To the Graduate Council:

I am submitting herewith a dissertation written by Yu Jiang entitled "Consumer Returns in Electronic Commerce." I have examined the final paper copy of this dissertation for form and content and recommend that it be accepted in partial fulfillment of the requirements for the degree of Doctor of Philosophy, with a major in Business Analytics.

Michael Galbreth, Major Professor

We have read this dissertation
and recommend its acceptance:

Michael Galbreth

Paolo Letizia

Yuanyang Liu

Huseyn Abdulla

Accepted for the Council:

Dixie L. Thompson

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(Original signatures are on file with official student records.)

Consumer Returns in Electronic Commerce

A Dissertation Presented for the

Doctor of Philosophy

Degree

The University of Tennessee, Knoxville

Yu Jiang

May 2025

This work is dedicated to my family.

To my mom, Ping Jiang, for your unconditional love.

To my grandparents, Changji Yang and Shufang Zheng, for your support.

To my furry boy, Nicolas, for your company with me.

I could not be who I am today without all of you.

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Per aspera ad astra

Through hardships to the stars

Abstract

This dissertation has two empirical essays that explore consumer returns in electronic commerce. The goal of this work is to help online retailers to improve customer satisfaction, enhance customer loyalty, and eventually increase profitability by optimizing consumer returns management strategies.

The first essay explores the effects of customer procrastination and reverse logistics time on customer loyalty from the customer co-production perspective. We construct econometric models for the entire online return process. Using a proprietary dataset from one reverse logistics management firm, we apply logistic regression and the Cox proportional hazards regression models to verify our hypotheses. We find that both customer procrastination and reverse logistics time negatively affect customer loyalty. Our results suggest that reducing customer procrastination or shortening reverse logistics time can decrease consumer return rates and enhance customer retention. Further analysis using consumer psychology theories indicates that customer procrastination is associated with demographic factors like gender and ethnicity. These results suggest that online retailers should reconsider consumer returns not merely as an unavoidable cost of doing business but as a strategic opportunity for fostering positive customer engagement. By leveraging returns as a touch-point for enhancing customer experience, retailers can drive future sales and achieve long-term profitability.

Motivated by differences in customer procrastination across gender and ethnicity, the second essay examines how gender and ethnic diversities impact consumer returns

in the luxury fashion industry. Although both gender and ethnicity are well studied in consumer behavior and retail operations, the academic literature lacks insights into how a consumer's gender and ethnicity drive their return behaviors. We address this gap by analyzing 1.8 million online transactions across the US, using algorithms to predict customers' gender and ethnicity from their names and neighborhood demographics. Through logistic regression and mediation analysis, we identify distinct return patterns across different demographic groups. These findings enable targeted operational strategies to reduce returns and increase retention, allowing firms to tailor marketing approaches to accommodate varying return tendencies among consumer groups, ultimately improving operational efficiency and supporting localized marketing strategies.

Table of Contents

List of Tables

List of Figures

Nomenclature

CEO	Chief Executive Officer
CLSC	Closed-Loop Supply Chain
FCC	Federal Communications Commission
FIPS	Federal Information Processing Standards
GDM	Global Diversity Marketing
NRF	National Retail Federation
OR	Odds Ratio
PC	Personal Computer
RMA	Return Merchandise Authorization

Chapter 1

Introduction

Consumer returns are a critical issue at the intersection of operations management and marketing, directly affecting customer retention, reverse logistics efficiency, and retailer profitability (Abdulla et al., 2019). The National Retail Federation (NRF) in 2024 has reported that the annual return rate was 16.9%, amounting to $890 billion in associated costs. Additionally, an NRF study completed in October 2024 highlighted that online return rates, on average, were 20% higher than overall return rates. Prior research attributes this huge gap between online and offline return rates to online shoppers' inability to physically inspect products prior to purchase (Griffis et al., 2012; Dzyabura et al., 2023; Nageswaran et al., 2025).

The higher online return rates are amplified by the rapid growth of e-commerce, demanding online retailers' prompt attention to the drivers of consumer returns decisions (Nageswaran et al., 2025). By understanding the factors behind product returns, online retailers can formulate data-driven return policies that harmonize customer satisfaction with operational effectiveness. Strategically crafted policies not only curb nonessential returns but also simplify reverse logistics processes and reduce financial losses (Abdulla et al., 2019). Eventually, proactively optimizing returns management can improve customer trust while strengthening sustainable profitability in the competitive digital marketplace.

This dissertation comprises two empirical essays to investigate consumer returns from different perspectives. The first essay investigates how customer efficiency and reverse logistics efficiency influence customer loyalty, measured by repurchase behavior, from the service co-production perspective. Leveraging a proprietary dataset from a reverse logistics firm, we quantify customer procrastination as a measure of customer efficiency and reverse logistics time as an indicator of reverse logistics efficiency. Our results show that both customer procrastination and reverse logistics time negatively impact customer loyalty after returning products. In addition, we also explore factors driving customer procrastination, identifying demographic patterns and psychological factors that contribute to customer delayed return behavior. Our main contribution is to integrate customer co-production into the reverse logistics framework, expanding beyond existing research on reverse logistics and customer loyalty.

Building on insights into the drivers of customer procrastination from my first essay, my second one focuses on two demographic factors, gender and ethnicity, as key determinants of return behavior in e-commerce. Using a large-scale transaction level dataset, we apply different name-based algorithms and geographic location data to predict gender and ethnicity. The results suggest that distinct return patterns come across demographic groups, indicating that targeted operational strategies can reduce return rates and improve customer retention. Our main contribution is to bridge consumer psychological theories with demographic analytics, offering actionable operational frameworks for diverse customer bases.

Incorporating proprietary datasets from online retailers and public demographic data, this dissertation unfolds across two main streams: (i) employing statistical models, econometric models, and consumer psychological theories to identify and analyze the factors driving consumer return behaviors, thereby unraveling complexities of decision-making processes in the e-commerce context, and (ii) developing innovative and data-driven strategies for firms to effectively reduce return rates while enhancing customer satisfaction and retention.

The remainder of this dissertation is organized as follows. Chapter 2, "*The Impact of Reverse Logistics on Customer Repurchase: A Service Co-Production Perspective*", studies how two main factors, customer procrastination and reverse logistics time, influence consumer repurchase behavior from the customer co-production perspective. Chapter 3, "*How do Gender and Ethnic Diversity Impact Consumer Returns?*", explores the impact of two demographic metrics, gender and ethnicity, on consumer returns. Finally, Chapter 4 discusses the key findings of both essays and the future research direction of consumer returns.

Chapter 2

The Impact of Reverse Logistics on Customer Repurchase: A Service Co-Production Perspective

2.1 Introduction

The National Retail Federation's (NRF) 2023 annual report reveals that total returns in the U.S. retail industry reached $743 billion, representing 14.5% of overall sales. This significant figure is largely attributable to the growing market share of online retail, which typically experiences higher return rates than traditional brick-and-mortar stores. The continuous expansion of e-commerce, alongside rising consumer expectations for free and hassle-free returns, has led industry experts to identify returns management as one of the most pressing challenges for retailers in the coming decade. As online shopping continues to proliferate, the efficiency of reverse logistics in processing returns will become increasingly crucial for retail operational strategies. An effective return management process not only enhances the potential for recovering greater salvage value from returned products but also positively impacts customer satisfaction and loyalty, which can translate into increased future purchases (Chandrashekaran et al., 2007; Walsh et al., 2008; Morgeson III et al., 2020).

Both customer and retailer actions play a critical role in determining the responsiveness of the return process. From the customer's side, there may be variation in the timeliness of returns. Some customers act promptly, while others may delay between generating a return label and delivering the package to the carrier. On the retailer's side, delays may also arise, such as in the inspection of returned items, the processing of products through reverse logistics, and the issuance of refunds, often adjusted for restocking fees or other penalties. This paper explores the relationship between these delays—whether due to customer procrastination or inefficiencies in the retailer's reverse logistics operations—and customer loyalty in online retail, as measured by subsequent purchasing behavior. The findings provide valuable insights into the potential advantages for online retailers in enhancing the responsiveness of their reverse logistics processes (as affected by both customer and retailer actions).

The shared responsibility for the return process between customer and retailer aligns with the concept of "co-production" (Parks et al., 1981). This concept had been originally introduced with respect to public services delivery to highlight that consumer involvement in public service has the potential to increase its effectiveness and efficiency. However, more recently, this theory of service co-production has found wide applications in other business contexts, such as consulting, healthcare, and retail. For instance, Xue and Field (2008) have examined the collaborative process between clients and consultants in knowledge-intensive services, whereas Andritsos and Tang (2018) have explored the joint participation of patients and healthcare providers in reducing hospital readmissions. In a retail context, it has been recently recognized that consumer "co-creation" of the product, such as when the consumer engages in customization, leads to increased willingness to pay, higher customer satisfaction and lower risk of product misfit (Franke et al., 2009; Valenzuela et al., 2009; Guo, 2024). Consistent with this perspective, we also are interested in studying how the efficiency of the returns process may be improved through the contribution of both the customer and the retailer. Specifically, we want to address the following research questions:

- What role does co-production play in the online returns process and how does it affect customer repurchase behavior?
- How does the timing of returns influence customer repurchase behavior in online retail settings?

Consider a typical customer experience with an online apparel retailer. The customer purchases an item, receives it, and may wear it on one or more occasions (within the allowable return window) to determine if they are satisfied with the purchase. After a few days (a "product experience" delay), the customer decides to return the item for a full refund. This process is typically initiated by the customer creating a return label. The customer's next step is to drop off the item to be shipped back to the retailer, which might not happen immediately after label creation (a "customer procrastination" delay). The product is then transported back to the retailer (a "transit time" delay), at which point the retailer needs to verify and process the return (an "inspection time" delay) before issuing a refund to the customer. Figure 2.1 depicts these four main stages of the online return process.

Stage 1 in Figure 2.1 is a standard element of online sales in the era of free returns, as customers will take some time to determine if they want to keep the product. Retailers can reduce friction, and perhaps speed up the returns process, by providing easy access to an automated return label when the customer decides to make a return. The delay in Stage 2 is caused by the customers themselves, as they may procrastinate before dropping off the return at a third-party shipper, similar to a brick-and-mortar customer delaying their trip back to the store to make a return. Stage 3, on the other hand, represents a delay unique to the online retail environment, reflecting pure shipping time due to the retailer's lack of a physical store presence. If the retailer takes an omnichannel approach by accepting returns of

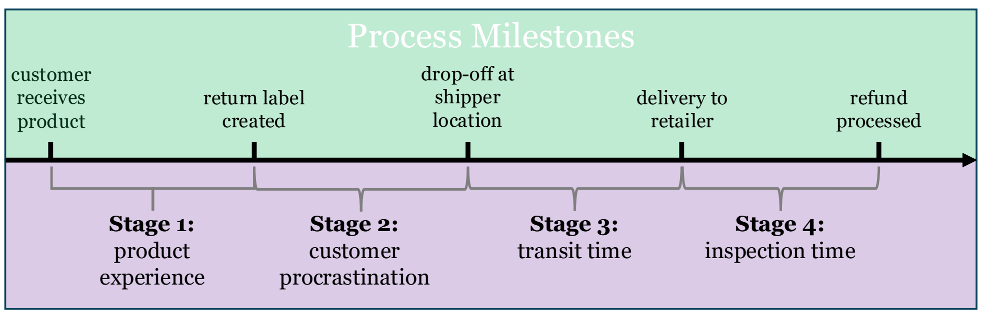

Figure 2.1: Online Return Process Timeline

online purchases at physical stores, Stage 3 might be eliminated, but only if return inspection is decentralized to the stores. If omnichannel returns are shipped to a central inspection location before processing refunds, the flow would be similar to Figure 2.1. However, this paper focuses on the business context of pure online retail. Similarly, Stage 4 involves a delay that typically does not exist in brick-and-mortar retail, where refunds are processed immediately at the time of the return. Our goal is to understand the impact of the Stage 2 delay, i.e., *customer procrastination*, and the combination of stage 3 and 4 delays, namely *reverse logistics time* on customer loyalty, as measured by subsequent customer orders. In doing so, we provide insights into the potential customer loyalty benefits of improving the responsiveness of reverse logistics for online retailers.

Our work yields several important findings. First, we find that both customer procrastination (delay between creating return labels and dropping off items) and reverse logistics time (delay in return processes and issuing refunds) negatively impact customer loyalty, measured by repurchase behavior. Second, customer procrastination has a significantly stronger negative effect on repurchase behavior than reverse logistics time, with each additional day of procrastination reducing repuchase odds by 3.5%, compared to 2.1% for reverse logistics time. Furthermore, this paper also shows that higher product prices intensify the negative relationship between reverse logistics time and customer loyalty but do not significantly moderate the relationship between customer procrastination and loyalty. Finally, our post-hoc analysis reveals that demographic factors, like gender, ethnicity, age, impact customer procrastination. Females and White customers procrastinate less than others while younger customers exhibit higher tendencies to delay returns. These findings emphasize customer co-production in online consumer returns, suggesting that online retailers should have effective communication and hassle-free return processes to reduce customer procrastination as well as reverse logistics time to enhance customer experience for customer loyalty.

This work expands the existing literature on consumer returns, customer procrastination, and reserve logistics by conceptualizing customer loyalty as being impacted by two fundamental effects: *customer procrastination* effect and *reverse logistics time* effect. *Customer procrastination* effect reflects customers' role in the efficiency of the service co-production, where delays are caused by the customer initiating the return process. *Reverse logistics time* effect encompasses the entire process from when the item is dropped off by the customer until the refund is processed. This effect measures online retailers' operational effectiveness and logistics partners in handling returns. In our empirical model, we quantify and estimate both effects, and examine their relative importance in shaping customer loyalty, measured by customer repurchase behaviors, on online return process.

The rest of this paper is organized as follows. In section 2.2, we review and summarize the related literature from both operations management and marketing. In section 2.3, we draw on relevant theory to develop our hypotheses. In section 2.4, we introduce our data and define our key variables. In section 2.5, we show the model estimation, for both the main model and post hoc analysis, and discuss the implications of our findings. This is followed by several robustness checks in section 2.6. Finally, in section 2.7, we conclude with a summary of the implications of this research.

2.2 Literature Review

Our paper contributes to and intersects with three streams of literature: (i) customer loyalty, (ii) reverse logistics responsiveness, and (iii) service co-production.

2.2.1 Customer Loyalty

Customer loyalty is commonly conceptualized in terms of actual repurchase behavior or a long-term commitment to a specific brand or organization. Singh (2006) defines customer loyalty as “the result of an organization creating a benefit for a customer so that they will maintain or increase their purchases from the organization.” Similarly, Aksoy et al. (2014) describe customer loyalty as “a deeply held commitment to re-buy or re-patronize a preferred product or service consistently in the future, despite situational influences and marketing efforts with the potential to cause switching behavior.” Beyond its definitions, customer loyalty is a critical strategic objective for modern businesses, providing numerous advantages beyond transactional exchanges (Duffy, 2003). A key benefit is its impact on profitability, as it reduces costs associated with acquiring new customers (Kumar and Shah, 2004). Retaining existing customers is more cost-effective than continuously seeking new ones, as loyal customers are generally less sensitive to price fluctuations (Kumar and Reinartz, 2016). Extensive research in relationship marketing (Palmatier et al., 2006), branding (Zeithaml et al., 2001), direct selling (Macintosh and Lockshin, 1997), customer satisfaction (Oliver, 1999), and customer value (Sirdeshmukh et al., 2002) consistently demonstrates that customer loyalty contributes to improved financial performance. However, the present study focuses on the antecedents of customer loyalty rather than its financial implications, emphasizing the factors that drive and sustain long-term consumer commitment.

The marketing and service literature is replete with studies identifying customer satisfaction as a primary determinant of customer loyalty (e.g., Lin and Wang 2006; Heskett et al. 1994). In particular, Chandrashekaran et al. (2007) demonstrate that satisfaction strength—inversely determined by the degree of uncertainty associated with service provision—plays a crucial role in converting stated satisfaction into loyalty. In a similar vein, Schirmer et al. (2018) show that the relationship between consumer satisfaction and loyalty is partially mediated by trust, which they define as confidence in the quality and reliability of a company’s products and services. Service quality has also been associated with customer loyalty (e.g., Wallenburg 2009; Kumar et al. 2011). The literature on service quality highlights two critical components: relational and operational elements. Relational elements encompass activities aimed at understanding customer needs and expectations (e.g., Bell et al. 2005; Payne and Frow 2005). In contrast, operational elements refer to the activities service providers undertake to maintain consistently high levels of productivity, quality, and efficiency (De Vries et al., 2018). Prior research has explored additional drivers of customer loyalty, including corporate and brand image (Melewar et al., 2020), perceived value—conceptualized as the ratio of perceived benefits to perceived costs (Yang and Peterson, 2004)—and switching costs, which involve consumers' investments of time, money, and psychological effort (Yang and Peterson, 2004).

Our article examines a novel and understudied driver of customer loyalty—reverse logistics responsiveness. To the best of our knowledge, there are only two works that have explored a similar relationship. Griffis et al. (2012) investigate repurchase behavior following consumer returns in online retail; however, their study does not consider the role of customers in the reverse logistics process. In our research, reverse logistics responsiveness encompasses both customer procrastination and reverse logistics time. A key contribution of our study is assessing which of these two delays—the customer's or the online retailer's—has a greater impact on repurchase behavior. Ertekin (2018) explores customer repurchase behavior in relation to satisfaction with in-store return experiences, emphasizing interactions with store assistants, including salesperson competence and selling pressure. In contrast, our study measures the return experience through reverse logistics responsiveness in processing returns. Moreover, we focus on online transactions, where customer interactions with salespersons are absent.

2.2.2 Reverse Logistics Responsiveness

There is a substantial body of analytical and empirical research examining the issue of consumer returns, with a central focus on retailers' strategies for preventing, forecasting, and managing returns (e.g., Shulman et al. 2009; Letizia et al. 2018, Shang et al. 2020). Reverse logistics responsiveness plays a critical role in returns management. Early research in this area primarily focused on designing and implementing cost-effective but inherently slow processes for recovering returned products (Stock, 1998; Daugherty et al., 2001). Over time, as the salvage value of returned products became more significant, the focus of reverse logistics literature shifted from cost-driven to profit-driven strategies. A key development in this shift was the recognition of the need to align reverse logistics processes with product time sensitivity. For example, time-sensitive products, such as personal computers, benefit from responsive, decentralized closed-loop supply chains (CLSCs), whereas less time-sensitive items, such as power tools, are better suited to cost-efficient, centralized CLSCs (Richey et al., 2004; Campos et al., 2017). This trade-off hinges on balancing the opportunity cost of value depreciation against the economies of scale achieved in recovery processes (Letizia et al., 2018). While our study also investigates reverse logistics responsiveness, it adopts a distinct perspective by examining its impact on customer repurchase behavior rather than the salvage value of returned products.

Reverse logistics responsiveness is also shaped by customer procrastination in returning purchased products. The concept of procrastination, originating in psychological research, refers to the act of delaying or postponing tasks, often leading to stress and reduced productivity (Solomon and Rothblum, 1984). Recent studies in operations management and marketing have further explored this phenomenon. For instance, Wagner et al. (2023) examine supplier procrastination in delivery consolidation, showing that efforts to consolidate shipments may lead suppliers to delay order fulfillment while awaiting additional parcels. Brigden and Häubl (2020) investigate consumer procrastination in addressing minor issues, such as scratched displays or missing buttons, revealing that delays in resolving small problems can result in their persistence and disproportionate negative consequences. Similarly, Janakiraman and Ordóñez (2012) explore the effects of deadlines on customer procrastination in a controlled laboratory setting. Building on this literature, our study positions customer procrastination as a critical determinant of reverse logistics efficiency. Specifically, we quantify its impact on customer satisfaction and loyalty, as measured by their willingness to place future purchase orders.

2.2.3 Service Co-Production

The concept of co-production was introduced by Parks et al. (1981) to emphasize the role of consumers as co-producers in enhancing the effectiveness and efficiency of service delivery. In a business context, co-production refers to the collaboration between companies and customers in the creation of products or services. Xue and Harker (2002) were pioneers in introducing the concept of customer efficiency, which underscores the customer's role as a co-producer in service co-production. Their study examines the impact of customer efficiency—captured through key customer characteristics—on online retail management. An "efficient customer" is defined as one who utilizes fewer resources to generate the same or greater output during their participation in the service co-production process. Xue and Harker (2002) also propose three dimensions of customer efficiency: transaction, value, and quality efficiency. Transaction efficiency is particularly relevant to services where outputs consist of a series of completed transactions, while inputs include the time invested by both the customer and the service provider. Given that reverse shipping performance is co-determined by both the customer and the shipper in terms of time, we apply the concept of customer transaction efficiency to our research context. Specifically, we posit that customers who spend less time dropping off a return to the shipper exhibit higher transaction efficiency. Building on this theoretical framework, Xue et al. (2007) utilize banking data to demonstrate the significant variation in customer efficiency across individuals and its subsequent impact on service delivery outcomes and customer retention. Similarly, Xue and Field (2008) explore customer efficiency in service co-production, highlighting the complexities introduced by higher levels of customer participation in ensuring an efficient service delivery process.

Our research aims to investigate the factors influencing customer efficiency in return shipping and its impact on post-return behavior. Prior studies on service co-production have demonstrated how customers actively participate in and contribute to the service process, particularly in contexts requiring direct interaction between customers and service providers (Bendapudi and Leone, 2003; Roels, 2014; Daw et al., 2024). However, while the literature predominantly highlights the positive effects of customer involvement, it is equally important to consider the challenges associated with customer-induced delays in the service process.

2.3 Theory and Hypotheses Development

Customer Procrastination and Customer Loyalty

Customer procrastination is a common consumer behavior characterized by a delay between intention and subsequent action (Steel, 2007; Zanjani et al., 2016). In the context of post-purchase activities, particularly within the reverse logistics process, customer procrastination manifests as a delay in returning a purchased product, even when customers recognize that retaining the product does not meet their needs (Abdulla et al., 2022). Existing studies have explored various factors contributing to customer procrastination in product returns. For instance, it has been shown that complex return policies and procedures can significantly delay return decisions (Su, 2009; Tran et al., 2018). Additionally, both theoretical and empirical studies suggest that return costs negatively influence consumers' willingness to return products (Anderson et al., 2009; Shehu et al., 2020). A lack of time is another key factor leading to customer procrastination in the returns process (Lee and Yi, 2022).

Shifting from the antecedents of customer procrastination, our focus lies in examining its impact on customer satisfaction and loyalty. From this perspective, prior research has identified several unfavorable consequences of customer procrastination, including adverse emotions such as regret and anger, unfavorable behaviors such as negative word-of-mouth, customer complaints, and customer attrition (Azimi et al., 2020). Prolonged retention of unsatisfactory products can degrade the customer experience and damage brand reputation, prompting customers to seek alternatives (Maxham III and Netemeyer, 2002; Grégoire et al., 2009; Khamitov et al., 2020). Additionally, holding onto unwanted items for an extended period serves as a persistent reminder of unmet needs, reinforcing customer dissatisfaction with their purchase (Minnema et al., 2016). This negative shopping experience can further diminish customers' perception of brand value and esteem (Yang and Peterson, 2004). Moreover, delays in returning products increase the likelihood of negative word-of-mouth, as dissatisfied customers may continue voicing their frustrations for a prolonged period (Richins, 1983). This poses a significant challenge for online retailers, particularly in the digital era, where online reviews reinforce the impact of customer dissatisfaction and rapidly shape brand perception. As such, our first hypothesis can be formalized as follows:

Hypothesis 1 (H1): *Customer procrastination is negatively associated with customer loyalty.*

Reverse Logistics Time and Customer Loyalty

For several decades, operations scholars have expanded the definition of reverse logistics from a narrow focus to a broader perspective. One of the earliest definitions was proposed by Murphy (1986), describing reverse logistics as the "*movement of goods from a consumer back towards a producer in a channel of distribution*". This definition narrowly confined reverse logistics to the flow of materials in the opposite direction of the primary supply chain, from customer to producer. Subsequent studies have broadened this definition by associating reverse logistics with product returns (Stock, 1998; Rogers and Tibben-Lembke, 2001). This evolving research highlights the importance of understanding how reverse logistics time affects customer loyalty, as timely and efficient reverse logistics processes are essential for maintaining customer satisfaction and fostering future loyalty.

Extended time to process returns and refund customers may have negative influences on customer loyalty. Most return policies initiate refunds only after the returned items are received, leading customers to experience uncertainty and concern about the timely reimbursement of their money (Griffis et al., 2012; Martínez-López et al., 2022). Delays in the reverse logistics process can increase customer impatience and anxiety, as customers may miss alternative opportunities to allocate their funds elsewhere (Yu et al., 2023). This opportunity cost can enhance customer dissatisfaction, contributing to a negative product return experience. Existing studies indicate that negative return experiences can erode customer satisfaction with retailers, as customers perceive that their needs are not prioritized (Kivetz and Simonson, 2003; Wetzel et al., 2014; Kim et al., 2021). Customers who experience slow return processes may be less likely to repurchase or recommend the retailer to others, potentially affecting a broader customer base for online retailers. In highly competitive markets, extended reverse logistics times can disadvantage online retailers, particularly when competitors offer more efficient return processes. Therefore, our second hypothesis can be stated as follows:

Hypothesis 2 (H2): *Reverse Logistics time is negatively associated with customer loyalty.*

The Moderating Role of Product Price

Product price plays a crucial role in business since it directly impacts consumer buying decisions (McCarthy et al., 1979; Lee and Winterich, 2022). Customers often perceive price as a signal of quality (Yao et al., 2020; Cronley et al., 2005). In e-commerce, price is an important factor in shaping customer-retailer relationships and service expectations throughout the purchase and return process. We propose that product price moderates the effects of customer procrastination and reverse logistics time on customer loyalty from disctinct perspectives because of customer-driven and retailer-driven effects.

Marketing and psychologist researchers have widely studied the emotional connections consumers develop with high-priced products (Pozharliev et al., 2015; Lee, 2021). Customers who purchase more expensive products may have a stronger attachment to the retailer since they involve more in the purchase decision (Park et al., 2014, 2024), aligning with the commitment-consistency theory. Cialdini (1984) first proposed the commitment-consistency theory to show that people have a strong desire to be consistent with their prior commitments, statements, and actions. When customers invest more financially in a retailer relationship through expensive purchases, they develop stronger psychological commitments that can stand negative experiences, including their own procrastination behavior. Besides commitment-consistency, how customers interpret the causes of their expericens also influences in their future buying behavior. Attribution theory (Heider, 1958) provides insights into how customers assign causality and responsibility in the purchase and return process. When customers procrastinate in returning products, the delay is customer-driven or self-attributes instead of attributed to the retailer. Therefore, customers may rationalize their procrastination as a reflection of their own decision-making process while reducing blame directed at the retailer. For high-priced purchases, this self-attribution matches their prior commitment to the retailer, creating cognitive consistency against dissatisfaction. Additionally, Chen and Hitt (2002) and Bell et al. (2005) show that customers spending more might have higher switching costs, making them more likely to stay loyal to the retailer. Considering the importance of higher spenders, retailers may prioritize retaining customers buying more expensive products (Pullman and Gross, 2004; Debenedetti et al., 2024). As a result, these customers, also known as *very important person (VIP) customers* may receive better post-purchase service, for example, expedited support for consumer returns, enhancing customer satisfaction and loyalty.

In conclusion, the negative effect of customer procrastination on customer future loyalty is mitigated by product prices because of stronger emotional attachment, higher switching costs, and better post-purchase service from more expensive products (Pozharliev et al., 2015; Lee, 2021). We formulate our third hypothesis below:

Hypothesis 3a (H3a): *The negative relationship between customer procrastination and customer loyalty weakens as product prices increase.*

In contrast to customer procrastination, attribution theory indicates that customers perceive delay in reverse logistics time as retailer-driven (Bower and Maxham III, 2012). It can strengthen customers' negative impressions of retailers when they attribute service failure to the retailer, especially for high-priced products. Expectancy-value theory (Atkinson, 1957) explains this amplification effect. Customers who spend more on products develop heightened expectations of service quality throughout the entire transaction process, including product returns. High-value customers expect faster return process since most refunds are only initiated after retailers receive and inspect returned items. Prolonged return timelines violate their expectations, creating greater disappointment proportional to their initial cost (Griffis et al., 2012). While customers who return low-priced items may be less concerned about waiting for a refund, for high-value customers, the delay in refund may restrict their ability to reallocate funds for alternative purchases, increase financial stress with substantial amount, and heighten negative emotions, such as regret or frustration (Lee and Morewedge, 2023). Thus, we have the last hypothesis about the moderating effect of product prices on reverse logistics time:

Hypothesis 3b (H3b): *The negative relationship between reverse logistics time and customer loyalty strengthens as product prices increase.*

We have the conceptual model shown in Figure 2.2.

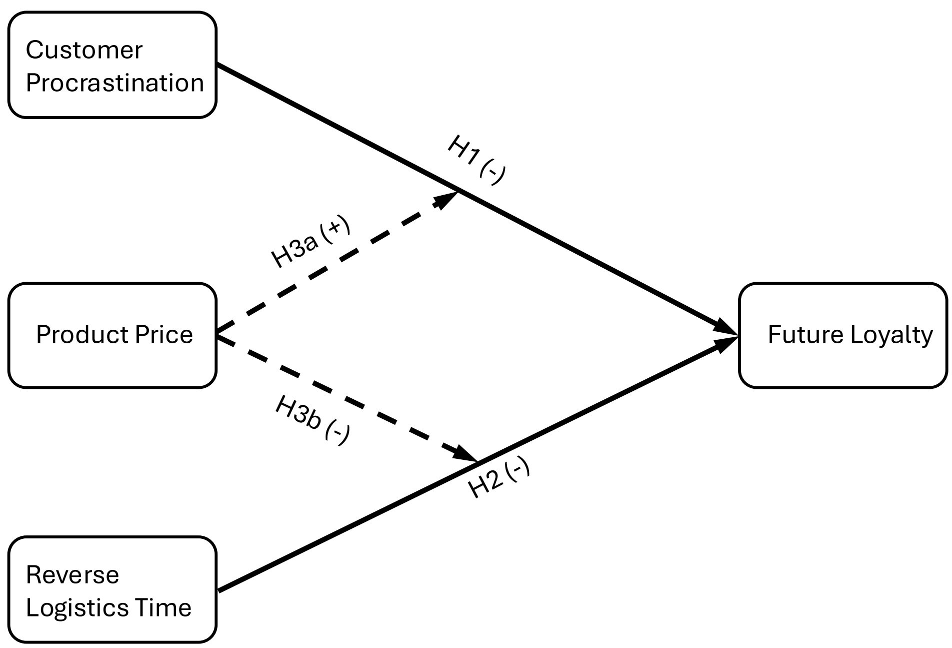

Figure 2.2: Hypotheses Formulation

2.4 Data Description

2.4.1 Study Setting

We examine our hypotheses using transaction-level data obtained from an online reverse logistics management firm. This firm assists with online return management process for various online retailers, operating in industries such as apparel, furniture, and technology accessories. For orders where customers request product returns, the return process begins with a Return Merchandise Authorization (RMA) created, providing created return labels. Customers later receive one return intructions email along with a prepaid shipping label. Next, customers prepare the returned package and drop it off at a designated shipping location. The firm partners with the third-party carriers, like USPS to collect and scan the packages at the drop-off, recording the drop-off timestamp. After the package is in transit, the carrier delivers it to the firms return processing centers. Upon receiving the returned product, the firm conducts a quality inspection to check the item's condition and determine eligibility for refund. The entire process is tracked through this firm's integrated return management platform, which captures timestamps for each stage starting from RMA creation to refund initiation. These timestamps help us to measure both customer procrastination (the time difference from RMA creation to package drop-off) and reverse logistics time (the time difference from package drop-off to refund processing).

We have collected data for 29,004 sales orders that were returned by customers, with the complete timestamps over a two-year span from July 2017 to March 2019. Instances where refunds were processed before retailers received returned items (i.e., zero reverse logistics time) were removed to obtain a dataset of 17,044 observations.

For our main analysis, we reallocate the full returns process from Figure 2.1 into in Figure 2.3, which delineates the two main effects for our main analysis: *customer efficiency* effect, measured by **customer procrastination**, the interval from when the return label is created to when the item is dropped off at one shipper

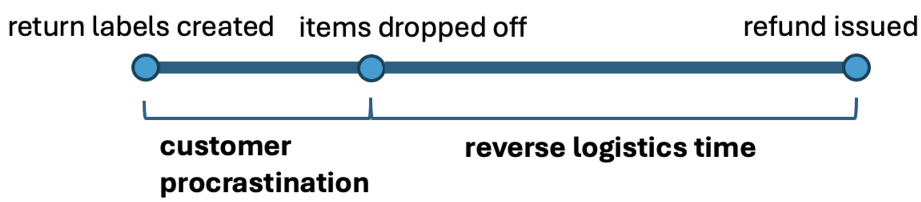

Figure 2.3: Online Return Process Timeline, Main Analysis

(corresponding to Stage 2 from Figure 2.1), and *reverse logistics efficiency* effect, measured by **reverse logistics time**, the time from item drop-off until the refund is issued.

2.4.2 Dependent Variables

Researchers have quantified customer loyalty in various ways throughout marketing and operations literature. De Vries et al. (2018) define customer loyalty based on repurchase behavior, particularly emphasizing the likelihood of customers returning after experiencing waiting time in a restaurant setting. Our paper adapts the similar approach by examining customer repurchase after returning online orders. We have two primary dependent variables to capture customer loyalty:

- *Time to repurchase*: the number of days between the refund date and the next order by the same customer at the same retailer.
- *Repurchase*: a binary variable indicating whether a customer placed a repurchase order (*repurchase = 1*) within the dataset timeframe.

The dataset is right-censored, ending on March 12, 2019. If a customer repurchased before this date (non-censored repurchase), both variables are straightforward to compute. If not (censored repurchase), we use the days between the refund date and the dataset cutoff for time to repurchase and set repurchase = 0. This computation method captures the right-censoring in the datadata with the time window. For censored observations, we do not know if the customer would eventually repurchase beyond the observation window. Using this technique allows us to correctly account for different observation periods across customers and avoids biasing results toward customers who repurchased after the time window ends.

The *time to repurchase* variable is highly right-skewed (see Figure 2.4), which may reduce efficiency in a logistic regression model. To handle right-censored data, we apply the Cox proportional hazards model (Cox, 1972), a common tool

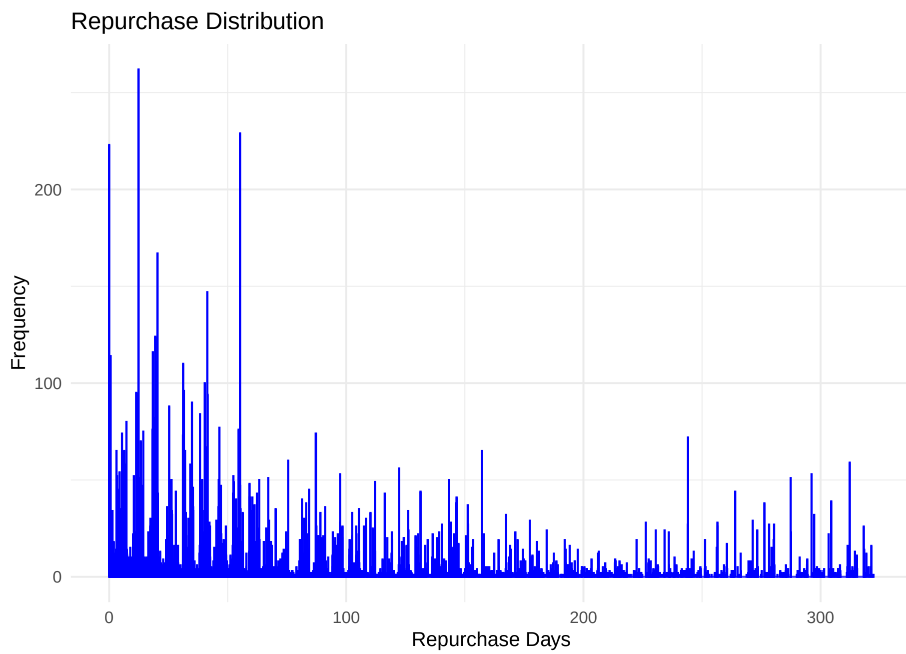

Figure 2.4: Repurchase Days

in survival analysis. This semi-parametric model estimates hazard ratios without assuming a fixed baseline hazard function. Traditionally, the Cox model is used in clinical research, the Cox model assesses factors affecting survival probabilities, where a lower hazard rate is preferred. In contrast, in our setting, the hazard rate represents customer repurchase, where a higher rate is desirable. This application demonstrates the model's versatility beyond survival analysis, offering insights into factors influencing repurchase behavior over time.

2.4.3 Independent Variables

This section describes the calcuation of our two primary variables of interest: **customer procrastination** and **reverse logistics time**.

Figure 2.3 depicts the initiation of the online return process occurs when a customer creates the return label. However, not all customers proceed to drop off the returned items immediately after generating these labels. Thus, we define **customer procrastination** as the time span, in days, from when the return label is created (*label_create_date*) to when the item is physically dropped off at one shipping location (*in_transit_update_date*). This metric captures the customer's promptness or delay in initiating the return process after deciding to return an item. Following the drop-off, the item enters the reverse logistics pipeline, beginning its journey back to the retailer. We quantify **reverse logistics time** as the interval from the item's drop-off date (*in_transit_update_date*) to the date the refund is issued by the retailer, (*refund_update_date*). It provides insight into the operational effectiveness of the retailer and logistics partners in managing returns and completing the refund process. We show histograms for two independent variables in Figure 2.5 and Figure 2.6.

2.4.4 Control Variables

We incorporate control variables from two levels of geographical granularity: census block groups and five-digit zip code areas. Census block groups, the smaller of the

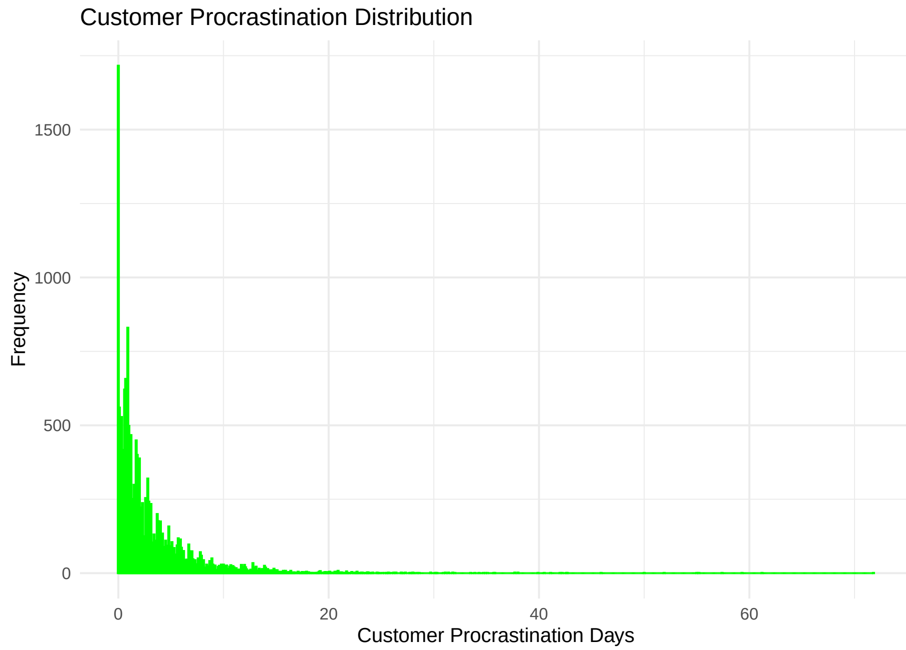

Figure 2.5: Customer Procrastination

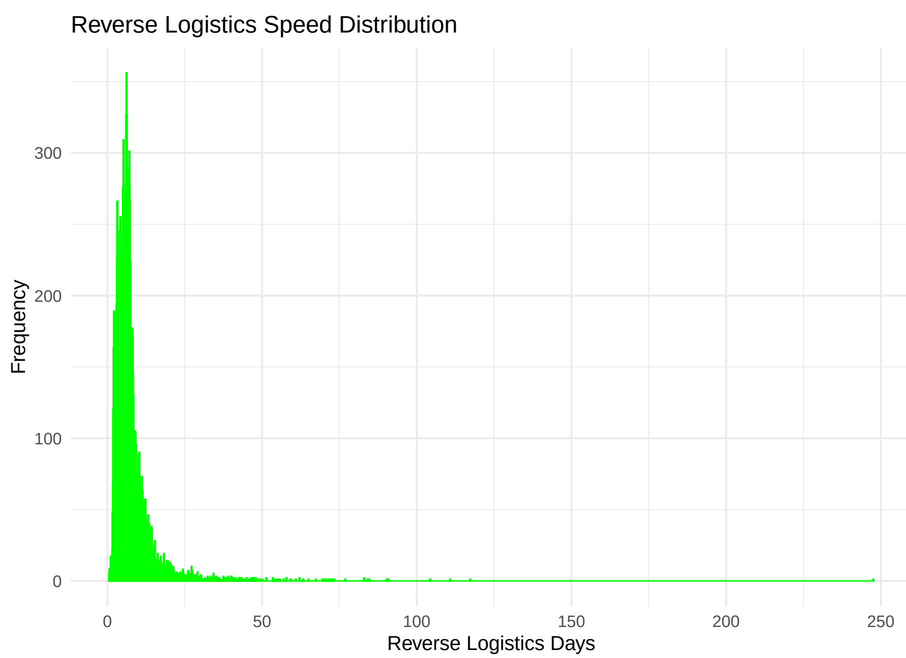

Figure 2.6: Reverse Logistics Time

two, usually contain a population of 600 to 3,000 people, typically approximately 1,500 individuals. On a broader scale, five-digit zip code areas typically cover around 10,000 individuals each, offering a wider geographical perspective.

Previous studies have shown that consumer returns are related to several control variables, including demographic and geographic information (Cui et al., 2021; Zhang et al., 2022). Informed by their findings, the control variables we consider include *median household income, average household size, percentage holding a bachelor's degree, population percentages across various age groups (under 18 year, 18 to 24 years, 25 to 34 years, 35 to 44 years, 45 to 54 years, 55 to 64 years, 65 years and older)*, and population percentages across different ethnic groups (*White, Black, Asian, Hispanic, and other race*), these variables are collected at the five-digit zip code level. At this geographic level, we encounter a small number of issues with missing data, leaving us with 16,885 records after excluding 159 zip codes for which the median household income is not provided (due to privacy concerns). We also collected data on the control variables at the census block group level, which we use as a robustness check in Section 2.6. Summary statistics for our main analysis are provided in Table 2.1.

2.5 Methodologies and Results

This section introduces our econometric models, logistic regression and the Cox model, and presents the model estimation results for both the main and post hoc analysis.

2.5.1 Main Analysis

We discuss our model estimations and results for Figure 2.3 as our main analysis.

We first use logistic regression model, also known as the logit model, for the dependent variable, repurchase, because of its binary metrics. A logistic regression is a widely used statistical model for binary dependent variables since it allows for

Table 2.1: Statistics Summary of Variables

Variables	Mean	Std. Dev.	Min	Max
Dependent Variables				
Time to Repurchase (unit: days)	81.62	81.48	0.00	322.27
Repurchase (dummy variable)	0.19	0.40	0.00	1.00
Independent Variables				
Customer Procrastination (unit: days)	3.10	4.14	0.00	71.79
Reverse Logistics Time (unit: days)	7.64	6.49	0.56	247.56
Control Variables				
Product Price (unit: $100)				
Apparel Company 1	1.76	1.19	0.00	10.50
Apparel Company 2	3.19	2.13	0.67	15.68
Apparel Company 3	2.75	2.08	0.08	13.75
Apparel Company 4	2.21	1.88	0.00	14.37
Apparel Company 5	0.84	0.53	0.00	6.24
Apparel Company 6	4.08	3.85	0.00	29.30
Apparel Company 7	4.44	3.87	0.00	40.66
Apparel Company 8	1.01	0.66	0.00	5.12
Apparel Company 9	3.33	2.86	0.00	27.94
Apparel & Accessories Company	1.04	0.66	0.25	3.73
Bags & Accessories Company	1.05	0.55	0.19	3.33
Bags & Technical Apparel Company	3.61	2.76	0.00	16.47
Crafts & Apparel Company	0.96	0.62	0.00	2.95
Footwear Company	2.54	1.64	0.00	6.15
Furniture Company	5.91	7.83	0.11	106.27
Home & Linen Goods Company	3.91	3.50	0.50	22.13
Jewelry Company	1.96	1.36	0.42	7.40
Tech Accessories	0.83	0.56	0.00	6.42
Total Shipping Cost (unit: $)	7.42	5.78	2.66	115.37
Total Return Quantity	1.88	3.12	1.00	111.00
Median Household Income (unit: $1,000)	92.55	40.28	14.26	250.00
Average Household Size	2.53	0.45	1.03	5.13
Bachelor's Degree Percentage (unit: %)	28.86	9.37	0.20	74.33
Age Group (unit: %)				
Under 18 Years	20.97	6.82	0.00	47.76
18 to 24 Years	8.74	5.99	0.00	92.67
25 to 34 Years	15.11	7.72	0.00	72.59
35 to 44 Years	13.11	2.87	0.00	29.87
45 to 54 Years	13.45	2.92	0.29	49.55
55 to 64 Years	12.77	3.16	0.00	47.80
65 to Over	15.84	6.25	0.00	82.75

Control variables are collected at the five-digit zip code level. The number of observations is 16,885.

the estimated probabilities directly related to the occurrence or non-occurrence of a particular outcome. This characteristic renders logistic regression particularly suitable for predicting the likelihood of binary events based on independent variables. We now define the logistic regression model in model (2.1).

$$
\begin{aligned}
log\frac{Pr(Repurchase = 1)}{1 - Pr(Repurchase = 1)} =& a_0 + a_1 CustomerProcrastination + \\
& a_2 ReverseLogisticsTime + a_3 ProductPrice + \\
& a_4 TotalShippingCost + a_5 TotalReturnValue + \\
& a_6 TotalReturnQuantity + a_7 MedHouseholdIncome + \\
& a_8 AvgHouseholdSize + a_9 BachelorPerc + \boldsymbol{aAgeGroup_z} + \\
& CompanyFixed + TimeFixed
\end{aligned} \tag{2.1}
$$

As we discuss earlier, logistic regression is insufficient for right-censored data. We defin the Cox model of customer repurchase in model (2.2).

$$
\begin{aligned}
h(t|\mathbf{X}) = h_0(t) \times exp(& b_0 + b_1 CustomerProcrastination + b_2 ReverseLogisticsTime + \\
& b_3 ProductPrice + b_4 TotalShippingCost + b_5 TotalReturnValue + \\
& b_6 TotalReturnQuantity + b_7 MedHouseholdIncome + \\
& b_8 AvgHouseholdSize + b_9 BachelorPerc + \\
& \boldsymbol{bAgeGroup_z} + CompanyFixed + TimeFixed)
\end{aligned} \tag{2.2}
$$

where t represents the survival time, time to repurchase, measured in days; $h(t)$ is the hazard function determined by a set of covariates, (*customer procrastination, reverse logistics time, product price, total shipping cost, total return quantity, median household income, average household size, bachelor's degree percentage, age group* *percentage*); h_0 is the baseline hazard and represents the hazard when all independent variables and control variables are equal to zero.

We show our model estimation results in Table 2.2. Both models incorporate several fixed effect terms (*Company Fixed Effect, Year Fixed Effect, Month Fixed Effect, Day of Week Fixed Effect, Holiday Fixed Effect*), which accounts for unobserved heterogeneity across online retailers. This term helps control for fixed effects that could influence repurchase behavior, ensuring that our analysis accurately reflects the impact of the studied variables.

Both logistic regression and Cox models examines the impacts of customer procrastination and reverse logistics time on the binary outcome, repurchase. We find a statistically significantly negative relationship between customer procrastination and repurchase ($a_1 = -0.036, p < 0.001$). The corresponding estimated odds ratio (OR=the probability/likelihood of repurchasing divided by the probability/likelihood of not repurchasing) for customer procrastination is $e^{-0.036} = 0.965$. Each additional day attributed to customer procrastination reduces the odds of repurchasing by about $(1-0.965)\times 100\% = 3.5\%$, translating to a substantial $(1-(e^{-0.036})^{10})\times 100\% = 30.2\%$ decrease in repurchasing likelihood given 10-day customer procrastination. The Cox model further investigates the timing of repurchases, indicating that each day of procrastination lowers the hazard rate by 2.5% ($b_1 = -0.025, p < 0.001$), meaning that a 10-day customer procrastination leads to a $(1-(e^{-0.025})^{10}) \times 100\% = 22.1\%$ reduction in the hazard rate. Therefore, **H1**, *"Customer procrastination is negatively associated with future loyalty"*, is fully supported empirically, not only confirming the detrimental effects of customer procrastination on repurchase likelihood but also on the timing until a repurchase occurs.

Similarly, for **reverse logistics time**, our analysis through logistic regression shows a significant negative correlation with repurchase likelihood ($a_2 = -0.021, p < 0.001$). Thus, we can have the estimated odds ratio, $e^{-0.021} = 0.979$, for **reverse logistics time**. This finding shows that each additional day of reverse logistics speed decreases the odds of repurchasing by approximately $(1 - 0.979) \times 100\% = 2.1\%$, all

Table 2.2: Main Analysis Results at 5-digit Zip Code Level

	Logit Model	Cox Model
(Intercept)	-1.999	
	(1.123)	
Customer Procrastination	-0.036^{***}	-0.025^{***}
	(0.006)	(0.005)
Reverse Logistics Time	-0.021^{***}	-0.013^{***}
	(0.004)	(0.004)
Control Variables	Included	Included
Company Fixed Effect	Included	Included
Year Fixed Effect	Included	Included
Month Fixed Effect	Included	Included
Day of Week Fixed Effect	Included	Included
Holiday Fixed Effect	Included	Included
AIC	14110.007	58955.267
BIC	14496.716	
Log Likelihood	-7005.004	
Observation Number	16885	16885
R^2		0.055
Events Number		3285

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$, $^{+}p < 0.1$ Robust standard errors of coefficients are presented in parentheses

else being equal. Each additional day in the reverse logistics process diminishes the odds of repurchasing by 2.1%, which for a 10-day delay, results in a $(1-(e^{-0.021})^{10}) \times 100\% = 18.9\%$ decrease in the likelihood of a future purchase. The Cox model's insights complement these findings by showing a 1.3% reduction in the hazard rate for each day's delay in reverse logistics ($b_2 = -0.013, p < 0.001$), culminating in a $(1-(e^{-0.013})^{10}) \times 100\% = 12.2\%$ reduction over 10 days. These results highlight the critical importance of optimizing reverse logistics operations to not just enhance the probability of repurchasing but also to expedite the repurchase cycle, thus supporting hypothesis **H2**, *"Reverse logistics time is negatively associated with future loyalty"*.

We can see that customer procrastination has a much bigger effect than reverse logistics time. The larger magnitude of the customer procrastination coefficient across both models suggests that delays caused by the customer have a more pronounced negative effect on repurchase likelihood than delays in the reverse logistics refund process. This insight is crucial as it highlights the relative importance of managing customer expectations and behaviors to enhance customer loyalty more effectively than logistical optimizations alone.

We construct another six models with interaction terms to investigate the product price moderating effect of customer procrastination and reverser logistics time on customer repurchase from model (2.3) to model (2.8) and then report the model estimated results.

$$\begin{aligned} log\frac{Pr(Repurchase=1)}{1-Pr(Repurchase=1)} =& c_0 + c_1 CustomerProcrastination + \\ & c_2 ReverseLogisticsTime + c_3 ProductPrice + \\ & c_4 CustomerProcrastination \times ProductPrice + \\ & c_5 TotalShippingCost + c_6 TotalReturnValue + \\ & c_7 TotalReturnQuantity + c_8 MedHouseholdIncome + \\ & c_9 AvgHouseholdSize + c_{10} BachelorPerc + \\ & \boldsymbol{cAgeGroup_z} + CompanyFixed + TimeFixed \end{aligned} \tag{2.3}$$

$$\begin{aligned} log\frac{Pr(Repurchase=1)}{1-Pr(Repurchase=1)} =& d_0 + d_1 CustomerProcrastination + \\ & d_2 ReverseLogisticsTime + d_3 ProductPrice + \\ & d_4 ReverseLogisticsTime \times ProductPrice + \\ & d_5 TotalShippingCost + d_6 TotalReturnValue + \\ & d_7 TotalReturnQuantity + d_8 MedHouseholdIncome + \\ & d_9 AvgHouseholdSize + d_{10} BachelorPerc + \\ & \boldsymbol{dAgeGroup_z} + CompanyFixed + TimeFixed \end{aligned} \tag{2.4}$$

$$
\begin{aligned}
log\frac{Pr(Repurchase=1)}{1-Pr(Repurchase=1)} =& e_0 + e_1 CustomerProcrastination + \\
& e_2 ReverseLogisticsTime + e_3 ProductPrice + \\
& e_4 CustomerProcrastination \times ProductPrice + \\
& e_5 ReverseLogisticsTime \times ProductPrice + \\
& e_6 TotalShippingCost + e_7 TotalReturnValue + \\
& e_8 TotalReturnQuantity + e_9 MedHouseholdIncome + \\
& e_{10} AvgHouseholdSize + e_{11} BachelorPerc + \\
& \boldsymbol{eAgeGroup_z} + CompanyFixed + TimeFixed
\end{aligned}
\tag{2.5}
$$

$$
\begin{aligned}
h(t|\mathbf{X}) = h_0(t) \times exp(& f_0 + f_1 CustomerProcrastination + f_2 ReverseLogisticsTime + \\
& f_3 ProductPrice + f_4 CustomerProcrastination \times ProductPrice + \\
& f_5 TotalShippingCost + f_6 TotalReturnValue + \\
& f_7 TotalReturnQuantity + f_8 MedHouseholdIncome + \\
& f_9 AvgHouseholdSize + f_{10} BachelorPerc + \\
& \boldsymbol{fAgeGroup_z} + CompanyFixed + TimeFixed)
\end{aligned}
\tag{2.6}
$$

$$
\begin{aligned}
h(t|\mathbf{X}) = h_0(t) \times exp(&g_0 + g_1 CustomerProcrastination + g_2 ReverseLogisticsTime + \\
&g_3 ProductPrice + g_4 ReverseLogisticsTime \times ProductPrice + \\
&g_5 TotalShippingCost + g_6 TotalReturnValue + \\
&g_7 TotalReturnQuantity + g_8 MedHouseholdIncome + \\
&g_9 AvgHouseholdSize + g_{10} BachelorPerc + \\
&\boldsymbol{gAgeGroup_z} + CompanyFixed + TimeFixed)
\end{aligned} \tag{2.7}
$$

$$
\begin{aligned}
h(t|\mathbf{X}) = h_0(t) \times exp(&i_0 + i_1 CustomerProcrastination + i_2 ReverseLogisticsTime + \\
&i_3 ProductPrice + i_4 ReverseLogisticsTime \times ProductPrice + \\
&i_5 TotalShippingCost + i_6 TotalReturnValue + \\
&i_7 TotalReturnQuantity + i_8 MedHouseholdIncome + \\
&i_9 AvgHouseholdSize + i_{10} BachelorPerc + \\
&\boldsymbol{iAgeGroup_z} + CompanyFixed + TimeFixed)
\end{aligned} \tag{2.8}
$$

Table 2.3 shows three logistic regression models with interaction terms, only with one interaction term, *Customer Procrastination* × *Product Price* in Logit Model 1, only with one interaction term, *Reverse Logistics Time* × *Product Price* in Logit Model 2 and with two interaction terms in Logit Model 3. From Logit Model 1 and Logit Model 3, we have statistically insignificant interaction terms, *Customer Procrastination* × *Product Price*, suggesting that product price may not significantly moderate the effect of customer procrastination on customer repurchase. It shows that **H3a**, *"The negative effect of customer procrastination on future loyalty diminishes with product prices"*, is not verified. To explore it more, we study factors driving

Table 2.3: Logistic Regression Estimation Results with the Product Price Moderator

	Logit Model 1	Logit Model 2	Logit Model 3
(Intercept)	-2.029	-2.094	-2.084
	(1.123)	(1.123)	(1.123)
Customer Procrastination	-0.042^{***}	-0.036^{***}	-0.042^{***}
	(0.008)	(0.006)	(0.008)
Reverse Logistics Time	-0.021^{***}	-0.015^{**}	-0.015^{**}
	(0.004)	(0.005)	(0.005)
Product Price	0.032^{***}	0.054^{***}	0.048^{***}
	(0.007)	(0.010)	(0.011)
Customer Procrastination × Product Price	0.002		0.002
	(0.001)		(0.001)
Reverse Logistics Time × Product Price		-0.002^{*}	-0.002^{*}
		(0.001)	(0.001)
Control Variables	Included	Included	Included
Company Fixed Effect	Included	Included	Included
Year Fixed Effect	Included	Included	Included
Month Fixed Effect	Included	Included	Included
Day of Week Fixed Effect	Included	Included	Included
Holiday Fixed Effect	Included	Included	Included
AIC	14069.694	14066.724	14066.974
BIC	14464.137	14461.167	14469.152
Log Likelihood	-6983.847	-6982.362	-6981.487
Observation Number	16885	16885	16885

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$, $^{+}p < 0.1$ Robust standard errors of coefficients are presented in parentheses

customer procrastination in Section 2.5.2, finding that incomes do not influence customer procrastination. The post-hoc analysis further explains why product prices fail to moderate the effect of customer procrastination. We have statistically significant negative interaction term, *Customer Procrastination* $\times$ *Product Price* from Logit Model 2 and Logit Model 3. It indicates that the negative effect of revese logistics time on customer repurchase becomes stronger as product price increases. This result supports **H3b**, *"The negative effect of reverse logistics time on future loyalty amplifies with product prices."*, showing that higher product prices exacerbate the negative impact of extended return processing time on customer future loyalty. We have the similar results for **H3a** and **H3b** from Cox models in Table 2.4, indicating the consistent and robust results.

2.5.2 Post Hoc Analysis

Our post hoc analysis focuses on factors driving customer procrastination. The original dataset does not provide customer demographic information but it provides customer names and addresses. We can extract customer genders and ethnicities from their names and addresses. We use two R packages to predict gender from first names, **gender** (Mullen, 2021) and **genderizerR** (Wais, 2006). The package, **gender**, employed by Sherman et al. (2023) and Adukia et al. (2023), searches the U.S. Social Security Administration's newborn names database, and retrieves the gender proportions for a given first name, and then assigns gender based on the highest probability. However, this database does not cover all first names out of the States. We use another package, **genderizerR**, utilized by Luo and Zhang (2022) and Cui et al. (2022), for gender predictions. This package determines genders based on name analysis from `https://genderize.io/`, which aggregates data from social media platforms to gneder probabilities related to given names. Finally, we have 13,677 females and 3,132 males after removing 76 unknown genders.

Table 2.4: Cox Model Estimation Results with the Product Price Moderator

	Cox Model 1	Cox Model 2	Cox Model 3
Customer Procrastination	-0.028^{***}	-0.025^{***}	-0.027^{***}
	(0.006)	(0.005)	(0.006)
Reverse Logistics Time	-0.013^{***}	-0.008^{+}	-0.008^{+}
	(0.004)	(0.004)	(0.004)
Product Price	0.020^{***}	0.037^{***}	0.034^{***}
	(0.004)	(0.006)	(0.007)
Customer Procrastination ×Product Price	0.001		0.001
	(0.001)		(0.001)
Reverse Logistics Time × Product Price		-0.002^{*}	-0.001^{*}
		(0.001)	(0.001)
Control Variables	Included	Included	Included
Company Fixed Effect	Included	Included	Included
Year Fixed Effect	Included	Included	Included
Month Fixed Effect	Included	Included	Included
Day of Week Fixed Effect	Included	Included	Included
Holiday Fixed Effect	Included	Included	Included
AIC	58921.543	58915.726	58917.115
R^2	0.057	0.057	0.057
Max. R^2	0.971	0.971	0.971
Num. events	3285	3285	3285
Observation Number	16885	16885	16885
Missings	0	0	0
PH test	0.000	0.000	0.000

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$, $^{+}p < 0.1$ Robust standard errors of coefficients are presented in parentheses

We determine customer ethnicities based on their names and geographic locations together (Stayman and Deshpande, 1989). We first predict ethnicity using different name components, only first names, only last names, full names. If at least two of three predictions have the same results, we assign it as the individual's ethnicity. Otherwise, we use the ethnicity with the highest percentage at the 5-digit zip code.

Besides two typical demographic metrics and other standard demographic measures, such as income and education level, we also incorporate a critical spatial dimension into our analysis. We consider the shortest distance between USPS store locations and customers' addresses using Google Maps API. After obtaining the shortest distance, we identified 12 observations where Google Maps API fails to return the distance measurements, possibly due to address formatting issues or other problems. Finally, the customer procrastination analytical dataset contains 16,797 observations after removing 12 rows without returning the shortest distances.

We construct the comprehensive linear regression model to study driving factors for customer procrastination in the model (2.9) and show the model estimation result in Table 2.5.

$$\begin{aligned} CustomerProcrastination = &\alpha_0 + \alpha_1 ShortestDistance + \alpha_2 Gender + \alpha_{3i} Ethnicity_i + \\ &\alpha_4 ProductPrice + \alpha_5 TotalShippingCost + \\ &\alpha_6 TotalReturnValue + \alpha_7 TotalReturnQuantity + \\ &\alpha_8 MedHouseholdIncome + \alpha_9 AvgHouseholdSize + \\ &\alpha_{10} BachelorPerc + \boldsymbol{\alpha AgeGroup_z} + TimeFixed \end{aligned} \tag{2.9}$$

Table 2.5: Customer Procrastination

	Linear Regression Model
(Intercept)	2.028^{**}
	(0.742)
Shortest Distance	0.018
	(0.027)
Gender Female	-0.339^{***}
	(0.084)
Ethnicity Black	-0.058
	(0.322)
Ethnicity Hispanic	-0.043
	(0.221)
Ethnicity White	-0.386^{*}
	(0.156)
Product Price	0.063^{***}
	(0.012)
Total Shipping Cost	0.028^{***}
	(0.007)
Total Return Value	-0.283^{***}
	(0.025)
Total Return Quantity	0.079^{***}
	(0.012)
Median Household Income	-0.000
	(0.001)
Average Household Size	0.109
	(0.152)
Bachelor's Degree Percentage	-0.014^{*}

Continued on next page

Table 2.5 – continued from previous page

	Linear Regression Model
	(0.005)
Under 18 Years	0.002
	(0.012)
18 to 24 Years	0.030***
	(0.008)
25 to 34 Years	0.041***
	(0.009)
35 to 44 Years	0.044**
	(0.016)
45 to 54 Years	0.032*
	(0.016)
55 to 64 Years	0.023
	(0.019)
Year Fixed Effect	Included
Month Fixed Effect	Included
Day of Week Fixed Effect	Included
Holiday Fixed Effect	Included
R^2	0.035
Observation Number	16797

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$, $^{+}p < 0.1$ Robust standard errors of coefficients are presented in parentheses

From the result, we have the statistically significantly negative relationship between female customers and customer procrastination ($\alpha_2 = -0.339, p < 0.001$), suggesting that females are significantly less likely to procrastinate than males. This result is consistent with existing literatures to show that females shop more and eventually do more consumer returns compared with males due to various reasons, for example, impulsive buying (Kollat and Willett, 1967; Coley and Burgess, 2003; Unal and Park, 2023). Customer identified as White show significantly lower levels of procrastination ($\alpha_{33} = -0.386, p < 0.05$) while procrastination for Black and Hispanic customers are statistically insignificant ($p > 0.1$). This finding aligns with prior research suggesting that higher power distance and individualism in the western culture may cause higher return rates (Hilafu et al., 2024). Other two demographic metrics, education level and age, also impact customer procrastination significantly. People with bachelor's degree may be more efficient in handling returns ($\alpha_{10} = -0.014, p < 0.05$) and younger customers (18-44 years) procrastinate more than older groups.

Besides demographic influences, economic considerations also impacts customer procrastination. Higher product prices, the total price of an order before returns, are positively associated with increased customer procrastination ($\alpha_4 = 0.063, p < 0.001$), showing the similar conclusion that high-value customers are more likely to keep more expensive products with stronger emotional attachment, higher switching costs, and better post-purchase service. Contrary to product prices, which is the refund after an item is returned, is negatively associated with customer procrastination since customers want to get their money back faster ($\alpha_6 = 0.283, p < 0.001$). The surprising result is that distances between USPS stores and customer addresses do not influence customer procrastination, indicating that returns delays are driven more by psychological and financial factors rather than physical accessibility.

The post-hoc analysis displays that demographic effects (gender, ethnicity, and age) play a more important role in customer procrastination than physical locations, like the shortest distance between customer addresses and USPS stores. It shows a promising future reseasrch direction - how demographic metrics impact consumer returns from the perspetive of consumer behavior.

2.6 Robustness Checkes

We conduct several robustness checks by introducing a new variable and at a different data collection level to verify the consistency and reliability of our results.

2.6.1 Total Return Time

We first combine **customer procrastination** and **reverse logistics time** for a new variable, **total return time** to measure the entire return process. We show the estimated models in model (2.10) and model (2.11) with the results in Table 2.6. We have the similar negative relationship between **total return time** and **customer repurchase** both from the logistic regression and Cox models, indicating that longer return time, whether due to customer procrastination or extended reverse logistics time, significantly impacts customer future loyalty.

$$\begin{aligned} log\frac{Pr(Repurchase=1)}{1-Pr(Repurchase=1)} =& \beta_0 + \beta_1 TotalReturnTime + \beta_2 ProductPrice + \\ & \beta_3 TotalShippingCost + \beta_4 TotalReturnValue + \\ & \beta_5 TotalReturnQuantity + \beta_6 MedHouseholdIncome + \\ & \beta_7 AvgHouseholdSize + \beta_8 BachelorPerc + \\ & \boldsymbol{\beta AgeGroup_z} + CompanyFixed + TimeFixed \end{aligned} \tag{2.10}$$

Table 2.6: Robustness Check at the 5-digit Zip Code level

	Logit Model	Cox Model
(Intercept)	-2.008	
	(1.123)	
Total Return Time	-0.026^{***}	-0.017^{***}
	(0.004)	(0.003)
Control Variables	Included	Included
Company Fixed Effect	Included	Included
Year Fixed Effect	Included	Included
Month Fixed Effect	Included	Included
Day of Week Fixed Effect	Included	Included
Holiday Fixed Effect	Included	Included
AIC	14067.765	58923.189
BIC	14454.474	
Observation Number	16885	16885
R^2		0.057
Event Number		3285
Missings		0
PH test		0.000

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$, $^{+}p < 0.1$ Robust standard errors of coefficients are presented in parentheses

$$
\begin{aligned}
h(t|\mathbf{X}) = h_0(t) \times exp(&\gamma_0 + \gamma_1 TotalReturnTime + \gamma_2 ProductPrice + \\
&\gamma_3 TotalShippingCost + \gamma_4 TotalReturnValue + \\
&\gamma_5 TotalReturnQuantity + \gamma_6 MedHouseholdIncome + \\
&\gamma_7 AvgHouseholdSize + \gamma_8 BachelorPerc + \boldsymbol{\gamma AgeGroup_z} + \\
&CompanyFixed + TimeFixed)
\end{aligned} \tag{2.11}
$$

2.6.2 Block Group Level

We consider collecting the demographic data at a finer scale, the block group level. Block groups show a more granular unit, providing a more precise measure of demographic influences on consumer behavior. We start with converting specific customers' addresses into coordinate points from Census Geocoder and then we use Federal Communications Commission (FCC) Area API to get Federal Information Processing Standards (FIPS) codes from coordinate points. After having FIPS codes, we can obtain control variables, **median household income**, **average household size**, **bachelor's degree percentage**, and **age groups**. We repeat our main analysis here and report results in Table 2.7.

2.7 Conclusion and Managerial Discussion

Consumer returns are a critical issue at the intersection of operations management and marketing, directly affecting customer retention, reverse logistics efficiency, and retailer profitability (Abdulla et al., 2019). The National Retail Federation (NRF) in 2024 has reported that the annual return rate was 16.9%, amounting to $890 billion in associated costs. Additionally, an NRF study completed in October 2024 highlighted that online return rates, on average, were 20% higher than overall return rates. Prior

Table 2.7: Robustness Check at the Block Group Level

	Logistic Regression	Cox Model
(Intercept)	-1.323	
	(1.072)	
Customer Procrastination	-0.037^{***}	-0.026^{***}
	(0.007)	(0.006)
Reverse Logistics Time	-0.020^{***}	-0.015^{**}
	(0.005)	(0.004)
Control Variables	Included	Included
Company Fixed Effect	Included	Included
Year Fixed Effect	Included	Included
Month Fixed Effect	Included	Included
Day of Week Fixed Effect	Included	Included
Holiday Fixed Effect	Included	Included
AIC	9976.785	39862.683
BIC	10353.332	
Observation Number	11888	11888
R^2		0.058
Events Number		2310
Missings		4997
PH test		0.000

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$, $^{+}p < 0.1$ Robust standard errors of coefficients are presented in parentheses

research attributes this huge gap between online and offline return rates to online shoppers' inability to physically inspect products prior to purchase (Griffis et al., 2012; Dzyabura et al., 2023; Nageswaran et al., 2025). The higher online return rates are amplified by the rapid growth of e-commerce, demanding online retailers' prompt attention to the drivers of consumer returns decisions (Nageswaran et al., 2025). By understanding the factors behind product returns, online retailers can formulate data-driven return policies that harmonize customer satisfaction with operational effectiveness. However, limited research explores how return process delays—caused by either the customer or the retailer—impact customer loyalty.

To address this research gap, we collect transaction-level data from one reverse logistics management firm to examine how delays in the return process affect customer loyalty using logistic regression model and the Cox model. Our empirical results provide several significant findings that advance understanding of the impact of delays, either from customer procrastination or reverse logistics time, in the online retail reverse logistics process. First, our analysis reveals that both customer procrastination and reverse logistics time negatively influence customer loyalty, measured by the likelihood and timing. Notably, customer procrastination has a significantly stronger detrimental effect on customer loyalty than extended reverse logistics time since each day of customer procrastination reduces repurchase odds by 3.5%, compared to 2.1% for reverse logistics time. This result highlights the importance of customer's role in the co-production of the return process. Second, we find that product price significantly moderates the relationship between reverse logistics time and customer loyalty with higher-priced products amplifying the negative impact of prolonged reverse logistics time. Interestingly, product price does not moderate the effect of customer procrastination on customer loyalty, which suggests that customers attribute self-delays differently from retailer delays. Finally, our post-hoc analysis indicates that customer procrastination varies across demographic groups. Females and White customers procrastinate less to return products, while younger customers (18-44 years) show greater delay.

These empirical findings offer theoretical contributions to the literature on consumer returns and customer loyalty. First, we extend service co-production theory, typically used in traditional service environments, to the e-commerce logistics, by conceptualizing the return process as a collaborative effort between customers and retailers. While existing literature has extensively studied reverse logistics from an operational or cost-efficiency perspective, our findings emphasize the dual effects from customer procrastination and reverse logistics time on customer loyalty. Second, our study enriches attribution theory by demonstrating that customers respond differently to self-attributed delays versus retailer-attributeed delays, with the latter having a disproportionate impact on high-value transactions. This finding suggests that attribution mechanism significanly moderate consumer responses to service failure. Third, we extend expectancy-value theory by finding that product price moderates the effect of retailer-induced delays but not customer-induced delays. This asymmetrical pattern reveals that attribution significantly influences how consumers respond to service failures in high-value transactions—specifically, whether they perceive the delay as the retailer's responsibility or their own. Finally, the customer procrastination post-hoc analysis results contribute to the emerging literature on consumer heterogeneity in co-production, which shows how demographic metrics influence consumer decisions.

This paper also provides actionable insights for online retailers to reduce product returns rate, improve customer loyalty and satisfication, and eventually increase profitability by optimizing consumer returns management strategies. Since customer procrastination has a stronger negative effect on loyalty than reverse logistics time, online retailers need to encourage prompt customer action in the returns process. For example, online retailers may include the pre-printed return labels in order packages so that customers do not need to print the return labels themselves. In addition, since high-value customers are more sensitive to retailer-attributed delays, it indicates that online retailers may take priority processing for premium product returns, creating tiered service levels that align with product price points. Finally, the demographic patterns we identified in procrastination behavior enable retailers to develop targeted return policies and communications tailored to specific customer segments, particularly younger customers who demonstrate greater return delays.

There are several limitations to our work in this paper that could be addressed in future research. Although our dataset covers a wide range of consumer products, the data is from a single reverse logistics management firm and may not represent the broader e-commerce context in terms of customer demographics, product types, and regional factors, which may limit the generalizability of the findings. Furthermore, new insights might be available if transactional data such as ours could be integrated with customer feedback or social media data, since this can provide a more comprehensive view of customer satisfaction and loyalty.

Chapter 3

How do Gender and Ethnic Diversity Impact Consumer Returns?

3.1 Introduction

One of the most apparent behavioral changes in retail has been the shift from brick-and-mortar to digital shopping, or e-commerce. It is renown that the factors affecting consumers' adoption of e-commerce are perceived usefulness and ease-of-use of online transactions, confidence in the digital technology, but also perceived risk of fraud or privacy violation (Lim et al., 2004; Sia et al., 2009). However, socioeconomic and demographic factors characterizing consumers' diversity have also been found to have a prominent impact on the adoption of e-commerce. Studies related to the consumers' online behavior point out that gender and ethnicity are among the main demographic determinants of the online shopping, especially in terms of the risk perceived in online transactions (Owens and Sarov, 2010).

A recognized benefit of e-commerce is that it enables firms to build online configurators through which consumers can tailor the products to their individual preferences and specifications. Product customization has become a must for many online businesses as increased competition and decreased profit margins have forced them to seek new ways of generating value for their customers. In particular, product customization is considered as one of the main ways for online firms to strengthen the user experience and build customer loyalty (Arora et al., 2021). However, there are also challenges that come with the growth of e-commerce, particularly the problem of consumer returns. In fact, online shopping does not allow consumers to "touch and feel" the product. As a consequence, consumers may end up purchasing a product that is not a good fit with their preferences, and thus decide to return the product after receiving and inspecting it. The volume of returns is significantly higher for online than for brick-and-mortar sales (Letizia et al., 2018). In this article, we study how demographic factors, such as gender and ethnic diversity affect two of the main aspects of e-commerce: product customization and product returns.

The founder and chief executive officer (CEO) of Global Diversity Marketing (GDM), Tariq Khan, declared in an interview with *The Hearing Journal* that "diversity [in race, gender, etc.] represents our differences and what makes us unique" (Hayes 2021). These words echo the fact that diverse and unique people may be interested in purchasing unique products, which can be created through customization. The process of searching for such products, however, could also be unsuccessful especially when the product traits are difficult to communicate digitally. Thus, consumers may end up returning the product that they purchase. In this article, we study how gender and ethnic diversity affect product returns in e-commerce. We have two main research questions:

- What is the effect of gender on consumer returns?
- What is the effect of ethnic diversity on consumer returns?

To answer these questions, we have collected a detailed data set from a leading company in the fashion luxury industry. The data set consists of approximately

1.6 million online transactions for a value-expressive product across the US, with the detail of whether the product was customized and eventually returned by the consumer. We have considered gender and ethnicity as determinants of consumer diversity. Particularly, ethnic diversity is a function of both the individual's ethnicity and the dominant ethnicity of the community, whereas gender diversity is a function of the individual's gender. We have aggregated the transactions data at a census block group level and merged them with data from the US Census at the same level. The resulting cross-sectional data set, together with our econometric approach, allows us to significantly contribute to the literature on e-commerce, product customization, and returns.

Our study generates the following important results. First, we find evidence that both gender and ethnic diversity are related to product returns. Our results empirically show that compared with males, females are more likely to do product returns due to consequences of impulse buying, and people from an ethnically diverse environment tend to do more product returns due to lacking majority influence. Second, we find that the decision to customize a product is also related to consumers' gender and ethnicity. In particular, our analysis shows that customized products have lower return rates compared with standard products. Third, we show that people from ethnicity-homogeneous communities tend to do fewer product returns than those from ethnicity-mixed communities.

Collectively, our findings suggest that firms should factor in gender and ethnicity of their customer base when making operations and supply chain management decisions. For instance, given the impact that these demographic variables have on the orders of both standard and customized products, companies could better forecast the sales of these products by considering gender and ethnic diversity of their customer base. Further, the fact that product customization is mainly driven by male population and ethnic diversity may suggest to firms that the manufacturing plants for customized products should be located where these demographic characteristics are more pronounced.

Consumer behavior involves consumer decision-making processes in both purchases and product returns. The main contribution of our paper is to empirically investigate consumer behaviors on product returns for gender and ethnic diversity. Although many empirical papers have studied consumer behavior impacts on product returns, most use laboratory experiment data, survey-based data, or field experiment data. Some adapt secondary data without collecting additional variables from existing columns. We collect secondary data from a leading luxury company, containing customers' names and addresses. Then, we extract gender from first names and obtain ethnicity from first, last, and full names and census block groups; then, we compare the community's dominant ethnicity and individuals' ethnicity to determine the community type. Later, we collect control variables at census block group levels instead of zip code levels.

We organize the rest of this paper as follows. Section 3.2 discusses the background and related literature review. Section 3.3 introduces theories and formulates hypotheses. Section 3.4 details data characteristics and studies dependent and independent variables. Section 3.5 presents the empirical models and reports estimation results. Section 3.6 displays the robustness check. Section 3.7 concludes this study and reflects on its limitations.

3.2 Literature Review

Our paper contributes to and intersects with three streams of literature: (i) consumer returns, (ii) gender in operations management, and (iii) ethnic diversity in operations management.

3.2.1 Consumer Returns

Abdulla et al. (2019) provide a comprehensive review and classification of the literature on consumer returns, including return policy, consumer behavior, planning and execution, and return management. Abdulla et al. (2019) state that operational planning and execution activities and return policies have an interactive influence on each other. Additionally, return policies affect consumer behaviors and return management, and vice versa. These four domains intersect. Both analytical and empirical papers investigate these four domains. Return policy domain research focuses on the design, description, and prescription within the framework of managerial decision-making processes. Two well-known analytical papers: Su (2009) look at how supply chain performance is affected by full returns policies and partial returns policies; Nageswaran et al. (2020) examine the best return policy for omnichannel retailers, taking into account how customers behave and returns that happen across channels. Empirical research in the return policy domain utilizes theories from economics and psychology. Wood (2001) show that lenient return policy can increase online orders and reduce product returns. Pei et al. (2014) investigate the reputation of online retailers and the perceived level of competition among them influence how the extent of returns impacts consumers' perceptions of return policy fairness and their intention to purchase. The planning and execution domain studies the return impact on forward logistics and supply chain management. Many classifiers in the planning and execution domain are self-explanatory, including pricing, inventory, supply chain coordination, forward channel design, competition, product assortment, and product characteristics. Early research that examines return policies and pricing decisions together primarily concentrates on signaling product quality. For example, Moorthy and Srinivasan (1995) examine the effectiveness of money-back guarantees as a signal of product quality and they argue that such guarantees can be an effective signal, but only when transaction costs are sufficiently high. Most papers in this area deal with uniform pricing strategies for a single product, for example, Hu et al. (2015). However, several pieces of work also explore how retailers make pricing and return policy decisions for both regular and opportunistic customers (Ülkü et al. (2013)). Many studies on customer product returns examine inventory management with a classic newsvendor modeling. Supply chain coordination investigation regarding product returns shows novel insights contributing to the existing literature on supply chain contracting and coordination (Cachon et al. (2018)). Analytical studies have explored the effectiveness of different channel structures in return policies. Vinhas and Anderson (2005) and Savaskan and Van Wassenhove (2006) discuss the impact of potential conflict and competitive retailing on channel structure. Shulman et al. (2010) focus on the impact of reverse channel structure and online channel mode selection on return policies. For competition, customer returns research often compares a monopoly, Shulman et al. (2010) to a duopoly, McWilliams (2012). Product quality and product modularity are two common product characteristics in analytical papers. Researchers also study the assortment decision affected return policy decision and vice-versa. The return management domain (Ambilkar et al. (2022)) focuses on the proficient acquisition, streamlined processing, and strategic disposition of returned items. We contribute to this literature by studying consumer diversity influences on consumer returns after quantifying consumer diversity.

3.2.2 Gender in Operations Management

Many scholars consider gender differences in operations management especially for their task performance. Cui et al. (2022) investigate the gender inequality in research productivity performance during the COVID-19 pandemic, showing that female academics' productivity dropped by 13.2% although the total research productivity increased by 35%. Eagly et al. (1992) study the gender impact on leaders evaluation, finding that though only a small overall tendency for females leaders to be devalued compared with male leaders, and this tendency is more pronounced under some contexts. Apesteguia et al. (2012) and Hoogendoorn et al. (2013) show the gender impact on team performance. Besides gender different task performance in operations management, some papers focus the gender impact on customer satisfaction. Mohr and Henson (1996) and Hekman et al. (2010) explore the impact of employee gender on customer satisfaction on service operations management. Other papers investigate the gender impact on online shopping. Kim and Krishnan (2015) state males and females behave differently for online shopping, saying that females are more likely to buy intangible products, such as clothing and fashion. Dittmar et al. (2004) compare gender differences on online buying and conventional buying, concluding that the online environment has a stronger effect on females.

However, only a few papers consider gender influence on online product returns as a measure of customer satisfaction. Even though some papers mention gender impacts on customer product returns, they do not study gender as an independent variable and product returns as a dependent variable. They simply use gender as the control variable or conduct a pilot study. For example, Sahoo et al. (2018) discuss the impact of online product reviews on product returns and they use gender as one of control variables. Xu and Jackson (2019) study the influential factors of return channel loyalty in an omni-channel retailing environment; they provide information on the gender distribution of the respondents, with 60.7% being female and 39.3% being male but this paper does not provide specific findings on the gender-based differences in product returns.

There is a scarcity of empirical research to study gender impacts on customized product returns. To our best knowledge, only Rintamäki et al. (2021) empirically show that 26-40 years old females were more likely to return in their pilot study but they do not study gender impacts on customer product returns for all age groups thoroughly. No empirical papers both consider product returns and product customization so far. Only one analytical paper, Esenduran et al. (2022) studies the relationship between product customization and product returns. We contribute to this literature by empirically investigating the gender impact on product returns and also considers the mediation effect of product customization.

3.2.3 Ethnic Diversity in Operations Management

Many studies explore the impact of employee ethnic diversity on operations management. Foley and Kerr (2013) study effects from ethnic scientists and engineers on the global activities of their firms, showing that ethnic innovators can facilitate the firm global expansion, disintegrate of innovative activity and form new affiliates. Østergaard et al. (2011) also say that employee ethnicity diversity can be positive for innovative performance since it broadens viewpoints and perspectives in firms. McKay et al. (2008) discuss ethnicity diversity impacts on employee sales performance.

Besides discussing the impact of ethnic diversity on employee performance on firms, some papers study the impact of consumer ethnicity diversity on buying behavior. However, these papers do not consider the impact of ethnicity distribution in an environment on individuals. Many existing papers only consider the impact of a single or two consumer ethnicities impact on buying behaviors. Donthu and Cherian (1994) only examine Hispanic consumer shopping behavior with the strength of ethnic identification. Sexton Jr (1972) solely analyze the black buyer behavior on the market for store shopping behavior, product buying behavior, and brand buying behavior. Shim and Gehrt (1996) mainly discuss Hispanic and native American adolescents shopping orientation on the retail market. Even when some papers include multiple ethnicities, they simply use a binary variable for consumers' ethnicity: either belonging to a specific ethnicity or not. He et al. (2020) discuss differences in buying behavior between Chinese-related ethnicity and non-Chinese ethnicity in the housing market. Hirschman (1981) study the differences between Jewish and non-Jewish subjects on consumer behavior in childhood exposure to information, adulthood information seeking, product innovativeness, product information transfer, and cognitive characteristics relevant to consumption information processing.

We contribute to this literature by comparing the individuals' ethnicity and the community's dominant ethnicity at the census block group level. We define ethnic diversity as the combination of the individual's ethnicity and community predominant ethnic group. Therefore, we have two different community types to reflect the ethnic diversity. For a given census block group, if there is no ethnicity percentage is more than 50%, we define it as one ethnicity-mixed community. If this community is predominantly consisting of one ethnic group, it is defined as one ethnicity-homogeneous community. There are two cases to compare the individuals' ethnicity with the dominant ethnicity in one ethnicity-homogeneous community. If the individual's ethnicity is different from the community dominant ethnicity, this individual is from a community predominantly consisting of a different ethnic group. If the individual's ethnicity is the same as the community dominant ethnicity, this individual is from a community predominantly consisting of the same ethnic group. Addtionally, we also use the Gini index in the robustness check to show the validation for our results, as it captures the overall diversity pattern rather than relying solely on a single cutoff point.

3.3 Theory and Hypotheses Development

Variations in shopping behaviors between males and females provide a multifaceted insight into customer product returns. Many studies have explored that females exhibit higher shopping frequency than males. Kim and Krishnan (2015) find that females show more interests in intangible products and they are more likely to buy more these products, for example, fashion. Pentecost and Andrews (2010) say that more than 50% females purchase fashion products at least once per month. Lambrecht and Tucker (2019) provide another explanation for females shopping more; they largely control household purchases. Kollat and Willett (1967) and Coley and Burgess (2003) find that females are more likely to purchase impulsively because of their higher shopping frequency compared with males. Researchers have focused on the gender impact on impulse buying for a long time. Coley and Burgess (2003) study that females are generally more emotional and psychological than males and females are more likely to engage in impulse buying as a way to manage their mood and relieve stress since they can obtain more pleasure from impulse buying; thus females are more susceptible to impulse purchasing. Melnyk et al. (2009) investigate gender differences in customer loyalty, revealing that women generally show stronger loyalty to individual service providers, while men are more loyal to groups or companies, which supports our hypothesis that females return more to one online shopping store than males. Some studies (Stern (1962), Hoch and Loewenstein (1991), Park and Lennon (2006)) show that impulse buying is motivated by interactions with a salesperson for customers. It also explains why females tend to do more impulse buying since they are easier to be more loyal to a specific individual. Later, Ridgway et al. (2008) use a survey study to verify that women have a higher impulsive buying than men. While the gendered nuances of shopping behaviors and impulse purchases have been extensively studied, it's equally important to consider the downstream consequences of these impulsive buying decisions. Ridgway et al. (2008) and Unal and Park (2023) explore higher product returns from higher impulsive buying. Hong and Pavlou (2014) also think that more impulse purchases will inevitably cause more product returns. Ghose et al. (2023) discuss that even though initially pressure-based interventions can dramatically increase product purchases, impulsive consumers will eventually issue a return.

Additionally, Rook (1987) discuss impulse buying negative consequences including financial hardships or emotional trauma. Many papers also study that negative emotions from impulse buying can lead to more product returns. Calvo et al. (2023) point out that customers usually find that products from impulse buying eventually do not suit their needs, which may cause some negative emotions. Xiao and Benbasat (2011) study that multimedia technologies like Flash or animations, similar to what fast-talking salespersons can do in physical shopping setting, can lead consumers to do impulsive purchase and then they may regret. Lee et al. (2023) talk about the negative emotions after impulse buying will motivate consumers to return the delivered products and impulsive buyers chose to return more. Silvera et al. (2008) analyze that feeling guilty is related to more product returns. Grolleau et al. (2016)

point out that males and females perceive guilt differently since Ludwig et al. (2017) find that females are easier to feel guilty than males and Zou et al. (2020) study that females have higher levels of both underpurchase and overpurchase regret than males.

Accordingly, we state our first hypothesis on the direct impacts of on product returns as follows:

Hypothesis 1 (**H1**): *Females have a higher likelihood than males of returning purchased products.*

Although communities are often considered to be geographically centered, the key aspect seems to be the importance of face-to-face interactions and the ethnicity effect may be strong among members who are geographically clustered (Yancey et al., 1976).

Based on the ethnicity percentage distribution for a given census block group, we call this census block group as an ethnically diverse community if there is no ethnicity percentage more than 50%; otherwise, we call this census block an ethnically homogeneous community with the highest ethnicity percentage. We calculate the total number of ethnically diverse communities for each state and then obtain the ethnically diverse communities percentage by dividing the total number of communities (ethnically diverse communities plus ethnically homogeneous communities), shown in Figure 3.1. For ethnically homogeneous communities, we compare individual's ethnicity with the community's predominant ethnicity. If the individual's ethnicity matches the community's predominant ethnicity, this person is from a community predominantly consisting of his own ethnic group. If the individual's ethnicity is different from the community's predominant ethnicity, this person is from a community predominantly consisting of a different ethnic group.

For a community with a single dominant ethnic group, whether individuals belong to the majority ethnic group or a minority within it, they will be influenced by conformity, according to the majority influence theory. Asch (1955) conducts several conformity experiments to demonstrate how individuals often conform to the majority

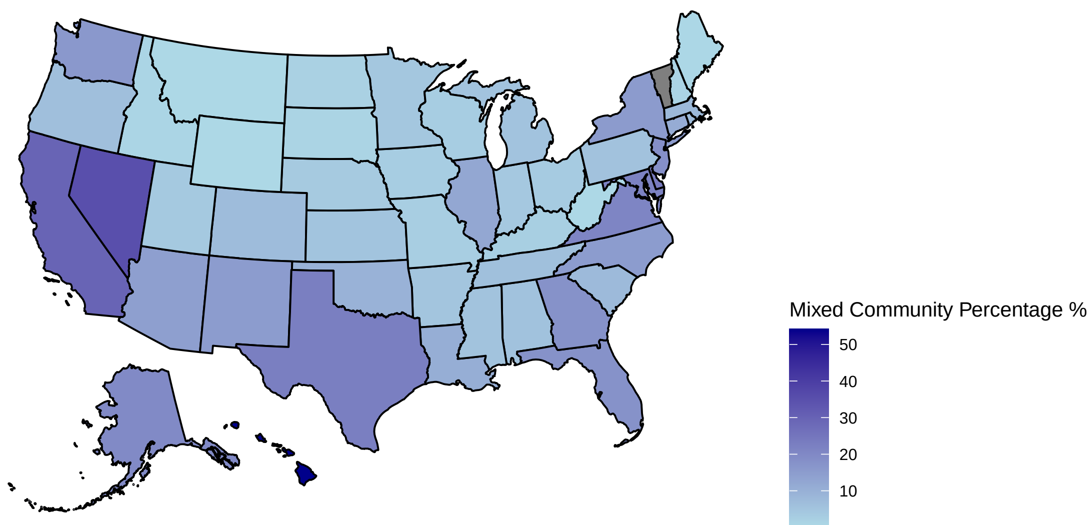

Figure 3.1: Ethnically Diverse Community Percentage in U.S.

even when the majority is wrong. Scharfstein and Stein (1990) mention that when managers make investment decisions, the labor market will update its beliefs based on whether the manager made a profitable investment and whether the manager's behavior was similar to or different from that of other managers. Additionally, Scharfstein and Stein (1990) refers to the "yes-man" effect, where individuals may be reluctant to disagree with others in the group, leading to a false consensus and the waste of information from other managers. Jones (1991) demonstrate how people may succumb to pressure from the majority when making moral decisions in workplace settings. Moussaïd et al. (2013) discuss the majority effect, described as a tendency for a large number of people sharing the same opinion to have a strong social influence on others, and explore how the majority effect, along with the expert effect (the presence of highly confident individuals), can impact the dynamics of opinion formation within a group. Therefore, we can see that individuals change their behavior or opinions to match their surroundings. In one community with a single dominant ethnic group, individuals conform to the community norms to keep similar items to avoid being out of step with the community, leading to fewer customer returns.

Each ethnically homogeneous community forms its own set of norms, including customers purchasing and returning habits. Therefore, individuals from a different ethnic background compared with the community's dominant ethnicity may adapt or assimilate to the predominant group's norms, including those related to consumer behavior. Kuran (1998) provide examples of how certain ethnic groups have adapted their behaviors to align with the norms of the majority group, leading to a process of assimilation. Olsen and Martins (2012) highlight that an assimilation strategy in diversity management may inhibit the expression of values and beliefs that are different from those of the dominant norms. In an ethnically homogeneous community, people may be more inclined to adhere to community norms because of strong group identity. If majority in this community tend to keep similar products, the community group norm can minimize product returns.

Another theory, the social identity theory can also explain why people from ethnically homogeneous communities are less likely to do product returns no matter whether their ethnic groups match the community majority. In ethnicity-homogeneous communities where a customer's ethnicity matches the majority, shared ethnic background can facilitate stronger community ties and this strong sense of community can keep the similar items and thus causing fewer product returns. For people living an ethnicity-homogeneous community where their ethnic groups do not match the majority, social identity theory may have a negative impact. Due to the mismatch between the individual and the predominant ethnicity of the community, they might feel less belonging, and therefore try to align their behaviors more with the mainstream to reduce potential conflicts or discomfort. Therefore, they try to keep similar items as the community majority does.

In contrast, ethnically-diverse communities, characterized by their ethnic diversity and lack of a single dominant group, present a different set of dynamics. Klocker and Tindale (2021) discuss complex dynamics and varied experiences in mixed-ethnicity families and communities. The diversity of norms and behaviors in mixed communities might lead to less clear or less consistent consumer behavior patterns, including product return habits. The lack of a dominant group might lead to weaker group cohesion and less pressure to conform to a specific set of norms, possibly resulting in varied purchasing and returning behaviors. Kim and Kang (2001) emphasize the need for advertisers to craft their advertising strategies to target specific ethnic groups for particular types of products. In the absence of a strong majority influence, individuals might rely more on personal preferences and individual decision-making processes, potentially leading to higher return rates.

Therefore, based on two community types and an individual's ethnicity, we propose another two hypotheses for ethnic diversity.

Hypothesis 2 (H2): *People from ethnically diverse communities do more consumer returns than those from ethnically homogeneous communities with one single dominant ethnic group.*

3.4 Data Description

In this section, we describe our study setting, and calculations for dependent and independent variables.

3.4.1 Study Setting

The setting for our research is a multinational firm, headquartered in Southern Europe and leader in the design, manufacturing, and distribution of luxury accessories. The diversified and widespread geographical presence across more than 150 countries is the company's main strength, with numerous manufacturing plants and distribution centers, and an extended network of retailers.

The company also operates an online channel through which consumers can purchase standard products or can customize the products according to their individual preferences. The company's product consists of five components and is available in about 900 models which differ by shape, color, and material of the components. Customization is performed through a configurator, which allows customers to select preferences for shape, color, art engraving as well as other features of the product, starting from the selected standard model. The company also offers the possibility to return the product, whether standard or customized, within 45 days and without charging any shipping fee. It is important to point out that the company adopts a tolerant "free" return policy for both standard and customized products in all countries. This implies that any difference in return decisions between standard and customized products is not ascribable to a different return policy.

We receive the annual transaction-level data spanning from January 1, 2022 to December 31, 2022 from this firm with 1,677,615 initial records. Our data comprises three components: the order, the return, and the U.S. Census data. For each order, we have detailed information on whether the product is customized by the consumer. After cleaning the order data, like removing rows without product information, eliminating rows with the price less than $50, only keeping U.S. transactions, etc, we have 1,249,106 order rows. Then we obtain the demographic data at the block group level, and have 1,178,777 observations after removing null addresses, removing rows that cannot return geographic code, and removing rows with null values for demographic data. We continue to extract individuals' gender from first names, and ethnicity from names (first names only, last names only, and full names). After removing 14,818 rows with unknown gender, we have 1,163,959 observations. We determined community types, ethnically homogeneous verse ethnically diverse, with combining the individuals' ethnicity and demographic data. See the data clean steps in Table 3.1. Finally, we aggregate the order and the return data by identifier.

3.4.2 Dependent Variables

The purpose of this study is to investigate the impact of gender and ethnic diversity on product returns. For each transaction level record, we use one dummy variable **Returns** as the dependent variable to indicate whether a product was returned (**Returns=1**) or kept (**Returns=0**) by the consumer. For the final dataset with 1,163,959 rows, 998,460 products were kept and 165,499 products were returned and thus the return rate is $165499/(165499 + 998460) \approx 14.2\%$.

3.4.3 Independent Variables

The original dataset does not provide customers' gender and ethnicity information. We retrieve gender and ethnicity from customer profiles from several packages.

Gender

The order dataset lacks customers' gender but provides their first names. After cleaning the first name column, seeing details in Appendix A, we use two R packages, **gender** and **genderizeR**, to predict individuals' gender from first names. The first R package, **gender**, developed by Mullen (2021), is employed by Sherman et al.

Table 3.1: Order Data Cleaning

Dimension	Remove/Add	Removal/Other Rate
Order Original 1,677,615	NA	NA
Order1 1,677,408	only consider data for year 2022 so we remove data from 2021-12-31	207/1677615=0.01%
Order2 1,608,422	remove the missing values from **MODEL** column	68986/1677408=4.11%
Order3 1,427,604	remove non-target product	180818/1608422=11.24%
Order4 1,427,604	create a dummy variable, customization	customization rate=215946/1427604=15.13%
Order5 1,377,496	remove products whose values are less than $50	50108/1427604=3.51%
Order6 1,377,496	add a column, net price	NA
Order7 1,377,491	remove rows where net price below zero	5/1377496 < 0.1%
Order8 1,362,355	only keep the product with quantity equal to 1	15136/1377491=1.10%
Order9 1,263,244	only focus on the U.S. market	99111/1362355=7.27%
Order10 1,263,243	only keep the dollar currency	1/1263244 < 0.1%
Order11 1,252,940	remove the payment column since it's the same and keep the unique item ID	10303/1263243=0.82%
Order12 1,249,106	remove sales from telesales channels	3834/1252940= 0.31%
Order13 1,248,712	remove null addresses	394/1249106=0.03%
Order14 1,248,458	fail to return FIPS codes	254/1248712=0.02%
Order15 1,178,777	remove rows with null values for median household income, average household size, and bachelor's degree percentage	69681/1248458=5.58%
Order16 1,163,959	remove unknown gender rows	14818/1178777=1.3%

(2023) and Adukia et al. (2023). It returns the proportions of females and males for a given first names and then determines gender from the highest probability using the period 1932 to 2012. It has one obvious shortcoming since not all first names are in the U.S. Social Security Administration database. Therefore, we introduce the second R package, **genderizeR** from Wais (2006), which is utilized by Luo and Zhang (2022) and Cui et al. (2022). This package operates based on one website, `https://genderize.io/`, sourcing users profiles from various social platforms to deduce gender from name occurrences and probabilities. See the example in Table 3.2 and Table 3.3 below to show how these two packages determine individuals' genders. After getting and comparing gender prediction results from two packages, we find that 1,102,624 rows have the same prediction results, 546,324 females, 541,482 males, and 14,818 unknown. It means that 1102624/(1102624 + 76153)=93.5% of predictions are consistent across **gender** anad **genderizeR**, indicating a high level of reliability in the gender prediction packages used. Therefore, if the gender prediction results are the same from two packages, we assign this predicted result into the gender column. If we have the unknown prediction result from **gender** package but have female or male prediction from **genderizeR**, we use specific gender results from **genderizeR** for the gender column. Eventually, we have 586,616 females, 577,343 males and 14,818 unknown genders. After excluding these unknown gender results, we have 1,163,959 observations. Some may worry that gender preferences in products could influence consumer returns. To address this concern, we conduct a t-test to confirm its gender-neutrality with a p-value of 0.780.

Ethnic Diversity

We define each community as a census block group and use the combination of community's predominant ethnicity and individual's ethnicity to measure ethnic diversity for a census block group. We predict individual's ethnicity and the ethnicity distribution for census block groups at first. Then we determine this block group is an ethnically diverse community if no ethnicity is more than 50%, otherwise

Table 3.2: Gender Prediction Example from **gender** Package

Name	**Proportion Male**	**Proportion Female**	**Gender Prediction**
Anthony	0.9946	0.0054	male
Daniel	0.9954	0.0046	male
Gabriel	0.9766	0.0234	male
Jake	0.9979	0.0021	male
Morgan	0.8533	0.1467	male
Mary	0.0036	0.9964	female

Table 3.3: Gender Prediction Example from **genderizeR** Package

Name	**Gender Count**	**Gender Probability**	**Gender Prediction**
Anthony	600500	1.00	male
Daniel	1725175	1.00	male
Gabriel	426540	1.00	male
Jake	135069	1.00	male
Morgan	18372	0.79	male
Mary	1011867	1.00	female

we assign the ethnicity with the highest percentage as the predominant ethnicity for this census block group. For ethnicity-homogeneous communities, we compare the individual's ethnicity with the dominant block group ethnicity to see whether these two ethnicities are consistent. Therefore, we can have two cases: people from communities predominantly consisting of their own ethnic group and people from communities predominantly consisting of a different ethnic group. The following begins by gathering individuals' ethnicity based on their names - considering first names only, last names only, and full names. In addition, we collect ethnicity at the census block group level for those unknown ethnicity out of names. Based on individuals' ethnicity data collection, we categorize all communities into two types based on ethnicity percentages: ethnically diverse communities and ethnically homogeneous communities.

Individuals' Ethnicity Collection from Names: Stayman and Deshpande (1989) say that many researchers collect ethnicity only based on individuals' last names but this method ignores individual perceptions and mental states, influencing by their surroundings. Therefore, we utilize customers' first, last, full names and block group data to predict their ethnicity; that is, we employ a combination of personal name analysis and demographic data from block groups to infer an individual's ethnicity. To predict ethnicity from first names, we employ the R package, **predictrace** (Kaplan (2021)), with data sourced from Tzioumis (2018), adapted by Huang et al. (2023) and Babar et al. (2023). We notice that some people have multiple ethnicities, like Asian & Hispanic, Asian & White, Black & White, Hispanic & White and we simplify these results into other, details in Table 3.4. We then consider another method from **predictrace** to extract ethnicity only from last names. Similarly, we simplify two races, Asian& Black, Asian& Hispanic, Black& White, and Hispanic& White into other and American Indian into Asian in Table 3.5. Later, we consider retrieving ethnicity from full names from another R package **rethnicity** (Xie (2022)), implemented in Chow et al. (2022) and Acciai et al. (2023) in Table 3.6.

Table 3.4: Individuals' Ethnicities only from First Names, **predictrace**

Individual Ethnicity	**Original Outcome**	**Adjusted Outcome**
Asian	30086	30086
Black	3224	3224
Hispanic	88252	88252
White	836272	836272
Asian, Hispanic	7	-
Asian, White	91	-
Black, White	65	-
Hispanic, White	335	-
Other	-	498
Unknown	205627	205627

Table 3.5: Individuals' Ethnicities only from Last Names, **predictrace**

Individual Ethnicity	**Original Outcome**	**Adjusted Outcome**
Two Races	29	-
American Indian	572	-
Asian	96959	97531
Asian, Black	1	-
Asian, Hispanic	3	-
Black	20884	20884
Black, White	3	-
Hispanic	197924	197924
Hispanic, White	1	-
White	681584	681584
Other	-	37
Unknown	165999	165999

Table 3.6: Individuals' Ethnicities from Full Names, **rethnicity**

Individual Ethnicity	**Original Outcome**
Asian	206176
Black	197378
White	516993
Hispanic	243412

Individuals' Ethnicity Collection from Census Block Groups: We observe that the unknown predicted ethnicity comes from first, last, and full names. It is not accurate enough to ensure one customer's ethnicity only from names. Therefore, we introduce another way to predict ethnicity - the highest ethnicity percentage for a given block group. We first extract coordinate points, the latitudes and the longitudes of most customers' addresses from Census Geocoder. For some addresses with unknown coordinate points, we use Geocodio to extract their latitudes and longitudes. After removing 283 untraceable addresses, we have 1.234972 million transaction observations. We use Federal Communications Commission (FCC) Area API to get Federal Information Processing Standards (FIPS) codes from coordinate points. It returns 15-digit FIPS codes at the block level and we use the 12-digit FIPS codes at the block group level. The process of extracting FIPS codes from addresses is shown in Figure 3.2 and the sample FIPS is in Figure 3.3. We can have the ethnicity distribution for each block group to calculate the ethnicity percentage, and then assign the highest percentage ethnicity to this block group. Following our previous simplified method, we add American Indian and Alaska native as well as Native Hawaiian and other Pacific islanders into Asian and combine some other race and two or more races into one category, two or more or some other race. See details in Table 3.7.

Individuals' Ethnicity Determination: Now, we collect ethnicity from first, last, full names, and block groups Walker and Herman (2021). For three columns of ethnicity results from names, if the same results appear at least two out of three, we assign it into the ethnicity column; otherwise, we assign unknown. For the unknown ethnicity from names columns, we determine ethnicity from the block groups. We get the final ethnicity distribution. We remove 2847 rows without ethnicity information, and the observation is 1.232125 million rows. For the final dataset, we remove another 51048 rows without the median household income information due to privacy issues, seeing the final table about ethnicity distributions from names and census block groups in Table 3.8.

Table 3.7: Individual Ethnicity Distribution from Census Block Groups

Ethnicity	Original Outcome	Adjusted Outcome
American Indian and Alaska Native	816	-
White	886418	885296
Asian	55907	58888
Black	55377	55274
Hispanic	164299	163498
Native Hawaiian and Other Pacific Islander	150	-
Some other Race	181	-
Two or More Races	811	-
Other	-	1003

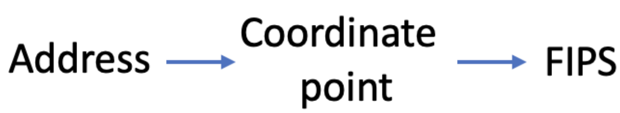

Figure 3.2: Process of FIPS Extraction

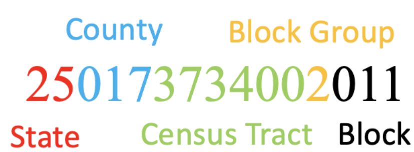

Figure 3.3: Federal Information Processing Standards (FIPS) code

Table 3.8: Final Individuals' Ethnicity Distribution

Individual Ethnicity	Count
White	798567
Asian	114605
Black	27001
Hispanic	223570
Other	216

After determining communities ethnicity distribution, we now create a dummy variable, **Community Type**, to reflect the community ethnic diversity.

Community Type: If no single ethnic group makes up more than 50%, we classify this community as one **Ethnically Diverse Community**. If any ethnic group percentage is more than 50%, we assign the ethnicity with the highest percentage as the single dominant ethnic group for this community, and define this community as **Ethnically Homogeneous Community**. Only $195804/(195804 + 968155) \times 100 \approx 16.8\%$ people live in ethnicity-diversity communities, indicating that most people prefer to live a community sharing the similar cultures and backgrounds.

3.4.4 Control Variables

Our model includes several control variables. Many empirical papers collect control variables at the zip code level (Chen et al. (2022)) but Geronimus and Bound (1998) show that the number of inhabitants from census block group is smaller than those from typical zip code level and census tract level. From the U.S. Census Bureau we obtained the following socioeconomic variables at 12-digit block group level, *Median Household Income*, *Average Household Size*, *Female Percentage* and *Bachelor's Degree Percentage*, to explore possible effects related to the economy and the education level across the United States. For some block groups with low population, the U.S. Census Bureau will not disclose the median household income for privacy protection. We remove 69681 rows without median household income, average household size and bachelor's degree percentage information. Therefore, we have obtain the final dataset with 1.163959 million rows. Besides the demographic control variables, we also contain product-level control variables, including *product customization* to reflect if the product is customized or not, *net price*, *sales channels* (mobile versus PC/laptop), and *customer account types* (registered customers versus guest customers). The statistics summary of control variables is shown in Table 3.9.

Table 3.9: Statistics Summary of Control Variables

Variable	**Mean**	**Std. Dev.**	**Min**	**Max**
Median Household Income (unit: $1,000)	106.15	51.67	2.50	250.00
Average Household Size	2.60	0.64	1.02	10.92
Bachelor's Degree Percentage (unit: %)	26.63	13.01	0.00	100.00
Net Price (unit: $100)	1.50	0.53	0.00	36.05
Age Group (unit: %)				
Under 18 Years	20.33	9.27	0.00	79.35
18 to 24 Years	8.87	9.06	0.00	99.83
25 to 34 Years	15.18	10.70	0.00	100.00
35 to 44 Years	13.47	6.23	0.00	77.59
45 to 54 Years	12.80	5.92	0.00	67.88
55 to 64 Years	12.86	6.55	0.00	77.63
65 Years and Over	16.50	10.73	0.00	100.00

3.5 Methodologies and Results

In this section, we first conduct the main analysis to verify our hypotheses and then conduct the mediation analysis for causality.

3.5.1 Main Analysis

Since we have the dummy dependent variable, **Return**, we construct three logistic regression models to examine the effects of gender and ethnic diversity on the likelihood of product returns. The first model (3.1) only includes **Gender** as a single independent variable; the second model (3.2) only uses **Ethnic Diversity** as a single independent variable, and the last model (3.3) contains two main independent variables along with other control variables. This hierarchical regression approach can study the isolated effects of each diversity dimension while minimizing overfitting concerns, preserving degrees of freedom, and avoid potential multicollinearity issues. The last full model tests whether these relationships keep consistent and robust when considering potential confounding factors, which provides a more stringent test of hypothesized relationships. We report the model estimation results in Table 3.10.

$$log\frac{Pr(Return=1)}{1-Pr(Return=1)} = a_0 + a_1 Gender \tag{3.1}$$

$$log\frac{Pr(Return=1)}{1-Pr(Return=1)} = b_0 + b_1 CommunityType \tag{3.2}$$

Table 3.10: Estimated Model Results

	Model 1	Model 2	Model 3
(Intercept)	-1.855^{***}	-1.663^{***}	-1.390^{***}
	(0.004)	(0.006)	(0.029)
Gender Female	0.112^{***}		0.128^{***}
	(0.005)		(0.005)
Community Type Ethnically Homogeneous		-0.163^{***}	-0.129^{***}
		(0.007)	(0.007)
Product Customization			-1.148^{***}
			(0.011)
Channel PC/Laptop			-0.116^{***}
			(0.006)
Account Guest			-0.589^{***}
			(0.006)
Net Price			0.012^{*}
			(0.005)
Median Household Income			0.002^{***}
			(0.000)
Average Household Size			-0.044^{***}
			(0.007)
Bachelor's Degree Percentage			0.007^{***}
			(0.000)
Under 18 Years			-0.003^{***}
			(0.000)
18 to 24 Years			-0.002^{***}
			(0.000)
25 to 34 Years			0.003^{***}
			(0.000)
35 to 44 Years			0.003^{***}
			(0.000)
45 to 54 Years			-0.000
			(0.001)
55 to 64 Years			-0.003^{***}
			(0.001)
AIC	951470.671	951360.583	921416.626
BIC	951494.606	951384.518	921608.104
Log Likelihood	-475733.336	-475678.291	-460692.313
Observation Number	1163959	1163959	1163959

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$, $^{+}p < 0.1$ Robust standard errors of coefficients are presented in parentheses

$$
\begin{aligned}
log\frac{Pr(Return=1)}{1-Pr(Return=1)} =& c_0 + c_1 Gender + c_2 CommunityType + c_3 Customization + \\
& c_4 SalesChannel + c_5 Account + c_6 NetPrice + \\
& c_7 MedHouseholdIncome + c_8 AvgHouseholdSize + \\
& c_{10} BachelorPerc + \boldsymbol{cAgeGroupPerc_z}
\end{aligned} \tag{3.3}
$$

The effect of gender on the likelihood of product returns is consistent in model (3.1) and model (3.3). In model (3.1), it indicates that female customers have approximately 12% higher odds of returning products compared with male customers ($a_1 = 0.112, p < 0.001, odds\ ratio = exp(0.112) \approx 1.12, increased\ percentage = (1.12 - 1) \times 100\% = 12.0\%$). After adding control variables, the gender effect on product returns persists and slightly strengthens in model (3.3), indicating 14% higher odds of product returns than males ($c_1 = 0.128, p < 0.001, odds\ ratio = exp(0.128) \approx 1.14, increased\ percentage = (1.14 - 1) \times 100\% = 14.0\%$). The robustness of the gender effect across both the simple and full models suggests that female customers consistently show a higher probability of product returns. Therefore, we have verified our first hypothesis, **H1**, *"Females have a higher likelihood than males of returning products"*.

Similarly, the effect of community type on the likelihood of product returns remains robust both in model (3.2) and model (3.3). In model (3.2), it shows that customers from ethnically homogeneous communities have approximately 15% lower odds of returning products compared with those from ethnically diverse communities ($b_1 = -0.163, p < 0.001, odds\ ratio = exp(-0.163) \approx 0.85, decreased\ percentage = (1 - 0.85) \times 100\% = 15.0\%$). After adding control variables, the community type effect on product returns holds steady, although slightly attenuated in model (3.3), 12% lower odds of product returns than those from ethnically diverse communities ($c_2 = -0.129, p < 0.001, odds\ ratio = exp(-0.129) \approx 0.88, decreased\ percentage =$

$(1 - 0.88) \times 100\% = 12.0\%$). Both results have verified that ethnic hommogeneity in communities is associated with lower product returns likelihood. As a result, we have verified our second hypothesis, **H2**, *"People from ethnically diverse communities do more consumer returns than those from ethnically homogeneous communities with one single dominant ethnic group"*.

3.5.2 Mediation Analysis

The amplification in magnitude from the model (3.1) to model (3.3) suggests that part of the gender effect on product returns is mediated by other variables. Based on existing literature, there is strong theoretical reason to believe that product customization may mediate the relationship between gender and product returns. Esenduran et al. (2022) establish that customers return fewer customized products, attributing this to both restrictive return policies for customized items and increased product satisfaction through better fit. Concurrently, Lee et al. (2002) document significant gender differences in mass customization preferences, with males and females showing varying inclinations toward customization across different product categories. The customization process inherently involves additional time investment from consumers. Tu et al. (2001) highlight how customization responsiveness affects delivery timelines, with customized products typically requiring extended periods for design, production, and delivery compared to standardized alternatives. Xia and Rajagopalan (2009) further emphasize the lead time necessarily associated with customized products. Drawing on time allocation theory, gender differences in discretionary time availability may influence customization choices. Females often face disproportionate responsibilities in domestic work and caregiving, potentially constraining their available time for engaging with customization processes. This systematic difference in time resources could lead females to prefer standardized, ready-to-use products that offer immediate utility, despite potentially lower product fit—a tradeoff that might subsequently manifest in differential return behaviors.

Therefore, we examine product customization as a potential mediating mechanism through which gender influences product returns, hypothesizing that gender-based differences in customization preferences partially explain the observed gender gap in return rates. Following the mediation analysis from Baron and Kenny (1986), we construct model (3.4), model (3.5), and model (3.6) and report the product customization mediator analysis results in Table 3.11:

$$log\frac{Pr(Returns = 1)}{1 - Pr(Returns = 1)} = d_0 + d_1 Gender \tag{3.4}$$

$$log\frac{Pr(Customization = 1)}{1 - Pr(Customization = 1)} = e_0 + e_1 Gender \tag{3.5}$$

$$log\frac{Pr(Returns = 1)}{1 - Pr(Returns = 1)} = f_0 + f_1 Gender + f_2 ProductCustomization \tag{3.6}$$

Step 1 shows the same results as model (3.1) in the main analysis that females show significantly higher odds of returning products than males. Step 2 establishes that female customers are substantially less likely to choose product customization compared to male customers ($e_1 = -0.305, p < 0.001$), which resonates with prior literature. In step 3, customization significantly strongly reduces the likelihood of returns ($f_2 = -1.113, p < 0.001$). The direct effect of gender on product returns remains significant but is reduced in magnitude ($f_1 = 0.080, p < 0.001$). The change in the gender coefficient from Step 1 (0.112) to Step 3 (0.080) indicates that approximately 28.6% of the gender effect on returns is mediated through product customization, suggesting that an important mechanism driving higher return rates among female customers is their lower utilization of product customization

Table 3.11: Product Customization Mediator

	Step 1	Step 2	Step 3
(Intercept)	-1.855^{***}	-1.536^{***}	-1.716^{***}
	(0.004)	(0.003)	(0.004)
Gender Female	0.112^{***}	-0.305^{***}	0.080^{***}
	(0.005)	(0.005)	(0.005)
Product Customization			-1.113^{***}
			(0.010)
AIC	951470.671	1007639.194	936452.487
BIC	951494.606	1007663.129	936488.389
Log Likelihood	−475733.336	−503817.597	−468223.244
Observation Number	1163959	1163959	1163959

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$, $^{+}p < 0.1$ Robust standard errors of coefficients are presented in parentheses

features, which are strongly associated with reduced returns. We have the product customization mediator diagram in Figure 3.4.

3.6 Robustness Checks

Our empirical analysis uses a large sample of online transaction data for product returns about one self-expressive product considering two main factors: gender and ethnic diversity. In order further to consider the impacts of gender and ethnic diversity with alternative explanation, we discuss some robustness checks below.

We classify a community type based on whether any single ethnicity comprises more than 50% of the population. To ensure the robustness of our classification, we also apply the Gini index as an alternative measure. Gini index is a measure of inequality among the values of a frequency distribution, such as levels of income. In our context, we use Gini index to reflect the inequality of the ethnic groups distribution.

For a population with values y_i, $i = 1$ to n, that are indexed in non-decreasing order ($y_i \leq y_{i+1}$) in equation (3.7).

$$G = \frac{1}{n}(n + 1 - 2\frac{\sum_{i=1}^{n}(n + 1 - i)y_i}{\sum_{i=1}^{n} y_i}) \tag{3.7}$$

A Gini index of 0 expresses perfect equality, where all values are the same (everyone has the same income). On the other hand, a Gini index of 1 (or 100%) expresses maximal inequality among values (for example, where only one person has all the income or consumption, and all others have none). In our scenario, the higher Gini index, the more homogeneous the community is. We have two models for the robustness check as follows in model (3.8) and model (3.9).

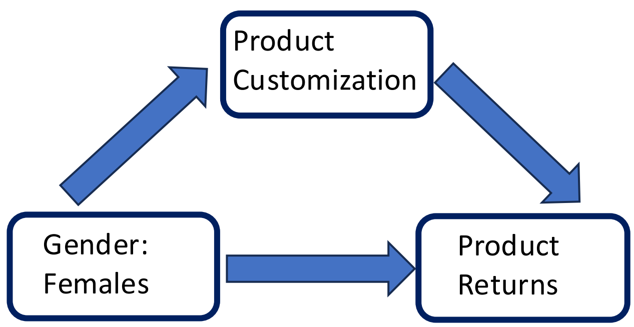

Figure 3.4: Product Customization Mediator

$$log\frac{Pr(Return = 1)}{1 - Pr(Return = 1)} = g_0 + g_1 Gini \tag{3.8}$$

$$\begin{aligned} log\frac{Pr(Return = 1)}{1 - Pr(Return = 1)} =& h_0 + h_1 Gender + h_2 Gini + h_3 Customization + \\ & h_4 SalesChannel + h_5 Account + h_6 NetPrice + \\ & h_7 MedHouseholdIncome + h_8 AvgHouseholdSize + \\ & h_{10} BachelorPerc + \boldsymbol{hAgeGroupPerc_z} \end{aligned} \tag{3.9}$$

After using the continuous variable, *Gini*, to replace the dummy variable, *community type*, we report the result of the robustness check in Table 3.12.

In the robust model (3.8), we only contain the Gini index as the independent variable. It shows a strong negative association between the Gini index and product returns ($g_1 = -0.803, p < 0.001$), indicating that customers from more ethnically homogeneous communities have substantially lower likelihood of returning products. This relationship persists in model (3.9), which includes all control variables ($h_2 = -0.590, p < 0.001$). This robust result verifies our second hypothesis as well. Notably, the gender effect remains consistent with our main analysis (($h_1 = 0.131, p < 0.001$)), with females showing approximately 14% higher odds of returns compared to males when we consider the Gini index and other controls. Similarly, the strong negative effect of product customization ($h_3 = -1.147, p < 0.001$) maintains its magnitude and significance, reinforcing our mediation results. These consistent findings across alternative specifications of community diversity strengthen the reliability of our primary conclusions regarding both gender effects and the mediating role of product customization in explaining return behavior.

Table 3.12: Robustness Check with Gini Index

	Robust 1	Robust 2
(Intercept)	-1.309^{***}	-1.067^{***}
	(0.013)	(0.034)
Gini	-0.803^{***}	-0.590^{***}
	(0.020)	(0.023)
Gender Female		0.131^{***}
		(0.005)
Product Customization		-1.147^{***}
		(0.011)
Channel PC/Laptop		-0.115^{***}
		(0.006)
Account Guest		-0.586^{***}
		(0.006)
Net Price		0.012^{*}
		(0.005)
Median Household Income		0.002^{***}
		(0.000)
Average Household Size		-0.047^{***}
		(0.007)
Bachelor's Degree Percentage		0.007^{***}
		(0.000)
Under 18 Years		-0.003^{***}
		(0.000)
18 to 24 Years		-0.003^{***}
		(0.000)
25 to 34 Years		0.002^{***}
		(0.000)
35 to 44 Years		0.002^{***}
		(0.001)
45 to 54 Years		-0.001^{*}
		(0.001)
55 to 64 Years		-0.003^{***}
		(0.001)
AIC	950399.263	921058.565
BIC	950423.198	921250.042
Log Likelihood	−475197.631	−460513.282
Observation Number	1163959	1163959

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$, $^{+}p < 0.1$ Robust standard errors of coefficients are presented in parentheses

3.7 Conclusions and Managerial Implications

This paper studies an intriguing and novel research question by addressing how gender and ethnic diversity affect product returns, particularly for one self-expressive product. Considering the complexity of consumer behavior and decision-making processes, exploring the impacts of gender and ethnic diversity offers a fresh perspective on operations and marketing.

We examine a proprietary dataset from a leading company in the fashion luxury industry. The dataset consists of approximately 1.6 million online transactions for one value-expressive product category across the U.S., including the details of whether each product was customized and whether it was eventually returned by the consumer. For each transaction-level record, we use one dummy variable, return, as the dependent variable and study the impacts of gender and ethnic diversity on it. Since the online transaction record does not provide these two key variables of interest, we estimate gender and ethnicity from consumer information using several algorithms. We initially use one R-package, gender, to predict gender from first names. This package searches the U.S. Social Security Administration's database of newborn names, determining proportions of females and males for a given first name and then assigning gender from the highest probability. Since not all names are in the U.S. Social Security Administration database, this package leaves some genders as unknown. To address this issue, we use another R-package, genderizerR, which searches various social platforms to obtain gender from name occurrences and probabilities. Between these two well-established algorithms, we are able to obtain reasonable gender determinations for all records. For ethnic diversity, we define each community as a census block group to determine a community's predominant ethnicity using U.S. census data. At the individual level, we predict ethnicity from first names only, last names only, and full names. After determining individuals' ethnicity, we check the community types based on the ethnicity percentage at the block group level. If there is no ethnicity percentage more than 50%, we define this community as an ethnically-diverse community; otherwise, we define it as an ethnically-homogeneous community. We find that only a few consumers in our dataset live in ethnically-diverse communities. For people living in ethnically homogeneous communities, if one individual's ethnicity matches the community's predominant ethnicity, this consumer belongs to the majority ethnicity for this community; if one individual's ethnicity differs from the community's predominant ethnicity, this consumer belongs to a minority ethnicity for this community.

Our paper contributes to the related literature on customer product returns by studying the impacts of gender and ethnic diversity. This research examines the intersection of two well-known phenomena in consumer behavior and retail operations. In consumer behavior, there is ample empirical evidence that behaviors vary across genders and ethnicities. In retail operations, the problem of consumer returns has become increasingly prevalent and costly. Despite the well-established nature of both of these phenomena, the academic literature lacks insights into how a consumer's gender and ethnicity might drive their return behaviors. We address this research need by estimating individual genders and ethnicities for each consumer in a large-scale online retail dataset, while also quantifying neighborhood ethnicities at the census block group level. This enables us to examine return behaviors by gender, as well as for in-group and out-group ethnicities. By better understanding expected return behaviors based on gender and ethnicity at the individual consumer level, firms can improve their inventory and reverse logistics planning as they endeavor to reduce the costly impact of consumer returns.

Our work empirically indicates that female consumers return more products (both standard and customized ones) than male consumers, though the mediation effect of product customization can reduce female consumer returns. People from ethnically homogeneous communities tend to return fewer products than those from ethnically diverse communities; that is, people tend to conform to their surroundings, and consumers in ethnically homogeneous communities are more hesitant to return a popular item. For ethnically homogeneous communities, people whose ethnicity matches the community's dominant ethnicity make fewer product returns than those whose ethnicity differs from the community's dominant ethnicity. Our findings suggest that, given the higher return rates among female consumers, companies could tailor their marketing strategies to address this trend. This could include more detailed product descriptions, realistic images, enhanced customization options. For ethnically homogeneous communities with lower product returns, companies could tailor their product assortments to better match the preferences of these communities. Retailers can localize marketing strategies and inventory management that aligns with the specific tastes and needs of these communities.

There are some limitations in this paper. First, due to data collection limitations, our paper only discusses a single one product, and thus the findings can be only applied to the similar product category. Future research could collect additional products datasets, for example, the electronic devices, to study whether gender and ethnic diversity have the similar effects on other product categories. Second, although we use four different methods (only first names, only last names, both first and last names, census block group level) to predict one's ethnicity, we cannot predict every single person's ethnicity exactly. Future research could conduct the survey to extract exact ethnicity for every participant.

Chapter 4

Conclusions

Consumers returns are a pervasive and costly problem in e-commerce, which demands inovative strategies to reconcile customer satisfaction with operational efficiency. This dissertation addresses this issue by examining the behavioral, operational, and demographic drivers of online returns through two empirical essays. The results advance the understanding of online consumer returns behavior by integrating operations management, consumer psychology, and demographic analytics.

The first essay, rooted in the service co-production theory, shows that customer procrastination and reverse logistics inefficiency significantly diminish customer post-return loyalty. This work bridges the gap between reverse logistics research and customer co-production literature by quantifying customer procrastination. The identification of demographic factors of customer procrastination provides insight for retailers to segment customers and tailor return policies accordingly.

Inspired by the factors driving customer procrastination, the second essay investigates how gender and ethnicity influence return behavior, which leverages name-based algorithms and geographic data to decode demographic patterns. Distinct return behaviors across groups emphasize the need for targeted operational strategies, such as personalized product recommendations or virtual fitting rooms, to mitigate consumer returns.

As consumer shopping behaviors evolve across different contexts, retailers are increasingly interested in identifying the factors that drive product returns under varying shopping scenarios. For example, the livestream e-commerce reshapes customers' buying behavior recently. Livestream e-commerce has rapidly emerged as a game-changing retail model, integrating entertainment and real-time purchasing. Distinct from traditional brick-and-mortar store shopping and conventional online buying, livestream shopping allows customers to have real-time interactions with sellers and offers special promotions that are typically unavailable in physical or online stores. Future research may explore how real-time interactions with streamers during livestreams affect product satisfaction and subsequent product returns decisions, particularly examining whether the heightened engagement reduces information asymmetry and customer expectation gaps. Additionally, studies might analyze how time-sensitive promotions and the experiential nature of livestream shopping influence purchase impulsivity and, consequently, return rates. The parasocial relationships formed between livestream hosts and viewers could also be examined as potential moderators of return behavior, potentially creating psychological barriers to returns despite product dissatisfaction. Furthermore, comparative analyses between return patterns in livestream commerce versus traditional online shopping could yield valuable insights into channel-specific strategies for return mitigation while maintaining customer satisfaction in this rapidly growing retail format.

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Appendix

A Individuals' Gender Prediction

After extracting the demographic data, we now have 1,178,777 observations. We first slice the first name column and then get unique first names, 97,236 for gender predictions. After checking first names, we notice that most have the standard format, while some have irregular format, like first-name A, first-name punctuation, first-name-A, A first-name (A means other parts). After removing part A or punctuation, we first apply the R package, **gender** and get the gender prediction 563,549 females, 543,643 males and 71,585 unknown gender. Then we apply the second package, **genderizeR**, for cleaned first names and have 571,340 females, 592,352 males and 15,085 unknown gender. After comparing the gender prediction results from two packages, we have 1,102,624 rows with the same results. Therefore, if the gender prediction results are the same from two packages, we assign this predicted result into the gender column. If we have the unknown prediction result from **gender** package but have female or male prediction from **genderizeR**, we use specific gender results from **genderizeR** for the gender column. ventually, we have 586,616 females, 577,343 males and 14,818 unknown genders. After excluding these unknown gender results, we have 1,163,959 observations.

Vita

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