Clearly, our results regarding the increase in the store sales do not change.

Fifth, we repeat the analyses for the impact of STS on the online channel by using two different units of analysis. To validate our results in §3.4.1, we first use state-month as our unit of analysis rather than DMA-month. We conduct this robustness analysis to dismiss any concerns that might result from the heterogeneity of DMAs. We show that the coefficient for the variable of interest, $GROUP * POLICY$, for online sales is negative and significant ($p < 0.05$) with the point estimate being -0.11. We also find that STS service does not have any impact on online consumer returns. Second, we perform the

same analyses by creating a treatment and a control group within each DMA. For this case, the control group consists of customers that are not within the influence area of a physical store (> 50 miles) and the control group consists of customers that are within the influence area of a store. Once again, the results indicate that the coefficient for the variable of interest, $GROUP * POLICY$, for online sales is negative and significant ($p < 0.001$) with the point estimate being -0.11 .

Sixth, we conduct the analyses for sales of high-value and low-value products both at the BM and online channels by using product categories rather than a value threshold (\$100). Categories that we explore for these analyses are bridal, gold, and silver. Overall, these three categories represent about half of the total sales. Products in the bridal category are the highest valued items in our data set. We find that online sales of bridal items decrease while BM sales of bridal items increase. For the gold and silver categories, we observe no change neither at the BM channel nor at the online channel. Hence, these findings further validate that customers switch from online to BM channel to purchase high-value products while they continue using the online channel to purchase low-value products after STS is implemented.

Finally, we also explore whether warranty sales change at the online and BM channels after STS service is implemented. Warranty options available for customers include buying a lifetime protection plan or a lifetime protection plan with a two-year theft replacement. Our dependent variables for the BM and online channels are the log of total warranty sales at store j during month t and at DMA d during month t , respectively. We find that online channel warranty sales decrease while BM channel warranty sales increase after STS service. Because consumers are more likely to purchase extended warranties for high-value products (Maronick 2007), our findings for warranty sales also support the channel switching behavior for high-value purchases after STS service. In the following subsections, we explore the preintervention trends both for the online and BM channels.

Analysis of Preintervention Trends

We now explore whether control and treatment groups in our models follow the same trend in the preintervention period. If the pre-STs trends that control and treatment groups follow were different, we could still find an effect with the DID analysis that is

arising from the difference in preintervention trends. In such a case, the effect that we find would be confounded with the pre-STS trends. To rule out any concerns about different pre-STS trends for the control and treatment groups in the online channel, we use the following model specification.

$$\begin{aligned} \log(\text{ONLINE SALES}_{dt}) = & \mu_d + \alpha_1 \text{GROUP}_d + \alpha_2 \text{TREND}_t + \alpha_3 \text{GROUP}_d * \text{TREND}_t \\ & + \alpha_m \text{CONTROLS}_{mdt} + \epsilon_{dt} \end{aligned} \quad (\text{B.1})$$

where TREND_t identifies the number of days since the beginning of the analysis period (September 2010). The results show that α_3 is not statistically significant ($p > 0.1$, $R^2 = 0.63$). Therefore, we can conclude that both the control and treatment groups follow the same trend in the online channel before STS service is implemented. Hence, we rule out any concerns that different pre-STS trends drive the observed results for the model in equation 3.1.

Although we do not report the model here due to space limitation, we conduct the same analysis for $\log(\text{CROSS RETURNS}_{dt})$ and find that the coefficient for the variables of interest, $\text{GROUP} * \text{TREND}$, is not statistically significant ($p > 0.1$, $R^2 = 0.63$). Hence, we conclude that control and treatment groups follow the same trend in the preintervention period.

Similar to what we did for the online channel, we use the following model specification to rule out any concerns about different pre-STS trends for the control and treatment groups in the BM channel.

$$\begin{aligned} \log(\text{STORE SALES}_{jt}) = & \mu_j + \delta_1 \text{GROUP}_j + \delta_2 \text{TREND}_t + \delta_3 \text{GROUP}_j * \text{TREND}_t \\ & + \delta_s \text{CONTROLS}_{s jt} + \epsilon_{jt} \end{aligned} \quad (\text{B.2})$$

where TREND_t counts the number of days since the beginning of the analysis period (September 2010). We find that δ_3 is not statistically significant ($p > 0.1$, $R^2 = 0.65$) and therefore, conclude that both the control and treatment groups in the BM channel follow the same trend before STS service is implemented.

We conduct a similar analysis to investigate the pre-STS trends for the aggregate impact

in §3.5.2 and find that the coefficient for the variable of interest, $GROUP * TREND$, is not statistically significant ($p > 0.1$, $R^2 = 0.78$). Hence, we conclude that the retailer's total sales in the U.S. and Canada followed the same trend in the pre-STS period.

Finally, we artificially select a wrong date for the service implementation in the pre-STS period and conduct the same analyses both for the BM and online channels. These analyses include a total of twelve months: six months before and six months after the artificial implementation date. In other words, the artificial implementation date is chosen in the middle of the original preintervention period. Hence, we divide the original pre-STS period into two parts for these analyses. Our results for the online channel show that the coefficient of the interaction term, $GROUP * POLICY$, is not statistically significant ($p > 0.1$). Similarly, the results for the BM channel show that the coefficient of the interaction term, $GROUP * POLICY$, is not statistically significant ($p > 0.1$). Therefore, these findings provide additional evidence to rule out any concerns that control and treatment groups may have different trends before STS is implemented.

Analysis with Fixed-Effects Models

We now investigate whether fixed-effects models generate the same results as the random-effects models. Note that the impact of time-invariant control variables are not observable with fixed-effects models. We report our findings in Table B.1. Each column in Table B.1 represents the test of a corresponding hypothesis and the the first row of each column identifies the dependent variable for that regression model. For each column, we report the results for the variable of interest, $GROUP * POLICY$, in the second row. The results of fixed-effects models show that our results do not change relative to random-effects models.

Table B.1: Fixed-Effects Models

	ONLINE SALES	HIGH SALES	LOW SALES	CROSS RETURNS	ONLINE RETURNS	TIME TO RETURN	STORE SALES
GROUP*POLICY	-0.14*** (0.05)	-0.15*** (0.05)	-0.002 (0.04)	0.48 ** (0.07)	0.10 (0.07)	-0.17 ** (0.06)	0.14*** (0.02)
ONLINE SALES	-	-	-	0.75*** (0.07)	1.08*** (0.03)	-	-
HOLIDAY	1.14*** (0.02)	1.15*** (0.02)	1.34*** (0.02)	0.13 (0.10)	-0.27*** (0.05)	0.19*** (0.03)	1.05*** (0.01)
SUMMER	-0.22*** (0.02)	-0.21*** (0.02)	-0.35*** (0.02)	-0.03 (0.05)	0.11*** (0.03)	-0.30*** (0.02)	-0.09*** (0.01)
PROMOTION	1.05*** (0.06)	0.92*** (0.06)	0.67*** (0.05)	0.48*** (0.11)	-0.50*** (0.11)	0.14 (0.09)	0.85*** (0.04)
<i>N</i>	5,024	5,007	4,970	1,160	4,667	4,667	15,672
<i>R</i> ²	0.47	0.42	0.52	0.35	0.35	0.07	0.58
HYPOTHESIS SUPPORT	H1A No	H1B No	H1B No	H2A Yes	H2B No	H2C Yes	H3 Yes

Note: Standard errors are reported in parentheses.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$