AN EMPIRICAL EXAMINATION OF NEW INNOVATIVE PROCESSES IN RETAIL

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ABSTRACT:

Dayton Steele: An Empirical Examination of New Innovative Processes in Retail (Under the direction of Saravanan Kesavan.)

Retailers constantly innovate to improve their operations to maintain a competitive advantage, which has become even more apparent following the challenges from the COVID-19 pandemic. One challenge with innovating, however, is that limited information is available to evaluate the effectiveness of the operations. Fortunately empirical methodologies of structural estimation and field experimentation can be used to help determine if innovative processes at retail chains are fruitful when implemented. Field experiments provide direct causal evidence on whether the innovations will work while structural estimation allows for examining counterfactual scenarios to evaluate outcomes from such process innovations. In this dissertation, we leverage structural estimation and field experimentation to study three topics on the frontier of innovations in retail operations: a) dynamic pricing of product drops in the presence of resellers, b) localization of inventory for e-commerce retailers, and c) increasing customer recycling through operational incentives.

The key results are as follows. In Chapter 2, through structural estimation we show that incorporating resellers into pricing improves retailer profit by 7% on average, and the impacts of the resale market to firm profit are heterogeneous across products based on the initial inventory relative to the initial demand. In Chapter 3, through structural estimation we find that distribution centers closer to the customer (front DCs) allow the e-commerce retailer to capture an average 10.7% benefit to profit by improving average promised delivery time by 28.3%. Front DCs allow to capture sales from high-margin SKUs with high demand where backup fulfillment results in much longer promised delivery time. In Chapter 4, through field experiments we find that the chosen value-based incentives and convenience-based incentives are ineffective at inducing customers to engage in recycling behavior, despite importance of these incentives toward recycling intentions reported in the literature. Our results suggest that offering programs to encourage e-waste recycling behavior can be a costly endeavor.

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CHAPTER 1: INTRODUCTION

Retailers constantly innovate to improve their operations to maintain a competitive advantage (Rigby, 2014), which has become even more apparent following the challenges from the COVID-19 pandemic (Yohn, 2020). One challenge with innovating, however, is that limited information is available to evaluate the effectiveness of the operations. Empirical methodologies of structural estimation and field experimentation can be leveraged to help determine if new innovative processes at retail chains are fruitful when implemented. Field experiments provide direct causal evidence on whether the innovations will work (List, 2011; Fisher et al., 2020) while structural estimation allows for examining counterfactual scenarios to evaluate outcomes from such process innovations (Reiss and Wolak, 2007). In this dissertation, we leverage structural estimation and field experimentation to study three topics on the frontier of innovations in retail operations: a) dynamic pricing of product drops in the presence of resellers, b) localization of inventory for e-commerce retailers, and c) increasing customer recycling through operational incentives. Each of these topics falls within a different category of the three major categories discussed in Caro et al. (2020), a special issue article in *Manufacturing & Service Operations Management* discussing problems on the frontier for research in retail operations.

Pricing with Resellers. Chapter 2 involves a partnership with a baby clothing retailer using "product drops," who was unsure whether it should change pricing as customers were reselling the product as new for profit. Product drops are a recent business strategy adopted by billion-dollar brands such as Supreme and Amazon that involve selling limited inventory on a specific date with the intent to drive scarcity, with the consequence that resellers can take advantage of the scarcity (Ufford, 2018; Van Elven, 2018; Griffith, 2019). Although we considered a pricing experiment, our partner retailer was ultimately uncomfortable with manipulating customer perceptions of the brand, motivating us to leverage structural estimation techniques.

Empirically examining how the firm should price with resellers introduced key challenges. First, prior literature in operations management (OM) has studied dynamic pricing but not in the context of product drops with scarcity and resellers. Scarcity and resellers require a model that captures strategic interactions between the retailer and customers who anticipate future inventory availability as well as a future resale market (Su, 2010). Second, the OM models were predominantly analytical (e.g., Su, 2010; Cui et al., 2014), but we wanted to study the problem empirically. Third, our partner did not have data on the resale market, requiring the research team to collect the data ourselves. In overcoming these challenges, we collect the resale data and build a dynamic discrete choice structural model that captures a range of elements relevant to product drops: scarcity impacts to consumers, operational costs of inventory management, pricing impacts to both resellers and traditional consumers, intertemporal pricing, and an equilibrium where strategic behavior is consistent with future outcomes.

We show that incorporating resellers into pricing improves profit by 7% on average. Further, the impacts of the resale market are heterogeneous across SKUs, ranging from -11% to 16% based on the initial inventory relative to the initial demand. Without requiring our partner to implement price changes, our structural model provides insights into how to price their product drops in the presence of resellers.

Benefits of Local Inventory. Chapter 3 quantifies the benefits of carrying inventory in front distribution centers (DCs) closer to the customer to improve demand from faster shipping speeds to customers. Given the recent massive growth of e-commerce through retailers such as Amazon, JD.com, and Walmart that have innovated through improved delivery speed to customers by leveraging closer DCs (Zhu and Sun, 2019; Soper, 2020), the question is of particular importance to any retailer investing in improving delivery speeds.

OM literature has documented demand benefits of improved delivery time (e.g., Cui et al., 2019; Fisher et al., 2020), but these benefits have not been incorporated into OM models of e-commerce inventory decisions where the manager considers the costs of achieving improved delivery (Chen and Graves, 2021; Perakis et al., 2020). For example, the useful newsvendor model from OM that has gained wide adoption from practitioners to help consider setting inventory levels when facing stochastic demand (Choi, 2012; Van Mieghem and Rudi, 2002; Bertsimas and Thiele, 2005) is limited because it assumes the demand distribution is exogenous to the inventory decision. We build and estimate a structural model that can be applied to local fulfillment decisions in e-commerce when the inventory decision changes promised delivery time. The model is parsimonious and can be used by practitioners.

We find that JD.com's current utilization of front DCs improves average promised delivery time by 28.3%, resulting in a 10.7% improvement in average profit. We identify the five best front DCs for reducing holding costs, which are marked by long backup delivery speed or large estimated local demand more so than large holding costs. If the loss in demand from backup fulfillment due to delivery time is ignored in the inventory decision, average promised delivery time worsens by 14.8% leading to an average profit reduction of 6.8%.

Incentivizing Recycling. Chapter 4 uses field experimentation to understand customer sensitivity to incentives offered by businesses to encourage e-waste recycling. We partner with Logitech, a consumer electronics company interested in improving its corporate sustainability goals (Logitech, 2021) through a return program to recycle products, similar to programs offered by North Face and The Body Shop (Leighton, 2020; Martin, 2019).

Prior academic literature has been limited in providing guidance. OM literature highlights the benefits of corporate social responsibility (CSR) in improving profitability (Flammer, 2015), but the impact to customer choices remains an open question (Caro et al., 2020). One specific area of focus for CSR initiatives is the circular economy, which has been an increasing area of focus for retailers (McKinsey, 2021; Walmart, 2017; Agrawal et al., 2021) due to the economic potential of trillions of dollars (*McKinsey Quarterly*, 2017; Accenture, 2017; Agrawal et al., 2019). While study of the supply-side of the circular economy such as developing industrial systems, designing circular processes, and transitioning to circular business models has gained recent attention in the OM literature (Agrawal et al., 2019; Atasu et al., 2008; Savaskan et al., 2004; Agrawal et al., 2021), the demand-side of attracting customers to participate in the circular economy has received little attention. Outside of the OM literature, e-waste recycling literature has primarily used observational studies (Shevchenko et al., 2019) where effect sizes are often captured by intentions from survey-based work (e.g., Delcea et al., 2020; Yin et al., 2014; Dixit and Vaish, 2015) instead of measuring the behavior directly, which may support invalid conclusions when used to inform operational decisions. Furthermore, existing studies focus on interactions between an individual and a recycling organization, with little guiding evidence for businesses like Logitech that want to build recycling programs. Additionally, while recycling generally incurs a handoff cost (Bourne et al., 2021; Shevchenko et al., 2019), reluctance to recycle e-waste is heightened by hibernation (Wilson et al., 2017; Bourne et al., 2021), where consumers may retain old products due to perceived residual value or lack of knowledge of how to recycle electronic devices. Therefore, our field experiments provide needed empirical evidence of the causal impacts of a business using different incentives to improve e-waste recycling behavior.

Through a set of field experiments, we find that the chosen value-based incentives (environmental incentives of planting trees) and convenience-based incentives (offering residential pickup for the return) are ineffective in isolation at inducing recycling behavior of end-of-life electronics products, despite importance of these incentives toward recycling intentions reported in academic literature (Shevchenko et al., 2019). We conclude that either the environmental incentive would need to be increased, the environmental incentive may need to be used in conjunction with the convenience-based incentive, or monetary incentives should be explored over non-monetary incentives (Singh et al., 2019; Shevchenko et al., 2019; Stern, 1999).

CHAPTER 2: INTERTEMPORAL PRICING WITH RESELLERS: AN EMPIRICAL STUDY OF PRODUCT DROPS

2.1 Introduction

Resale markets account for billions of dollars in transactions across a variety of industries and continue to grow (Griffith, 2019; Maheshwari, 2019; Kodali et al., 2008). For example, the resale market for apparel was a $24 billion industry in 2019 and is expected to grow to $51 billion by 2023 (Maheshwari, 2019). Billion-dollar platforms have emerged to allow for consumers to more easily engage in peer-to-peer resale of new apparel such as eBay, StockX, and GOAT group (Griffith, 2019; Patel, 2020). In response to the emergence of resale platforms, retailers deploy different strategies to manage resale markets of their products. Some firms embrace resellers (Courty and Davey, 2020), some discourage them (Von Wilpert, 2019), and some sue to ban them (Cui et al., 2014). Analytical research in Operations Management (OM) provides conflicting views on the impacts of the resale market on firm profit. Su (2010) concludes the resale market can negatively impact firm profit whereas Cui et al. (2014) concludes that resellers may benefit the firm. Empirical examination of the impact of resellers on firm profit is limited.

A related question is whether retailers can benefit from incorporating resale data in their decision-making process. In the past, resale largely occured in distributed channels such as other stores outside of the purview of the retailer, limiting the retailer's ability to collect resale data. Now, with the growth of resale marketplaces on platforms like Facebook and eBay, retailers can collect resale data with appropriate investments in data collection activities. However, it is not clear whether resale data will be useful to improve decisions such as pricing. In fact, existing literature on dynamic pricing tends to omit the possibility of resale (e.g. Elmaghraby and Keskinocak, 2003; Cachon and Swinney, 2009), assume the size of the resale market is limited (e.g. Ozer and Phillips, 2012; Gowrisankaran and Rysman, 2012), or assume "no resale" as a condition (e.g. Talluri and van Ryzin, 2005; Nair, 2007). In this paper, we examine the impact of resale marketplaces on retailer profit as well as the value of incorporating resale marketplace data for retailer pricing decisions.

Empirically examining the impact of resale markets on a retailer's profit and its pricing strategy has three key challenges. First, we need a model that captures the strategic interactions between the retailer and its customers in the presence of a resale market. The firm considers how customer behavior differs when purchasing for personal consumption or purchasing to profit from resale in the future; customers consider whether to purchase from the firm or to purchase from a resale market in the future. Second, the firm may also change its prices over time, so the model needs to incorporate dynamic pricing. Researchers who have examined the resale market in Marketing have noted the difficulty in developing a model that incorporates both strategic behavior and dynamic pricing, but acknowledge its value in allowing for valid resale counterfactuals (Shiller, 2013; Ishihara and Ching, 2019; Lewis et al., 2019). Third, estimation of such a model would require data from both the primary market, where initial sales occur, and the resale market, where resale sales occur. Generally, resale market data is not easily available as resale typically occurs in various platforms outside the purview of the focal firm (Leslie and Sorensen, 2014), requiring the researcher to collect data from multiple sources (Zhu, 2014; Shiller, 2013). We overcome all three challenges in this paper. We build a structural model that combines a demand-side and a supply-side to examine dynamic pricing in the presence of resellers. To estimate the model, we collect primary market data through a partnership with a firm and then collect resale data from that firm's resale marketplace.

Our dataset comes from partnering with an online baby clothing retailer that employs a "product drop strategy," generally releasing new products on Tuesdays at 9pm. Product drops occur when a firm releases a limited-edition product line on a specific date for a short period of time (Ufford, 2018). The product drop strategy is growing in importance as several well-known apparel brands such as Gucci, Louis Vutton, Supreme, Adidas Yeezy, and Nike Air Jordan have found considerable success with its use (Van Elven, 2018). In fact, *The New York Times* labeled 2016 the "Year of the Drop" (Paton, 2016). Leading up to the drop, these companies exert considerable marketing effort in generating consumer hype to build demand (Von Wilpert, 2019). Our partner retailer generates hype through Facebook for weekly products being released, using baby models for clothing and creative advertising. Due to the hype, demand is substantially higher in the first period than in the following periods. Thus, the retailer attempts to price in a way to capture as much demand as possible in the first period to stockout quickly to create a sense of urgency for its customers. Similar to other fashion apparel settings, inventory costs are known to be high (Fisher and Raman, 1996). Unlike traditional fashion apparel settings that may be concentrated around a "selling season" with a standard duration (Fisher and Raman, 1996), product drop settings require stocking out as quickly as possible with variable stockout timings across products.

Once our retailer stocks out of a given product, a resale market unfolds on Facebook where consumers engage in a peer-to-peer marketplace for unused products. Our partner retailer closely monitors the resale marketplace and takes it into account in pricing. In fact, the retailer administers one of the largest resale marketplaces for their product. Despite monitoring its resellers, our partner lacked evidence for whether and by how much pricing decisions improved to justify the use of resources for monitoring. In our sample, the average markup of prices from the primary market to the resale market is 23%. This is not an uncommon situation. The resale market for new products can be quite profitable as demonstrated by the presence of a large resale market for sneakers and streetwear from brands such as Supreme and Adidas Yeezy, which is expected to grow from $2 billion in 2019 to $6 billion by 2025 in North American alone (Griffith, 2019). Given that resellers are extracting meaningful profit, our focal retailer wondered how its own profit was impacted, motivating our research.

It was not clear to our retailer how pricing differently would impact profit. On one hand, increasing the initial price could allow the firm to extract profit from resellers (Su, 2010). However, only 30% of the retailer's products stockout in the first week. Raising prices to deter resellers might backfire if it leads to more unsold inventory after the first period, increasing holding costs and requiring a steep discount to sell-through in future periods. On the other hand, lowering prices could allow the firm to stockout sooner to reduce holding costs. Stocking out quickly would be consistent with our focal retailer's strategy to create a sense of urgency for its customers. However, this could leave money on the table as firm profits transfer to resellers.

The presence of a resale market complicates the dynamic pricing problem for our partner retailer as well as for other companies that use product drops. Resellers help the retailer sell-through quickly by creating additional demand for the retailer's products, which may in turn allow the firm to raise the initial price without incurring steep markdowns in the future. However, the presence of a resale market undermines the scarcity strategy (Stock and Balachander, 2005), an essential component of the product drop business model, as customers have an additional opportunity to purchase the product after the firm stocks out (Su, 2010). So, the retailer may need to offer lower prices to incentivize customers to purchase now instead of waiting for the resale market. Thus, evaluating how resellers impact our retailer's profit requires a model that can capture firm holding costs and allow for pricing over any number of periods, neither of which have been incorporated in prior OM analytical models with resale markets (Su, 2010; Cui et al., 2014). In this paper, we aim to answer the following research questions: 1) To what extent does the presence of a resale marketplace impact retailer profitability, and how should the retailer respond? 2) To what extent does incorporating data from resale marketplaces in retailers' pricing decisions improve profitability?

Our key methodological challenge involves incorporating the strategic nature of the retailer and its customers with the availability of a resale market. To answer our research questions we need to specify a tractable framework that can be estimated using data from a firm using product drops. We then need to perform policy experiments to find how changes to the system impact firm profit. These needs motivate our use of a structural modeling approach. As noted in Erdem and Keane (1996), by specifying a structural model we can estimate primitives to consumer and firm behavior that are policy invariant. We can then use our model to perform policy evaluation relative to the estimated primitives that define the data observed (Reiss and Wolak, 2007).

Our model incorporates a demand-side for strategic customers and a supply-side for strategic pricing decisions with inventory. Our demand model is distinguished from other models for strategic consumers that ignore resale markets (e.g. Nair, 2007; Gowrisankaran and Rysman, 2012) because consumers make purchase decisions based on future outcomes in the resale market in addition to future outcomes in the primary market. Our supply model is distinguished from other models with strategic pricing decisions that either ignore strategic consumer behavior (e.g. Aguirregabiria, 1999) or ignore operational costs to the firm (e.g. Ishihara and Ching, 2019; Nair, 2007). In our model, the firm incorporates strategic consumer behavior while balancing its own operational costs of holding inventory.

In addition, our empirical context involves resale of new apparel which is different from the vast majority of prior literature that focuses on resale of used goods (e.g. Ishihara and Ching, 2019;

Shiller, 2013; Chen et al., 2013; Tanaka, 2013) or ticket resale (e.g. Courty, 2003; Su, 2010; Cui et al., 2014; Cachon and Feldman, 2020). The motivation to resellers of used goods or tickets is different from resellers of new apparel. Resellers of used goods use resale to reduce the effective price for personal consumption (Chevalier and Goolsbee, 2009); resellers of tickets gauge resale values based on the known timing of an event (Geng et al., 2007). Unlike used goods and tickets, resellers of new apparel sacrifice personal consumption and gauge resale values based on the firm's uncertain stockout timing to leverage limited competition in the resale market. As a result, the modeling approaches used previously cannot be applied to resale of new apparel. Our model accounts for the differences in resale behavior for new apparel.

Our study provides the following insights. First, we find that failure to incorporate the resale market into the pricing decision decreases firm profit by 7.0%. Incorporating the resale market implies that the retailer should price lower upon release than when ignoring the resale market. Second, the presence of a resale market reduces firm profit by 0.7% on average, with impacts for individual SKUs ranging from -11.4% to 15.7%. Whether the resale market benefits or hurts profit depends on the SKU's inventory relative to the market size. For example, when inventory is relatively large, reducing the price becomes more attractive to the firm because it incentivizes resellers to purchase the product to help reduce high holding costs. Third, we find heterogeneity across SKUs regarding the impacts of resale response strategies a firm may consider such as banning resale, promoting resale, or maintaining the current level of resale. For our partner retailer, the best single response strategy is to ban the resale market for all products. If the firm could optimally assign the response per SKU, then profit would increase by 7.4%.

Our paper makes the following contributions. Our work adds to the extensive literature on dynamic pricing by showing that intertemporal pricing that ignores resellers can lead to losses. We complement the analytical literature that has studied resellers (Cui et al., 2014; Su, 2010) by examining the theoretical predictions from these papers using proprietary data from our partner retailer. Interestingly, in the context of resale of apparel, we find opposite directional insights of Cui et al. (2014) regarding the impact of firm profit based on relative inventory to demand. Our insights differ because retailers for apparel incorporate holdings costs, whereas these costs may be ignored for sellers of tickets (Cui et al., 2014). When inventory is relatively large, resellers help the firm reduce holding costs by reducing the time to stockout with their purchases; otherwise, resellers increase firm holding costs by increasing time to stockout as availability of a resale market reduces the sense of urgency for consumers to purchase in the primary market. Methodologically, we develop a structural model that can be used to examine dynamic pricing in the presence of strategic consumers and resellers. In order to apply the model to the data at our partner retailer, our model captures a range of elements relevant to product drops: hype and scarcity impacts to consumers, operational costs of inventory management, pricing impacts to both resellers and traditional consumers, intertemporal pricing, and an equilibrium where strategic behavior is consistent with future outcomes.

Our paper has the following managerial contribution. Retailers are facing increasing competition from online marketplaces and it is unclear how retailers can effectively respond to them (Caro et al., 2020). To our knowledge, we are one of the first papers to demonstrate that retailers can leverage resale marketplace data to make better pricing decisions. We quantify the benefits of using resale data in pricing for our partner retailer and generalize insights for other firms using product drops with resellers. Further, managers can use our model to understand the impact of the resale market in their specific context in order to inform strategies to respond to resellers such as banning or promoting resale.

2.2 Related Literature

We now review prior literature relevant to the behavior of retailers who engage in product drops, the behavior of consumers who engage in resale of new apparel, and structural modeling of a firm pricing with resellers.

2.2.1 Product Drops

Product drops result from two key concepts studied in literature: hype and limited release strategy. Companies that effectively deploy product drop strategies effectively generate hype around exclusive products (Faris, 2014). The marketing literature refers to hype as "buzz." Xiong and Bharadwaj (2014) study how prerelease buzz can be used in predicting new product sales. Prerelease buzz can boost awareness of a new product (Liu, 2006), generate favorable customer attitudes (Janiszewski, 1993), and function as an indicator to customers for the popularity and quality of the product (Godes and Mayzlin, 2004).

Limited release strategies involve selling limited inventory with no replenishment. The key decision for the firm is how to price to sell their limited inventory. Elmaghraby and Keskinocak (2003) give a review of analytical work on dynamic pricing with limited release strategies, which they refer to as "no replenishment." Firms may face no replenishment if restocking is not feasible due to long replenishment with a short selling season. DeGraba (1995) and Stock and Balachander (2005) document how no replenishment strategies may lead to "buying frenzies" when the availability of a product is uncertain. Stock and Balachander (2005) propose certain scenarios for profitable "scarcity strategies" (Dye, 2000; Brown, 2001) where firms intentionally limit their inventory to entice customers to purchase. Combined with product hype, limited-release strategies ensure that the firm depletes inventory quickly, making product drops a viable business strategy.

Product drops have similarities to flash sales which have been studied at companies such as Rue La La (Ferreira et al., 2016). Ferreira et al. (2016) characterize flash sales as "sample sales" with extremely limited-time discounts. Often brands utilize sample sales as a channel to offload overstock inventory (Wolverson, 2012). Flash sales leverage "events" with a set timer on when the bargain pricing expires. Flash sales are similar to product drops in the sense that the organizer of the flash sale often generates hype around upcoming flash sales and utilizes scarcity around the number of units remaining at the discount. Flash sales generally differ from product drops in that flash sales target low consumption valuation customers that did not purchase the product at the prior market rates, whereas product drops target brand loyalists with high consumption valuation who respond to limited availability (Faris, 2014). Our focus is on product drops, but future research could explore how resale markets evolve from flash sales.

2.2.2 Resale Markets of New Apparel

The textbook theory for how resale markets manifest is that consumer valuations change over time so that resellers can capture profit by selling to high-valuation customers at a later point in time (Courty, 2003; Leslie and Sorensen, 2014; Cui et al., 2014; Geng et al., 2007). At the point of purchase, future valuations are uncertain so that resellers strategically consider the profitability of engaging in resale. Also, consumers who intend to purchase the product for consumption strategically may consider future outcomes, including the price faced in the resale market (Su, 2010; Cui et al., 2014). Literature on strategic consumer behavior has studied when consumers anticipate future outcomes including future price changes (Elmaghraby et al., 2008; Su, 2007), future availability of inventory (Liu and van Ryzin, 2008; Cachon and Swinney, 2009), and future valuation uncertainty (Courty, 2003). In our context, all of these outcomes are incorporated into consumer strategic behavior.

How resellers exist in an apparel context is at first puzzling, as markdown pricing is common (Fisher and Raman, 1996). If the price declines over time then it seems like resellers would only lose profit. This is contrary to other contexts like ticket resale where "low-to-high" pricing may occur so that resellers can rationally expect a price increase in the future to allow for profit when competing with the firm (Cui et al., 2014). However, with resale of apparel, resellers who purchase the product early to compete with the firm at a later point would lose profit. Unlike for tickets, however, the product value is not tied to an event date (Geng et al., 2007) so that resellers can realize profits after the firm stocks out. Under a product drop strategy, the firm needs to stockout in a timely fashion. In other words, resellers in a product drop context capitalize on the fact that the firm cannot hold inventory indefinitely to capture future high-valuation consumers. In this way, resellers can realize profits through limited competition with other resellers after the firm stocks out. Unlike other resale papers, our work studies the behavior of resellers of new apparel where the evolution of the resale market differs in timing and firm pricing strategy.

2.2.3 Related Structural Models

Structural models for consumer and firm behavior have gained prominence in the OM community (Terwiesch et al., 2020) with a variety of applications to such industries as call centers (Aksin et al., 2013), retail (Bray et al., 2019; Moon et al., 2018), air-travel (Li et al., 2014), and healthcare (Olivares et al., 2008). Our work builds on dynamic pricing models with strategic consumers that leverage structural models, built on the foundational structural modeling papers of Rust (1987), Hotz and Miller (1993), Berry et al. (1995), and Aguirregabiria (1999). Several structural dynamic pricing models have considered strategic customers (Nair, 2007; Gowrisankaran and Rysman, 2012;

Hendel and Nevo, 2013) where the firm leverages markdown pricing to capture consumers that wait for the firm to drop the price as average valuations lower in later periods. In all of these papers consumers strategically incorporate future pricing, but none of them incorporate customers strategically considering a resale market.

There are a few structural papers that have considered resellers but in different contexts. One stream considers ticket resale (Leslie and Sorensen, 2014; Zhu, 2014) and another stream considers video game resale (Shiller, 2013; Ishihara and Ching, 2019). Ticket resale differs from resale of apparel because ticket value is based upon the timing of an event (Geng et al., 2007) whereas resale of apparel is based on the firm's stockout timing. Video game resale differs from resale of apparel because resellers of video games have already received consumption utility (Shiller, 2013) whereas resellers of apparel keep the product in the box, sacrificing consumption utility. In this sense, video game resale considers resale of used products (Ishihara and Ching, 2019) where the used good market impacts customer purchases by reducing the effective price to the customer (see Chevalier and Goolsbee, 2009, for an example of used textbooks). Instead of examining ticket and video game resale, our study empirically examines the impact of the resale market in the apparel industry for a firm using a product drop strategy.

2.3 Data

We leverage data from CompanyX (masked for confidentiality), an online fashion retailer of limited-release baby clothing in the United States. New products are released once a week at a predesignated date and time, with a "drop date" generally on Tuesdays at 9pm. These product drops generate considerable hype, with 81% of sales generated in the first week of product release. Leading up to the product drop, the firm promotes the product on social media platforms such as Facebook, giving announcements on upcoming products displayed on baby models as well as the day and time each product will be released. In addition to the firm generating hype, consumers become passionate about the products and often share on their own social media platforms a desire to purchase upcoming products. CompanyX mentioned that some customers may even treat purchasing popular products as a competition among other customers.

The products released are defined in the data by the stock-keeping unit (SKU), consisting of three attributes: product category, product size, and collection. CompanyX's core business comes from three product categories: rompers/bubbles, dresses, and sets. Rompers and bubbles are both one-piece garments with shorter leg-length than dresses, whereas sets are two-piece matching shirt/skirt garments. Each product may be one of eight baby sizes. The collection is a limited campaign regarding styling choices for the garments to be released each week. Each of the three product categories will have similar, but slightly different styling for a given collection. The collection serves as the primary differentiator across product drops each week, as each drop will generally include a few collections that leverage some combination of product categories and sizes. Figure 2.1 gives examples of products offered on CompanyX's website.

Figure 2.1: Examples of Products in Each Product Category

(a) Rompers/Bubbles (b) Sets (c) Dresses

CompanyX does not replenish its inventory after the drop date, as product drops entail limited-release quantities. CompanyX faces two major decisions: first, how many units per SKU to produce leading up to the product drop, and second, how to price these units. The initial drop quantity is a complicated decision, incorporating material availability from suppliers, lead-time of production, and uncertainty in the number of interested customers at the point of production. We do not have data on the factors influencing production, but our partner retailer informed us of a long lead time of about six months to produce new products. We do have data on the week-to-week pricing decisions, so we focus our attention on CompanyX's pricing decisions. Since CompanyX never replenishes inventory, by the time of the product drop we can think of the production decision as independent from the pricing decisions.

CompanyX faces an interesting base of customers because a resale market emerges for products once CompanyX stocks out. The resale market transactions occur peer-to-peer on Facebook, where sellers post a price at which other potential customers in the Facebook group can purchase. Resellers purchase the product from CompanyX with the intent to profit through resale. Since apparel products lose value once worn, the value of a CompanyX product depreciates immediately after use. Therefore, upon receiving the product the customer must decide to open the packaging for use or to keep the packaging intact for resale.

CompanyX captures data on its own sales transactions through its eCommerce platform Shopify, but has limited data on the resale market transactions. In our study we close CompanyX's data gap on resale information by manually collecting data from one of the largest Facebook resale groups that is representative of the resale marketplace. We collect the data manually because at the time of data collection, scraping data would violate the Terms of Service for accessing Facebook. Manual data collection does not violate these terms. As observation potentially involves privacy concerns, we obtain IRB approval for the study.

Because we needed to manually collect resale data, CompanyX restricted the primary market data to only those SKUs for which we collected resale data. Section 2.3.1 provides details on the primary market data provided, and Section 2.3.2 provides details on our resale data collection strategy and the data collected. Our data set for analysis includes 2,485 week-SKU observations across 408 SKUs with 36,456 purchases in the primary market between February 2016 and December 2018, and 994 purchases in the resale market.

2.3.1 Primary Market Data

The retailer manages all transactions through Shopify, a mainstream ecommerce platform. Shopify stores four data types: orders, products, customers, and site traffic. CompanyX provided order data linked to products and site traffic on the date of each product drop. Due to privacy concerns, CompanyX did not share customer information with us.

Our key data elements consist of the date, price, and order quantity for each week-SKU observation. Table 2.1 shows that weekly primary market sales for an SKU are on average 36.65. Average primary market price per SKU is between \$17.99 and \$42 with an average price of \$28.59. The average first day traffic varies between 2,241 to 13,215 visitors and starting inventory can be as low as 11 units[1] or as high as 246 units. Thus, the firm faces a wide variety of demand relative to its inventory position. First day traffic is not known at the time of producing the products for a given drop date, but the firm can adjust its drop date pricing to reflect updated market conditions.

[1]Recall that our SKUs differ by size, where the firm may carry small inventory for very small or very large sizes.

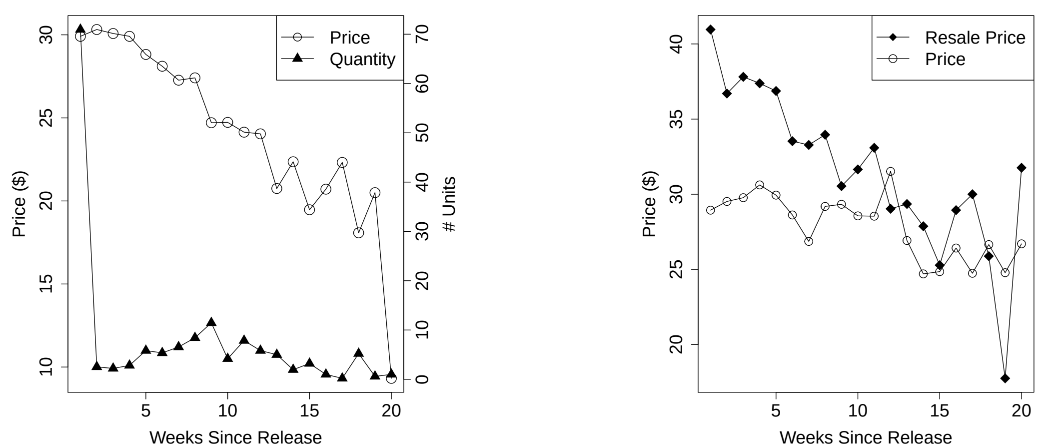
The average starting inventory across SKUs is 89.35, with an average stock-out time of 5.09 weeks. We observe that 30.1% (123/408) of SKUs stockout in the first week, with less than 10% of SKUs stocking out in more than 11 weeks.

Table 2.1: Summary Statistics per SKU

Variable	Mean	StDev	Min	Max
Sales per week	36.65	38.29	1.38	218
Primary market price	28.59	3.51	17.99	42
Starting inventory	89.35	45.81	11	246
Starting market size	7249.84	2623.90	2241	13215
Resale quantity	5.62	5.59	1	35
Resale price	36.27	8.37	15	90
Weeks to stockout	5.09	5.45	1	20

Panel (a) of Figure 2.2 shows the average price and quantity across SKUs in our data set by how many weeks since each SKU has been released. We notice a striking decline in average sales from the first week to future weeks, resulting from the initial hype in the first week dissipating. Notice too that the longest shelf-life for an SKU in the dataset is 20 weeks, for only 3 of the 408 SKUs. Thus, Panel (a) demonstrates the key elements of a product drop strategy to build hype to generate large sales on the first week and to release products for a limited time.

Figure 2.2: Average Price, Quantity, and Resale Price Paths Across SKUs



(a) Average price and sales paths across SKUs

(b) Average price and resale price depending on SKU stockout time in weeks

Notice also that the average price declines as SKUs remain in stock longer, demonstrating that CompanyX reduces the price over time. Per SKU, however, the price does not necessarily decline as 88.2% of the time the price remains the same as in the period before, 10.2% of the time the price decreases through a markdown, and 1.6% of the time price increases through a markup.

2.3.2 Resale Data

Resale transactions on Facebook are initiated with the seller posting the product name, a photo, size, and condition. Figure 2.3 gives an example comparison of the product listing from CompanyX's website compared to a listing in the Facebook page for the resale market. In this example, we can see that the price is higher in the resale market than in the primary market. Further, we can see that the product is still in its packaging in the resale market.

Figure 2.3: Comparison of product listings from CompanyX and Facebook resale

(a) "Space Moon" (name masked) bubble hosted in primary market at $29.

(b) Reseller selling "Space Moon" bubble still in packaging at $40.

As mentioned in Section 2.3, we must collect our resale data manually to not violate the terms and conditions of Facebook. Since the retailer offers many SKUs, it is infeasible for us to collect resale data for all SKUs. Instead, we focus on a subset of SKUs and collect data using the following approach. First, we randomly select collection-category combinations to search for data on Facebook. Randomization avoids biases in selecting products, such as due to alphabetical ordering or seasonality in product drop dates. Next, we search the Facebook group to filter for Facebook posts that contain the collection-category combination. Finally, we capture the text in each Facebook post and extract the relevant pieces we need to capture the transaction: product name, size, price, condition. We collect data for new products only, either displayed from the photo of products still in packaging or noted with condition NWT (new with tags) or NIB (new in box).

We manually collect data on 994 resale transactions across 408 SKUs. The resale quantity represents 2.7% (994/36,456) of the firm's inventory sold. Examining Table 2.1, the average SKU has a resale quantity of 2.44 with a markup of $6.47, or 23% (35.06/28.59-1). Panel (b) of Figure 2.2 depicts the average price and resale price across SKUs that stocked out in the same period. We again see that the average price for products that stockout later is lower, driven by markdowns.

We also see that the resale price is highest, and has the highest margin, for SKUs that stock-out quickly. The average resale profit is generally positive, but resellers will not always return a profit.

2.4 Model

We specifically focus on a retailer using a product drop strategy for apparel, but our modeling framework could be used for other durable products where the firm releases limited inventory. We model a monopolist firm that sells a fixed capacity to consumers who may resell the product as new.

We model the interaction between a retailer leveraging a product drop strategy and consumers who consider a resale market once the firm stocks out of inventory. The firm decides how to price its inventory in each period, while balancing operational costs of carrying inventory. Consumers decide whether to purchase the product for consumption, purchase the product to resell later, or wait until the next period. Both the firm and consumers behave strategically when making decisions by considering future outcomes. Following prior literature, we develop a utility maximization framework that specifies how the firm and consumers make their decisions strategically.

2.4.1 Preliminaries

Let $j = 1, ..., J$ be the index of products, and $t = 0, ..., T_j, T_j + 1$ be the number of weeks since the drop date. A given product j stocks out in period T_j, and in period $T_j + 1$ a resale market unfolds. We can think of the market for a given product j as being in two "meta-states:" $\{\mathcal{P}, \mathcal{R}\}$ where $t = 0, ...T_j \in \mathcal{P}$ denotes primary market (the firm still has inventory) and $t = T_j + 1 \in \mathcal{R}$ denotes the resale market (the firm has sold out of inventory). In meta-state $\mathcal{P}$, the firm makes pricing decisions and consumers decide whether to purchase from the firm to either consume the product or resell later or wait to purchase the product at a later time. In meta-state $\mathcal{R}$, the firm no longer carries inventory and a resale market unfolds. In the resale market, all the resellers sell the product purchased previously to remaining customers. The firm plays a strategic game of how to price the product anticipating consumer actions in both $\mathcal{P}$ and $\mathcal{R}$, whereas the consumers play a strategic game in meta-state $\mathcal{P}$ of whether to purchase the product today, to consume or to resell, or wait for a future state in either $\mathcal{P}$ or $\mathcal{R}$.

Let M_{jt} be the potential market size for product j in time t. Let I_{jt} be the firm's inventory at the beginning of the period t for product j. Denote the state space for a given product j in period t by $S_{jt} = \{M_{jt}, I_{jt}\}$. Consistent with Nair (2007), we assume states are observable to consumers and the firm. As the firm never replenishes inventory, inventory will only be 0 in the final period $T_j + 1$, so that in meta-state $\mathcal{R}$, $I_{jTj+1} = 0$. The firm and customers are strategic, taking into consideration utility for the current period in state S_{jt} and utility in future periods across possible future states. In considering future utility, the firm and consumers on average correctly guess the future pricing behavior of the firm and the expected resale price based on S_{jt}, and on average correctly anticipate the transitions from M_{jt} to M_{jt+1} as well as I_{jt} to I_{jt+1}. Prices in the primary market evolve according to a firm pricing policy $p(S_{jt})$, whereas prices in the resale market evolve according to an equilibrium price denoted by $r(S_{jT_j+1})$.

For meta-state $\mathcal{P}$, the sequence of events in each period t for product j is as follows: 1) Market size M_{jt} and inventory I_{jt} are realized. 2) Firm sets price p_{jt}. 3) Consumers make purchase decisions, to consume or to resell, that result in sales q_{jt}. 4) Period t transitions to $t + 1$, where $t + 1$ remains in meta-state $\mathcal{P}$ if $q_{jt} < I_{jt}$ or transitions to meta-state $\mathcal{R}$ if $q_{jt} = I_{jt}$.

For meta-state $\mathcal{R}$, the sequence of events is: 1) Market size M_{jT_j+1} realized. 2) Resale market clears at an equilibrium resale price r_{jT_j+1} with sales q_{jT_j+1}, determined by cumulative purchases from resellers (some number out of $\sum_{t=0}^{T_j} q_{jt}$) in meta-state $\mathcal{P}$ and demand in meta-state $\mathcal{R}$.

To simplify notation, unless specified we drop the j subscript as we treat products independently. Given the nature of product drops, treating products independently is reasonable as customers arrive to purchase a specific product which does not affect sales of other products, as demand for fashion apparel depends more on taste such as design or color than objective consumer needs (Fisher and Raman, 1996). Similar to other dynamic discrete choice models in Industrial Organization and Marketing, we make this assumption for tractability (Nair, 2007). We do not rule out that consumers may purchase several different products, but assume that availability of other products does not impact the consideration of a given product. Additionally, we assume that consumers only buy one of each product, which is again a common assumption in discrete choice models (e.g. Hendel and Nevo, 2006; Nair, 2007). The assumption of single-unit demand is realistic to our context because the firm places a maximum order quantity of one to allow more customers to purchase the product, similar to other companies following product drop strategies (Lu, 2018; Alvarez, 2016). We also observe in the resale market that all of our resale transactions involve sale of a single unit.

We now formalize a model to capture the key components of this scenario. We first outline our demand model for consumer purchase decisions. Then we discuss how the resale market unfolds between consumers. Next we outline our supply model for firm pricing decisions. Last, we describe how an equilibrium occurs between consumers and the firm based on our demand and supply model.

2.4.2 Demand Model

We model consumers as making a discrete choice depending on the actions available in each period. As noted earlier, the action space for consumers is different in meta-state $\mathcal{P}$ and $\mathcal{R}$. The action space of consumers in meta-state $\mathcal{P}$ is $\mathcal{A}^{\mathcal{P}} = \{F, S, W\}$, which respectively denote purchase and consume from **F**irm, purchase and **S**peculate for resale,[2] and **W**ait. Consumers that purchase and consume from firm exit the market after purchasing the product. Consumers that purchase and speculate must wait until period $T + 1$ to resell the product, and take no other actions toward the product until $T + 1$. Only consumers that speculate can choose to resell. Consumers can wait to perform these actions at a later period. In meta-state $\mathcal{R}$, consumers can no longer purchase from the firm nor wait as this period covers the entire span of the resale market. Thus, denote the action space in state $\mathcal{R}$ as $\mathcal{A}^{\mathcal{R}} = \{R, E\}$ where consumers can either purchase and consume from the **R**esale market or **E**xit and choose an outside option to not purchase the product. To summarize, consumers face the following choice sets:

- (Primary market) If $t \in \mathcal{P}$, then the consumer choice set is $\mathcal{A}^{\mathcal{P}} = \{F, S, W\}$.
- (Resale market) If $t \in \mathcal{R}$, then the consumer choice set is $\mathcal{A}^{\mathcal{R}} = \{R, E\}$.

For each action $a \in (F, S, W, R, E)$, we define the utililty to customer i at time t as the sum of the expected utility from taking that action U_t^a and a privately observed idiosyncratic shock ϵ_t^a. We assume the privately observed idiosyncratic shocks to each decision are distributed as iid type

[2]Our terminology "speculate" is similar to Su (2010) and Cui et al. (2014) where consumers purchase the product only with the intention to resell for profit. In their models, speculators have no value for the product. In our model, all customers have some consumption valuation for the product at the time of purchase, but can choose to take a speculation action if the expected profit outweighs their consumption valuation.

I extreme value.[3] We now define the utility functions for each action taken by the consumer.

We start with examining the utility from consumption in the primary market. Consumers that choose to consume in the primary market receive utility

$$u_t^F = U_t^F + \epsilon_t^F = \gamma + \gamma^0 \mathbb{1}_{t=0} - \alpha p_t + \epsilon_t^F$$

where consumers take into account the consumption value of the product and sensitivity to the firm's price. The parameter γ represents the present discounted utility of product consumption. Recall that in the product drop strategy the firm undertakes marketing efforts to increase awareness of the product on the date of the product drop, a strategy known in Marketing literature as generating "pre-release buzz" that can be critical to the success of fashion products which have decaying lifecycles (Houston et al., 2018; Xiong and Bharadwaj, 2014). The parameter γ^0 represents the additional utility from consumption when buying the product at the height of pre-release buzz, or upon release in $t = 0$, represented by the indicator variable $\mathbb{1}_{t=0}$. The parameter α represents the price sensitivity relative to consumption. Through idiosyncratic shocks our model allows for heterogeneity in consumption valuations by customer that change period-to-period (Courty, 2003).

Before defining the utility for resale or to wait, we need to describe how the consumer discounts future utility as under both actions the consumer considers future outcomes. Let δ_c be the discount rate for next-period utility. Similar to other empirical work, we fix the discount factor due to the difficulty of its identification (Nair, 2007; Ishihara and Ching, 2019; Moon et al., 2018). Since we examine weekly purchase decisions, we set $\delta_c = .99$ to account for weekly discount. This is the discount factor set in a retail context with weekly sales by Slade and G.R.E.Q.A.M. (1998) and can also be reached by scaling the monthly discount factor set in Nair (2007), as $.99 \approx .975^{1/4}$.

Now we examine the utility from choosing to speculate. The intent of a consumer purchasing to speculate is ultimately to return profit at the future resale price. Consumers that choose to

[3] A random variable distributed as type I extreme value refers to a Gumbel random variable with location parameter $-\lambda$, where $\lambda \approx .577$ is Euler's constant, and scale parameter normalized to 1. We set the location parameter for technical convenience as in Nair (2007) and normalize the scale parameter to 1 for identification of the parameters as discussed in Train (2009).

speculate receive utility

$$u_t^S = U_t^S + \epsilon_t^S = E[\tilde{r}_t|S_t, p_t] - p_t - \tau + \epsilon_t^S$$

where the consumer incorporates expected profit, determined by the difference in the expected discounted resale price $E[\tilde{r}_t|S_t, p_t]$ and the price paid p_t in the primary market, and the discounted utility of resale transaction costs τ as modeled in Leslie and Sorensen (2014) and Cui et al. (2014). While consumers that speculate intend to return profit, the expected profit may be positive whereas the realized profit could be negative. In other words, consumers that speculate face a gamble (Su, 2010). $E[\tilde{r}_t|S_t, p_t]$ is a complicated function because the customer faces uncertainty in transitions in the primary market, including when the firm will stock out, as well as the resale price r_{T+1}. Since $E[\tilde{r}_t|S_t, p_t]$ incorporates discounting across an uncertain number of periods, discounting is brought within the expectation. We examine $E[\tilde{r}_t|S_t, p_t]$ more closely after defining the other consumer utility functions.

Next we examine the utility for waiting in the primary market. When consumers wait, they discount the expected value of utility in the next period. Consumers that choose to wait receive utility

$$u_t^W = U_t^W + \epsilon_t^W = \delta_c E[u_{t+1}|S_t, p_t] + \epsilon_t^W$$

where $E[u_{t+1}|S_t, p_t]$ is the ex-ante discounted utility from behaving optimally in the next period. Once we define utility from actions in the resale market we can examine this function more closely.

Now we turn to the utility received from choosing to purchase for consumption in the resale market. Similar to consumer consumption value in the primary market, consumers that purchase in the resale market receive consumption utility γ with price sensitivity α. Now, the hype period is no longer relevant, and consumers face a resale price r_{T+1}. Consumers that choose to purchase in the resale market receive utility

$$u_{T+1}^R = U_{T+1}^R + \epsilon_{T+1}^R = \gamma - \alpha r_{T+1} + \epsilon_{T+1}^R$$

Finally, consumers that choose the outside option in the resale market receive utility

$$u^E_{T+1} = U^E_{T+1} + \epsilon^E_{T+1} = \epsilon^R_{T+1}$$

where we normalize expected utility from the outside option to zero.

We now provide expressions for the discounted expected resale price and the waiting function, starting with the waiting function. For $t \in \mathcal{P}$, consumers solve $\text{argmax}\{u^F_t, u^S_t, u^W_t\}$ and in period $t \in \mathcal{R}$, consumers solve $\text{argmax}\{u^R_{T+1}, u^E_{T+1}\}$. Recalling from earlier that $E[u_{t+1}|S_t, p_t]$ denotes the utility a consumer should expect from behaving optimally in the next period when choosing to wait, then by noting that the action spaces $\mathcal{A}^{\mathcal{P}}$ and $\mathcal{A}^{\mathcal{R}}$ are disjoint, we can take conditional expectations based on the probability of stockout to see the utility from waiting is

$$\begin{aligned}
u^W_t &= \delta_c E[u_{t+1}|S_t, p_t] + \epsilon^W_t \\
&= \delta_c(E[u_{t+1}|S_t, p_t, I_{t+1} > 0]P(I_{t+1} > 0) + E[u_{t+1}|S_t, p_t, I_{t+1} = 0]P(I_{t+1} = 0)) + \epsilon^W_t \\
&= E[\mathbb{1}_{I_{t+1}>0}]\delta_c E[\max\{u^F_{t+1}, u^S_{t+1}, u^W_{t+1}\}|S_t, p_t, I_{t+1} > 0] \\
&\qquad + E[\mathbb{1}_{I_{t+1}=0}]\delta_c E[\max\{u^R_{T+1}, u^E_{T+1}\}|S_t, p_t, I_{t+1} = 0] + \epsilon^W_t
\end{aligned}$$

For notational convenience, let $W(S_t, p_t) \equiv U^W_t$, where we describe $W(S_t, p_t)$ as the value function for waiting. Given that random shocks are distributed as type I extreme value, the value function $W(S_t, p_t)$ for waiting can be described as a combination of two "alternative-specific" value functions (see Rust, 1987; Nair, 2007) derived from the logit inclusive value of maximizing expected value in the following period, depending on which choice set is given. Taking conditional expectations based on the probability of stocking out, we can write the waiting function as:

$$\begin{aligned}
W(S_t, p_t) = E[\mathbb{1}_{I_{t+1}>0}]\delta_c \int &\log[\exp(\gamma + \gamma^1 \mathbb{1}_{t=1} - \alpha p_{t+1}) + \exp(E[\tilde{r}_{t+1}|S_{t+1}, p_{t+1}] - p_{t+1} - \tau) \\
&+ \exp(W(S_{t+1}, p_{t+1}))]dF(S_{t+1}, p_{t+1}|S_t, p_t, I_{t+1} > 0) \\
&+ E[\mathbb{1}_{I_{t+1}=0}]\delta_c \int \log[\exp(\gamma - \alpha r_{t+1}) + 1)]dF(S_{t+1}, r_{t+1}|S_t, p_t, I_{t+1} = 0)
\end{aligned} \tag{2.1}$$

where Equation 2.1 is a contraction mapping that can be used to solve for $W(S_t, p_t)$.

In a similar fashion, we can write the expected resale price in a given period as the discounted value of the expected resale price in the next period

$$E[\tilde{r}_t|S_t, p_t] = E[\mathbb{1}_{I_{t+1}>0}]\delta_c \int E[\tilde{r}_{t+1}|S_{t+1}, p_{t+1}]dF(S_{t+1}, p_{t+1}|S_t, p_t, I_{t+1} > 0)$$
$$+ E[\mathbb{1}_{I_{t+1}=0}]\delta_c \int r_{t+1}dF(S_{t+1}, r_{t+1}|S_t, p_t, I_{t+1} = 0) \quad (2.2)$$

which is also a contraction mapping. Given the idiosyncratic errors are type I extreme value, our logit probabilities follow the logit form. For time period t, the choice probability (also referred to as market share) for action k can be expressed as

$$s^a(S_t, p_t) = \frac{\exp(U_t^a)}{\sum_{j\in\mathcal{A}^{\mathcal{P}}} \exp(U_t^j)} \text{ where } t \in \mathcal{P}, a \in \mathcal{A}^{\mathcal{P}} = \{F, S, W\}$$
$$s^a(S_{T+1}, r_{T+1}) = \frac{\exp(U_{T+1}^a)}{\sum_{j\in\mathcal{A}^{\mathcal{R}}} \exp(U_{T+1}^j)} \text{ where } T+1 \in \mathcal{R}, a \in \mathcal{A}^{\mathcal{R}} = \{R, E\}$$

We now aggregate across customers to give the expected demand at time t, whether in the primary market (purchases for consumption or speculation) or in the resale market (purchases for consumption), as

$$\tilde{Q}_t = \begin{cases} \tilde{Q}_{\mathcal{P}}(S_t, p_t) = M_t[s^F(S_t, p_t) + s^S(S_t, p_t)] & \text{if } t \in \mathcal{P} \\ \tilde{Q}_{\mathcal{R}}(S_{T+1}, r_{T+1}) = M_{T+1}s^R(S_{T+1}, r_{T+1}) & \text{if } t \in \mathcal{R} \end{cases}$$

We treat the number of customers that arrive on the first day of the product's release as the total market size, which diminishes over time as customers make purchase decisions. Consumers that purchase for consumption exit the system and consumers that purchase to speculate take no other actions until the resale market. As consumer awareness is at its peak upon product release, we assume no new customers join the system. Due to censoring, we define firm sales as $q(S_t, p_t) = \min(\tilde{Q}_{\mathcal{P}}(S_t, p_t), I_t)$. Both market size and inventory diminish by the sales in a given period, so that our state transitions in the primary market from period t to $t+1$ take the form

$$\{M_{t+1}, I_{t+1}\} = \{M_t - q(S_t, p_t), I_t - q(S_t, p_t)\}$$

where M_0 is measured as the website traffic that arrives on the first day of the product's release.

The resale market, at period $T+1$, is a terminal state where sales of the product conclude.

2.4.3 Resale Market Equilibrium

As noted earlier, the resale market unfolds in period $T+1$, and all sales in this state come from speculate decisions in periods $t \in P$. Let q_t^S be the number of purchases for speculation in time t. We model the equilibrium as a simultaneous equation where the supplied quantity q_{T+1}^S comes from $q_{T+1}^S = \sum q_t^S$ and demand q_{T+1}^D unfolds based on the market price r_{T+1}.

We assume that resellers set prices competitively and that the market clears according to efficient rationing, a common assumption for the resale market in other works (see Su, 2010; Cui et al., 2014). In pricing competitively, each reseller maximizes its resale price to maximize utility according to a pure-strategy Nash equilibrium. For how the market clears, we adopt the interpretation of Su (2010), page 30: "Buyers arrive one by one in order of decreasing valuations, and each may purchase the lowest-priced unit remaining." When all resellers sell their capacity, the only pure strategy Nash equilibrium is for all resellers to set the market clearing resale price[4] r_{T+1} such that $q_{T+1}^D = q_{T+1}^S$. Hence, we characterize the resale market equilibrium according to the relation

$$q_{T+1}^S = \sum_{t=1}^{T} q_t^S$$

$$q_{T+1}^D = M_{T+1} s^R(S_{T+1}, r_{T+1})$$

$$r_{T+1} : q_{T+1}^D = q_{T+1}^S$$

Based on the resale equilibrium conditions, the market clearing price satisfies inverting the demand function at q_{T+1}^S. We provide the derivation for r_{T+1}^* in Appendix A.1. Based on the

[4] Our model realizes the dis-utility of price and transaction cost to the reseller at the time of purchase, making these costs sunk at the point of the resale market. Assuming the market clearing resale price is non-negative the proof is straightforward. Consider a given reseller. Not selling the capacity would generate no income so the reseller should sell the capacity. Setting price slightly higher would result in not selling capacity by efficient rationing. Setting the price slightly lower would result in less income.

functional form for s^R, the market clearing resale price is given as[5]

$$r^*_{T+1} = \frac{\gamma - \log(\frac{q^S_{T+1}}{M_{T+1} - q^S_{T+1}})}{\alpha}$$

2.4.4 Supply Model

We model the firm's pricing decision in each period of the primary market under a product drop strategy. The firm chooses its prices to maximize expected current and future discounted profit, composed of revenue and operational costs. We incorporate two types of costs to the firm: holding costs resulting from maintaining inventory and price adjustment costs. Recall that in a product drop strategy the firm never restocks inventory, so we do not incorporate ordering costs and treat production costs as sunk at the point of the product release when the pricing decisions begin. The firm discounts future periods with discount factor δ_f. We set $\delta_f = .99$ for the same reasons we set $\delta_c = .99$ for consumers. We formalize a model that incorporates the elements outlined above.

First, we model fixed and variable holding costs. Fixed holding costs could arise from employee allocation per product (Montgomery et al., 1971), regardless of the units in inventory, as well as limited website space to ensure consumers can find products easily (Wang and Sahin, 2018). We model fixed holding costs with the parameter μ. Variable holding costs could arise from warehouse costs for product storage and administrative costs to maintain inventory of each unit of a product (Russell and Taylor, 2006). We model variable holding costs as incurred at the end of the period as in Eppen and Iyer (1997), where we attribute an $\$\iota$ holding cost to the inventory remaining at the end of the period.

Holding costs introduce the central problem for a firm with product drops: how to seek the largest price possible while selling out in a timely fashion to minimize holding costs. Eppen and Iyer (1997) describe a similar tradeoff in the fashion context as a "dump problem" where the firm should dump inventory at a critical point to ensure holding costs are not too high while maintaining the ability to fulfill future high-valuation demand. Given that both fashion and product drop contexts

[5]The inversion implies that resale prices could feasibly be negative. For $\alpha > 0$, negative resale prices would occur for large, negative γ or speculation representing a large fraction of the market size. Neither of these occur in our empirical application.

emphasize selling all inventory in a relatively short product cycle (Ferreira et al., 2016), we may expect higher holding costs compared to other industries.

Second, we model fixed costs for price adjustment. Prior literature describes price adjustment costs as menu costs, which can be physical such as labor and material price adjustment costs, managerial from decision-making costs, or customer-induced from price change perception costs from consumers (Stamatopoulos et al., 2020).[6] Menu costs introduce an additional complexity to the product drop strategy where the firm faces a cost to change the price as its inventory position evolves, whether through markdowns to avoid holding costs when inventory becomes excessive or through markups to capture high valuation consumers when inventory becomes scarce. As in Aguirregabiria (1999), we model fixed menu costs differently for markups and markdowns. We incorporate indicator variables to the firm profit function for increasing (markup) or decreasing (markdown) the price, with effects captured with η^+ and η^- respectively.

Now we can define the firm's profit function. Let q_t be expected sales as defined in the demand section as a result of the pricing decision p_t at state S_t, and $I^e_{t+1} = I_t - q_t$ denote expected next period inventory resulting from q_t. We model the firm's expected one-period profit function as:

$$\begin{aligned}\pi(S_t, p_t)^e &= q_t p_t - \mu - \iota I^e_{t+1} - \eta^+ \mathbb{1}(p_t > p_{t-1}) - \eta^- \mathbb{1}(p_t < p_{t-1}) \\ &= \Pi(S_t, p_t)^T \theta_u\end{aligned}$$

where $\Pi(S_t, p_t) = [q_t p_t, -1, -I^e_{t+1}, -\mathbb{1}(p_t > p_{t-1}), -\mathbb{1}(p_t < p_{t-1})]^T$ and $\theta_u = [1, \mu, \iota, \eta^+, \eta^-]^T$. We can interpret $\Pi(\cdot)$ as an operator on first-period profit determined by the demand side at the choice of p_t in state S_t, whereas θ_u captures the linear effect of firm-side cost parameters. The expected one-period profit above is entirely specified by the model's states and primitives. However, as a researcher we have uncertainty about the actual expected profit that is observable to the firm, which we capture with the unobservable ξ^p_t for the price chosen in period t (Aguirregabiria, 1999).

[6]Menu costs are still relevant in an online retail environment. While technology enhancements have led to reductions in physical menu costs, managerial costs may have increased due to the added complexity of changing prices through online systems (Chen et al., 2011). In fact, Zbaracki et al. (2004) estimate managerial and customer menu costs to be 6 and 20 times higher than physical menu costs.

Then, the firm's one-period payoff function (Aguirregabiria and Mira, 2010) used in choosing p_t is

$$\pi(S_t, p_t, \xi_t^p) = \pi(S_t, p_t)^e + \xi_t^p \tag{2.3}$$

The firm prices in each period to maximize its total discounted expected profit. Since the firm prices at the beginning of each period, profit is not discounted in the first period. The firm's decision problem is then

$$\arg\max_{p_t} \sum_{t=0}^{\infty} \delta_f^t \pi(S_t, p_t, \xi_t^p) \tag{2.4}$$

2.4.5 Equilibrium

In this section we describe the mechanics behind how an equilibrium forms between consumers and the firm to result in a resale market. A Nash equilibrium requires that no consumer nor the firm can benefit from deviating from their choice given the options faced. Consumers behave optimally based on the actions of other consumers and the firm, as discussed in the demand model, whereas the firm behaves optimally based on the actions of its consumers, as discussed in the supply model. However, the optimal strategies of other agents are uncertain due to private idiosyncratic shocks. Uncertainty in q_t comes from the demand side from private shocks to each customer on whether to purchase the product. Uncertainty in p_t comes from private shocks to the firm on which price to choose. Consumers and the firm have rational expectations on future outcomes, but the realization of the future may differ from their expectations. Uncertainty has important implications for the agents in the model, and accounts for variations in the data that can be used for estimation in the next section.

2.5 Estimation

2.5.1 Overview

In this section we provide an overview of the steps required to estimate the demand and supply parameters from the Model section. We assume that consumers and the firm behave optimally according to our model so that the equilibrium in the data reveals primitives of the actions observed.

Our key computational challenge is to incorporate strategic behavior on both the demand-side and supply-side while maintaining tractability. We choose to use a limited information approach to reduce computational burden as jointly estimating the parameters for demand and supply would require re-solving the equilibrium at each guess of the parameters (Nair, 2007). We estimate our parameters in two steps where the first step estimates the demand primitives from our model conditional on beliefs formed in the data, and the second step estimates the supply parameters conditional on the estimated demand response to pricing decisions (Nair, 2007; Benkard, 2004, are examples of similar two-step approaches). Within our two-step approach, we use the following computational techniques:

Step 1: Estimate demand parameters

- Estimate consumer beliefs of state transitions through regressions. Compute the expected resale price function by solving a contraction mapping based on beliefs.
- Estimate consumer primitives through a Nested Fixed Point Algorithm (NFXP) (Rust, 1987) where the inner loop solves a contraction mapping for the value function for waiting - conditional on consumer beliefs, the expected resale price, and the choice of the primitives - and the outer loop solves for the primitives that maximize the likelihood of purchase decisions in the data.

Step 2: Estimate supply parameters

- Estimate firm payoffs from the model by solving a contraction mapping for a policy operator that defines the firm value function at each price (Aguirregabiria and Mira, 2010) - conditional on the expected demand response from the first stage - for the choice of the cost parameters.
- Estimate the cost parameters by maximizing the likelihood of pricing decisions observed in the data.

2.5.2 Demand Estimation

Our ultimate goal in demand estimation is to estimate our demand primitives $\theta_d^p = \{\gamma, \gamma^0, \alpha, \tau\}$. However, since consumers behave strategically, we first need to specify consumer beliefs on future transitions that enter the utility function before building the likelihood function. We characterize consumer beliefs with parameters θ_d^b and describe how we estimate them. As done in other similar empirical contexts (e.g. Nair, 2007; Gowrisankaran and Rysman, 2012), we assume that consumers form rational expectations so that on average they anticipate the correct transitions for inventory and prices. After we have estimated θ_d^b, we leverage the consumer utility model from the Model section to calculate purchase probabilities in the data for a guess of the primitives θ_d^p. These purchase probabilities can be used to compute a novel likelihood function to estimate θ_d^p. Thus, our demand estimation returns a set of estimated demand parameters $\hat{\Theta}_d = \{\hat{\theta}_d^b, \hat{\theta}_d^p\}$.

2.5.2.1 Consumer Beliefs

We need to formulate consumer beliefs about future states required to incorporate strategic behavior into the consumer utility function. We assume customers have Markovian beliefs so that only the current state impacts beliefs on the next state, following prior literature (e.g. Nair, 2007; Gowrisankaran and Rysman, 2012). To decide whether to purchase from the firm, the consumer needs to forecast to solve for the discounted future resale price $E[\tilde{r}_t|S_t, p_t]$ and compute the waiting value function $W(S_t, p_t)$. Specifying consumer beliefs allows us to compute expected transition probabilities to solve the contraction mappings for $W(S_t, p_t)$ in Equation 2.1 and $E[\tilde{r}_t|S_t, p_t]$ in Equation 2.2 from the Model section. For brevity, we present our specification of consumer beliefs and how we estimate them in Appendix A.2.

2.5.2.2 Estimation of Demand Primitives

In this section we describe our approach to estimating the consumer preference parameters defined in our model, $\theta_d^p = \{\gamma, \gamma^0, \alpha, \tau\}$. In the prior section we discussed how consumers form beliefs on transitions to future state variables, characterized by parameters θ_d^b. Using the belief parameters as inputs, we can leverage the model to make predictions for purchase decisions at a given set of preference parameters. To estimate θ_d^p, we build a likelihood function that can be used to maximize the likelihood of purchase decisions observed in the data according to our model's predictions.

In the data we observe two types of purchases q_{jt} for a given product j in time period t. Consumers make purchases in the primary market, comprised of consumption and speculation decisions, with observations $\{q_{jt}\}_{t=1}^{T_j}$ and consumers make purchases in the resale market, comprised of consumption decisions, with observations q_{jT_j+1}. Thus, we build a likelihood function with two key pieces: one piece comes from the likelihood of purchases in the primary market, and one piece comes from the likelihood of purchases in the resale market. In the primary market, purchase decisions are made based on the price and the inventory which determines consumer beliefs for future states. In the resale market, which occurs when firm inventory is zero, purchase decisions are made based on the price. Thus, in general we can describe our likelihood function as

$$L(\boldsymbol{q_j}|\boldsymbol{I_j}, \boldsymbol{p_j}, r_j; \hat{\theta}_d^b, \theta_d^p) = \left[\prod_{t=1}^{T_j} f_{q|p,I}(q_{jt}|p_{jt}, I_{jt} > 0; \hat{\theta}_d^b, \theta_d^p)\right] f_{q|r,I}(q_{jT_j+1}|r_{jT_j+1}, I_{jT_j+1} = 0; \hat{\theta}_d^b, \theta_d^p)$$

where $f_{q|p,I}$ is the likelihood of the purchase quantity in the primary market at price p and inventory I, $f_{q|r,I}$ is the likelihood of the purchase quantity in the resale market at resale price r, and $\hat{\theta}_d^b$ are the estimated parameters from the prior section that characterize consumer beliefs on state transitions.

We provide a summary of our approach to derive the likelihood function below. The technical details are provided in Appendix A.3. Recall that purchases in the primary market can come from either consumption decisions or speculation decisions, which we denote q_{jt}^F and q_{jt}^S respectively. However, we do not observe q_{jt}^F and q_{jt}^S directly in the data, but we do observe the total q_{jt}. Therefore, we need a way to formulate the likelihood components using the model's predictions of q_{jt}^F and q_{jt}^S, despite only observing q_{jt}. Our approach in deriving the likelihood function for primary market purchases, $f_{q|p,I}$, is to bundle the model's predictions for consumption and speculation since $q_{jt} = q_{jt}^F + q_{jt}^S$ in the primary market. Our approach in deriving the likelihood function for resale market purchases, $f_{q|r,I}$, is to leverage the fact that resale market sales come from purchases in the primary market. It turns out that the probability of observing q_{jT_j+1} resellers can be expressed as a convolution of the purchase probabilities for speculation in each period of the primary market. Since the final period of the primary market involves stocking out of inventory, both $f_{q|p,I}$ and $f_{q|r,I}$ incorporate censoring. In section 2.5.4 we explain identification of the parameters using our approach in more detail.

2.5.3 Estimation of Firm Costs

In this section we outline our approach to estimating the supply-side parameters $\theta_u = \{\iota, \eta^-, \eta^+, \mu\}$. Previously we estimated the demand beliefs parameters θ_d^b and the demand preference parameters θ_d^p which can be used as inputs to the firm pricing model in gauging the demand response to pricing decisions. Because consumers behave strategically, the firm can only use our estimated demand inputs as informative if the firm's pricing occurs as expected in the equilibirum in the data. This motivates our use of the conditional choice probability (CCP) approach to estimating θ_u (Hotz and Miller, 1993), which estimates the parameters based on strategic behavior relative to the equilibrium observed in the data (Bajari et al., 2007). The key advantage to the CCP approach is that it eliminates the need to re-solve the equilibrium for a change in θ_u (which would change consumer beliefs θ_d^b), which greatly improves computation.

In order to use the CCP approach we will need to modify our model to allow for the firm to make a discrete choice in prices. For price levels that are representative of prices the firm feasibly chooses from, we can express the optimal decision in each period as an optimal discrete choice in prices (Aguirregabiria, 1999).[7] Once we have made this modification, the CCP approach provides a mapping from the payoff functions in the model to the choice probabilities of pricing decisions observed in the data (Hotz and Miller, 1993). These choice probabilities can be leveraged to formulate a pseudo-maximum likelihood function (PML) to consistently estimate our firm cost parameters θ_u, as described in Aguirregabiria and Mira (2010). We choose the PML over other estimators because it is easy to solve numerically, provides a unique solution as the PML is globally concave in our application, and aligns with using a maximum likelihood approach for demand estimation. The PML estimator takes the form (Aguirregabiria and Mira, 2010):

$$Q(\theta_u, \beta) = \sum_{j=1}^{J} \sum_{t=1}^{T_j} \log P(p_{jt}^d | S_{jt}; \theta_u, \beta)$$

where $P(p_{jt}^d | S_t; \theta_u, \beta)$ is the conditional choice probability for discrete price $p_{jt}^d \in \{p^1, \ldots, p^D\}$ when the firm receives unobserved utility $\xi_\beta(p_{jt}^d)$ to one period profit as in Equation 2.3. We

[7] Modifying the pricing decision to be discrete is in fact more realistic for consumer pricing, which is necessarily discrete at the \$.01 level. In our specific context, pricing is discrete at the whole \$1 level.

specify $\{\xi_\beta(p^d) : d = 1, \ldots, D\}$ as iid location-zero Gumbel random variables with scale parameter $\beta > 0$ that will need to be estimated. Further details on our CCP formulation are in Appendix A.6.

We also make two adjustments relevant for our empirical application. First, we perform an adjustment to the PML to weight by quantity sold in the period so that our estimator becomes $Q(\theta_u, \beta) = \sum_{j=1}^{J} \sum_{t=1}^{T_j} q_{jt} \log P(p_{jt}^d | S_{jt}; \theta_u, \beta)$. Varin and Vidoni (2005) refer to this likelihood function as a composite likelihood function with weights q_{jt}, noting that the estimated parameters are consistent and asymptotically normally distributed. Since we do not have a balanced panel as T_j differs across products, using the traditional PML estimator would overweight those products with long stockout periods which would bias the firm's holding costs downward. Second, to improve fit to the data, we model the scale parameter as different across product categories. We do a similar adjustment to that in Aguirregabiria and Alonso-Borrego (2014) where we weight the scale of the Gumbel distribution within the product category, β_c, by the average revenue for an SKU in the product category, π_c, giving $\beta = \beta_c / \pi_c$.

We estimate our parameters $\{\theta_u, \beta\}$ from $\arg\max_{\theta_u, \beta} Q(\theta_u, \beta)$. In Appendix A.7 we outline the computational procedure used to estimate the supply-side parameters.

2.5.4 Identification

In this section we discuss identification of the parameters for consumer preferences and firm cost parameters.

We start with identification of the demand primitives. In an ideal setting, the quantity speculated would be directly observed so that we do not have to bundle consumption and speculation decisions in our likelihood function in the primary market. One practical way to achieve this would be to tie the customer in the primary market to the reseller in the secondary market through a mechanism such as the customer name. Unfortunately we cannot tie the customer name because the firm does not provide us customer details for privacy reasons. Instead, we leverage a novel likelihood function in Section 2.5.2.2 that utilizes our model's setting that all resellers sell their capacity at the market clearing price to allow for identification. Since the resale quantity represents the sum of prior speculation purchases, the convolution of speculation decisions allows our estimation to disentangle speculation decisions from consumption decisions in the primary market. In other words, the observed resale quantity serves as an additional source of variation to identify the resale transaction cost τ. If we observe in our data that average resale quantity is small despite high resale prices, resale transaction costs must be high.

Since speculation decisions are disentangled from consumption decisions, identification of the demand parameters tied to consumption follows similar arguments to in other papers (e.g. Nair, 2007; Ishihara and Ching, 2019). The variation in primary market prices and resale market prices identify price sensitivity, α. If we observe in our data that small increases in price lead to large increases in purchases, then consumers are highly sensitive to price. Consumption valuation, γ, is identified by the average purchase quantity relative to the market size, conditional on prices. Since we fix the utility for the outside option to zero, if we observe in our data that few purchases occur relative to the market size, then the value of γ will be negative and large in magnitude. The impact of hype, γ^0, is identified by the additional sales observed in the hype period.

Identification of the supply parameters comes from the observed stockout times, inventory held period-to-period, and price changes period-to-period. Recall that the firm makes pricing decisions based on demand, so these arguments are conditional on the demand at each price the firm considers. The fixed holding cost μ is identified by the average stockout time. When stockout times are long, the fixed holding cost must be small. The variable holding cost ι is identified by the variation in inventory held period-to-period. If the firm prices high early so that a large stock of inventory is held in early periods, then variable holding costs ι will be small. The price adjustment costs η^- and η^+ are identified by the variation in period-to-period price adjustments. When markdowns (markups) are limited, the price adjustment cost for η^- (η^+) is large. Finally, the scale parameter β is identified from the variation in prices from the model's prediction. Little variation in prices from the model's prediction implies small variance on the private shocks to the firm. We do not need to fix the scale parameter as in other choice models (Train, 2009) because the first entry of θ_u is fixed at 1 (Slade and G.R.E.Q.A.M., 1998).

2.5.5 Estimation Results

Table 2.2 presents the estimated demand primitives $\hat{\theta}_d$. We estimate $\hat{\theta}_d$ for each product category, as beliefs on price and inventory transitions are different as explained in Appendix A.2. We provide estimation results for parameters such as the transaction cost τ. The values of the estimated parameters cannot be interpreted as dollar values because the magnitudes are relative to the standard deviation of the idiosyncratic shocks, which we fix for identification (Train, 2009).

Table 2.2: Demand Primitives by Product Category

	Rompers[a]	Sets[a]	Dresses[a]
γ^0	3.167 (0.019)***	2.909 (0.031)***	3.061 (0.036)***
γ	-3.211 (0.035)***	-4.227 (0.054)***	-4.505 (0.091)***
τ	19.259 (0.028)***	23.427 (0.054)***	16.775 (0.058)***
α	0.149 (0.001)***	0.109 (0.002)***	0.115 (0.003)***
Observations	1389	541	555
LR index[a]	1.000	1.000	0.975

[a] The estimated parameters are presented with their respective (standard errors). Standard errors are computed using the Fisher information matrix.

[b] The LR (Likelihood Ratio) Index is a measure of goodness of fit defined as 1 - (log $\hat{L}$/ log L_0), where log $\hat{L}$ is the log-likelihood of the estimated model, and log L_0 is the log-likelihood under the null hypothesis that all parameters equal zero (as presented in Aguirregabiria and Alonso-Borrego (2014)). Recall that we fix the standard deviation of the idiosyncratic shocks to $\pi/\sqrt{6}$ for identification.

[c] ***,**,* denote significance at the .01, .05, .10 significance level, respectively.

The parameters support our intuition. Customers are price sensitive in all categories, reflected by significant $\hat{\alpha}$ with positive values. The hype period generates a boost in sales, reflected by significant $\hat{\gamma}^0$ with positive values. Resale transaction costs represented by $\hat{\tau}$ are significant with positive values, consistent with resellers incurring costs from listing the product (Cui et al., 2014). Finally, while $\hat{\gamma}$ is negative and significant, this is compared to the outside option. We interpret $\hat{\gamma}$ as "base utility" from consuming the product, which could be normalized to 0 instead of normalizing the outside option to 0. In other words, the outside option is generally more preferable for customers, which could be explained by passive customers that only purchase if they experience a high idiosyncratic utility, captured by our shocks ϵ. This explanation is particularly relevant to a fashion context with product drops. Customers may purchase the product for specific idiosyncrasies to their preferences such as unique apparel patterns (Fisher and Raman, 1996) or changing valuations over time (Courty, 2003) due to factors like timing of gifts or need for the product immediately.

In Table 2.3, we present the estimated supply parameters for the firm. Based on discussions with our partner retailer, holding costs and price adjustment costs are the same across products so we estimate the parameters across the product categories. This is also consistent with Aguirregabiria (1999).

Table 2.3: Supply Side Parameters

	Estimate (Standard Error)[a]
ι	1.86 (0.868)**
μ	185.30 (23.917)***
η^-	784.15 (145.107)***
η^+	1565.72 (474.561)***
β	0.12 (0.029)
Observations	1669.00
LR index[b]	0.52

[a] Standard errors are computed using the Fisher information matrix.
[b] The LR (Likelihood Ratio) Index is a measure of goodness of fit defined as 1 - (log $\hat{L}$/ log L_0), where log $\hat{L}$ is the log-likelihood of the estimated model, and log L_0 is the log-likelihood under the null hypothesis that all parameters except β are equal to zero (as presented in Aguirregabiria and Alonso-Borrego (2014)).
[c] ***,**,* denote significance at the .01, .05, .10 significance level, respectively.

The firm parameters also support our intuition. Since $\hat{\iota}$ is positive and significant with a value of 1.86, the firm has variable holding costs. Since $\hat{\mu}$ is positive and significant with a value of 185.30, the firm also has fixed holding costs. In Appendix A.8, we provide a discussion of the estimated values of $\hat{\iota}$ and $\hat{\mu}$. Last, markdown and markup costs, represented by $\hat{\eta}^-$ and $\hat{\eta}^+$ respectively, are positive and significant. The large values for price adjustment costs is supported empirically given 88% of price transitions do not result in price changes. Moreover, $\hat{\eta}^+ \gg \hat{\eta}^-$, consistent with the results in Aguirregabiria (1999). In our context, this difference could result from price change perception costs from consumers (Stamatopoulos et al., 2020), where consumers have sentiments of "price gouging" when the firm attempts to raise the price. Through conversations, our partner retailer reinforced concerns of raising prices as many customers would complain. Our partner retailer also mentioned that direct labor costs increase in responding to consumer concerns through phone calls and emails. Labor costs from markdowns may be lower as employees can more easily assuage concerns of price reductions, as justified to clear inventory.

2.6 Counterfactual Analyses

We now examine our research questions of interest through counterfactual analyses, where we examine how different policies and scenarios affect firm profit. Our key takeaways are as follows:

1. *How does overlooking resellers in pricing impact profit?* We find that failure to incorporate the resale market into pricing leads to an average reduction in profit of 7.0% (up to 19.5%) at our partner retailer. Incorporating the resale market implies that the firm should price lower upon product release than when ignoring the resale market.

2. *How does the resale market impact firm profit?* We find that the presence of a resale market reduces firm profit by 0.7% on average, with impacts for individual SKUs ranging from -11.4% to 14.7%. Whether the resale market benefits or hurts profit depends on the SKU's inventory relative to the market size.

3. *How should the firm respond to the resale market?* We find heterogeneity across SKUs regarding the impacts of resale response strategies a firm may consider such as banning resale, promoting resale, or maintaining the current level of resale. For our partner retailer, the best single response is to ban the resale market for all SKUs. If the firm could optimally assign the resale response per SKU, then profit would increase by 7.4%.

In what follows we detail how we reach these insights. First, we examine the impacts to profit from ignoring the resale market in pricing decisions. Second, we measure the impact of the resale market on our retailer's profit. Finally, we examine how the firm should respond to resellers if the firm considered promoting or banning resale, either for all SKUs or on a per SKU basis. Appendix A.10 details how we compute the equilibrium for a given set of parameter values.

Appendix A.11 discusses our predicted equilibrium's fit to the data. Our predicted equilibrium fits the data well across a variety of metrics for the primary market and resale market, as all metrics are within 10% of what we observe in the data.

2.6.1 Pricing Implications from Resellers

In this section we examine what would happen if the firm ignored the resale market in its pricing decision, despite the fact that a resale market actually exists.

Our approach to simulate this scenario requires two steps. When ignoring the resale market, the firm prices as if a resale market does not exist, which occurs when resale transaction costs τ are prohibitively high (Leslie and Sorensen, 2014; Cui et al., 2014). Hence, first, we solve for the equilibrium pricing policy when $\tau \to \infty$, so that $p_{\{\tau\to\infty\}}$ describes the pricing policy when the firm ignores resellers. Second, since resellers actually exist, we use $p_{\{\tau\to\infty\}}$ to compute an equilibrium where consumers engage in resale as observed in the data, with resale transaction costs $\tau = \hat{\tau}$.

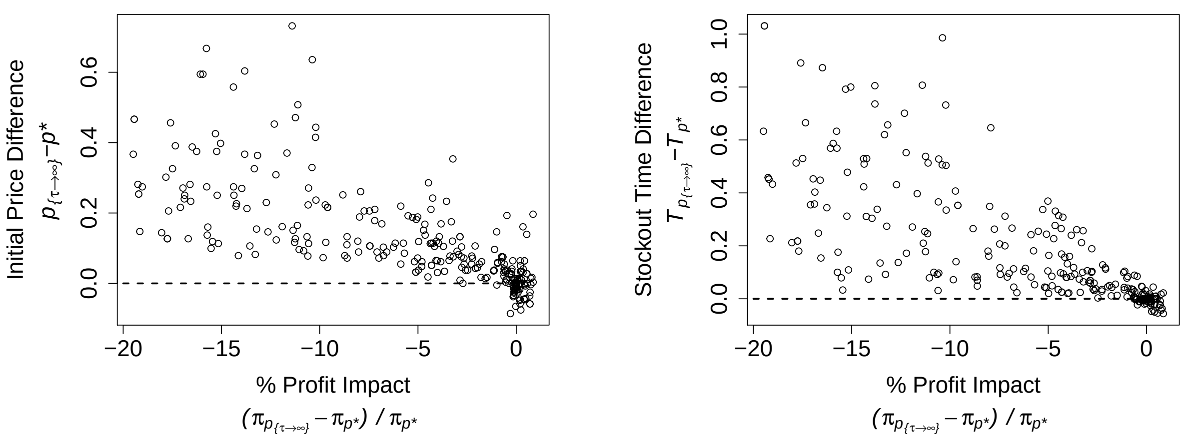
When we implement the steps above to simulate a situation where the firm ignores resellers, resellers behave as in the data but the firm does not. We can then compare the profit from the equilibrium where the firm pricing ignores resellers, $\pi_{p_{\{\tau\to\infty\}}}$, to the profit that our model predicts in the data where the firm pricing correctly incorporates resellers, π_{p^*}.

We find that ignoring resellers can have negative impacts on profit, reducing profit by an average of 7.0%, with reductions as large as 19.5%. We explore this result in more detail in Figure 2.4.

Figure 2.4: Impact of Ignoring Resellers in Pricing to Profit, Initial Pricing, and Stockout Timing

(a) Profit Reductions Align with Pricing Too High Initially When Ignoring Resellers

(b) Profit Reductions Align with Longer Stockout Times When Ignoring Resellers



Panel (a) of Figure 2.4 shows that profit reductions result from the firm pricing too high on release of the product when ignoring resellers (i.e. $p_{\{\tau\to\infty\}} - p^* > 0$). Larger reductions in profit, moving left on the x-axis, align with larger differences in initial price, moving up the y-axis. Similarly, Panel (b) shows that profit reductions align with longer stockout times when ignoring resellers (i.e. $T_{p_{\{\tau\to\infty\}}} - T_{p^*} > 0$). Combining the insights from these two charts, ignoring resellers in the pricing decision results in pricing too high initially, leading to increased stockout times and increased holding costs, thus reducing profit. In turn, we find that ignoring the resale market most adversely impacts the firm for SKUs with large initial inventory, where pricing too high exaggerates the difficulty of stocking out, incurring large holding costs.

The presence of a resale market requires the firm to reduce its price because consumers have an additional option to wait to consume at a later time (Su, 2010). Without incorporating the resale market into its pricing decision, the firm expects a lower waiting function than is actually the case, leading to an overestimate of demand, so that the firm inappropriately prices too high.

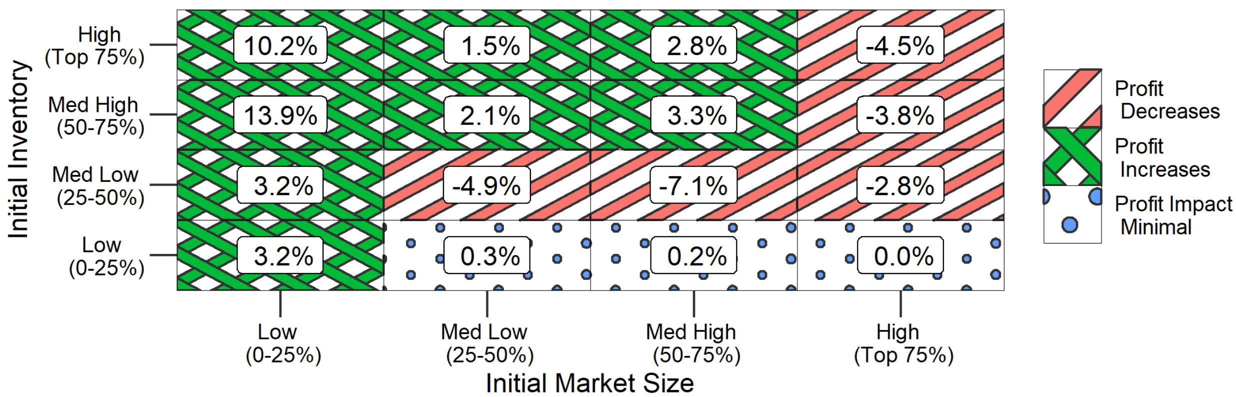
Our result is similar to Cui et al. (2014) who find that the presence of a resale market impacts the optimal price. However, we find that the resale market requires the firm to reduce the initial price whereas Cui et al. (2014) find that the resale market allows the firm to increase the initial price. The key difference is that our setting is similar to fashion settings where markdown pricing is optimal (Fisher and Raman, 1996), whereas Cui et al. (2014) find "low-to-high" pricing to be optimal for ticket pricing. Under markdown pricing, most resellers purchase from the firm at the end of the selling horizon as the price will be lowest at this point for larger resale markups. Since resellers anchor their purchases on possible future price drops, increasing the value of waiting, the optimal initial price in our model is lower with resellers. Under "low-to-high" pricing, resellers benefit from purchasing earlier to receive higher profit. Since resellers anchor their purchases on the price today, the optimal initial price in Cui et al. (2014) is higher with resellers.

2.6.2 Impact of Resale Market on Firm Profit

We now examine the impact that the resale market has on firm profit. Using the logic in the previous section, we can generate a counterfactual setting without resellers by setting resale transaction costs prohibitively high, so that $\tau \to \infty$. Unlike in the previous section where we only solved for the firm pricing policy without resellers, $p_{\{\tau\to\infty\}}$, we now generate the equilibrium where consumers in fact have prohibitively high transaction costs. By doing this, we can compare the profit that our model predicts in the data when a resale market exists, π_{p^*}, to a counterfactual scenario without resellers, $\pi_{p^*_{\{\tau\to\infty\}}}$.

We find that on average the presence of resellers reduces firm profit by 0.7%, but the impact of resellers is not uniform across SKUs. Figure 2.5 plots the average impact of the resale market based on the quartile in the data of initial inventory and initial market size. We classify each quartile as Low (0-25%), Medium Low (25-50%), Medium High (50-75%), and High (75-100%). From the top-left corner, we can see that when inventory is relatively large compared to the market size, the resale market benefits the firm. When inventory is relatively large, the stockout time is long so that the firm faces large holding costs. Without resellers, the firm can consider reducing the price to shorten stockout times and reduce holding costs, but at a loss in revenue. In the presence of resellers, reducing the price becomes more attractive to the firm because it incentivizes resellers to purchase the product to help the firm stockout more quickly. In this region, our model shows that when the firm reduces its price, it gains from large reductions in holding costs that offset reductions in revenue. Appendix A.12 gives a more detailed discussion on the impacts of resellers for the regions in Figure 2.5.

Figure 2.5: Impact of Resellers to Profit by Initial Market Size and Initial Inventory



The bottom-right corner in Figure 2.5 represents the opposite extreme, where inventory is small compared to market size. When inventory is small, the product becomes scarce and the firm can stockout easily regardless of the price it chooses (within the bounds in the data). Thus, the presence of resellers has minimal impact to the firm in this region.

From the top-right corner in Figure 2.5, the firm is negatively impacted by resellers when inventory is moderate relative to market size. In this region, the firm cannot stock-out easily due to scarcity, so now the firm needs to consider if reducing its price is necessary to avoid holding costs. Our model shows that even when optimally reducing its price, the firm still incurs additional holding costs in this region. The negative impacts of resellers, giving consumers additional value to wait to purchase later, offsets the positive effects of resellers of helping the firm stock-out by purchasing more units. As a result, the presence of the resale market hurts the firm for these SKUs.

Similar to Cui et al. (2014), we find that the effects of the resale market to firm profit are different depending on inventory relative to market size. But, we find the opposite result of Cui et al. (2014) who show that the firm benefits from resellers when capacity is relatively small but do not benefit from resellers otherwise. In our setting we incorporate operational costs that may be relevant to the firm stocking out in a timely manner, whereas Cui et al. (2014) only examine revenue. As discussed in the prior section, resellers require the firm to reduce the price due to an increased waiting function. Resellers may help the firm to avoid substantial holding costs (inventory relatively large), or may hurt the firm when price reductions do not lead to holding cost reductions (inventory relatively moderate).

2.6.3 Impact of the Firm Response Strategy to Resellers

Prior literature has suggested that firms may have the opportunity to change resale transaction costs to either encourage or discourage resale (Cui et al., 2014). We examine three strategies that a firm may consider: the firm can ban the resale market by making resale transaction costs prohibitive, promote resale by making transaction costs lower, or maintain the status quo by keeping transaction costs at the current level. We first examine the best *single* response strategy where the firm chooses the same response strategy across all SKUs. Then, motivated by our result in Section 2.6.2 that the impacts of the resale market are different across SKUs, we examine the best *differentiated* response strategy where the firm can choose a different response strategy on a per-SKU basis.

Our approach to examine each scenario mirrors prior sections by changing the value of resale transaction costs τ. The impact of banning the resale market can be examined by recycling the counterfactual in the prior section where $\tau \to \infty$. To examine the impact of promoting resale, we consider a case where the firm reduced resale transaction costs by half, so that $\tau = .5\hat{\tau}$. Then, we can compare the profit from banning resale, $\pi_{p^*_{\{\tau \to \infty\}}}$, and the profit from promoting resale, $\pi_{p^*_{\{\tau \to .5\hat{\tau}\}}}$, to the profit from the status quo for the predicted equilibrium in the data, π_{p^*}. In Section 2.6.2 the benchmark for comparison was a scenario without resellers, whereas the benchmark for comparison in this section is the status quo.[8]

We find that the best single strategy for our partner retailer would be to ban resale, as banning resale would improve profit by 1.3% on average while promoting resale would improve profit by 0.8%. Interestingly, either banning or promoting resale would improve profit *on average*, which

[8]Section 2.6.2 examined the impact of resellers, so the benchmark was a scenario without resellers. This section examines how a firm can change the status quo to improve profit, so the benchmark is the status quo.

results from the impacts of the resale market not being uniform across SKUs as discussed in Section 2.6.2. Profit impacts from banning resale range from -10.5% to 17.3%, whereas profit impacts from promoting resale range from -14.1% to 32.3%. Thus, our partner retailer should be careful in exercising its best single strategy if the distribution of SKUs changes by initial market size or initial inventory.

Given that the impact of the resale market is heterogeneous across SKUs, we now consider the impacts of using a differentiated response strategy by tailoring the strategy per SKU. For example, the firm could ban the resale market for some SKUs while promoting the resale market for other SKUs. The firm may be able to change resale transaction costs on a per SKU basis by changing product characteristics (Deng, 2018) or by managing the resale market for certain SKUs (Courty and Davey, 2020). Table 2.4 presents the impacts from choosing the optimal differentiated strategy, as well as the worst case impacts under the wrong differentiated strategy. We can see that banning resale is optimal for the largest share of SKUs (43.8%) and promoting resale would be the worst strategy for the largest share of SKUs (45.4%). Optimally assigning the response strategy per-SKU would result in a profit gain of 7.4%, whereas choosing the wrong response strategy per-SKU would hurt profit by an average of 4.4%. Thus, understanding the impact of the resale market for each SKU presents a large opportunity to choose the optimal response strategy, but also highlights risk from choosing the wrong response strategy.

Table 2.4: Impact of Differentiated Resale Response Strategy to Profit on a Per-SKU Basis

	Optimal		Worst Case	
Strategy	% of SKUs	Profit Gain	% of SKUs	Profit Loss
Ban Resale ($\tau \to \infty$)	43.8%	10.9%	23.3%	4.6%
Promote resale ($\tau = .5\hat{\tau}$)	31.7%	9.3%	45.4%	8.4%
Status quo ($\tau = \hat{\tau}$)	24.5%	0%	31.3%	0%
Total		7.4%		4.4%

2.7 Conclusion

Due to the growth of resale marketplaces, the managerial question of “How do resellers impact my profit?” continues to grow in importance. Prior literature often overlooks the relevance of resellers to the firm’s pricing decision, provides conflicting answers on the directional impacts of resellers on firm profit, and provides limited exploration into quantifying the impact of resellers on firm profit. Our study attempts to add clarity in each of these dimensions by developing an empirical framework and applying it to a real-world context. We developed a structural model that incorporates strategic behavior from consumers and the firm who incorporate the resale market into their decisions. Through a partnership with an online retailer of baby clothing, we gathered data from both the primary market and resale market to estimate our model and perform counterfactual experiments.

We present empirical support that resale markets have implications for retailer profit. We find that if the firm ignores resellers in the pricing decision then profit decreases by 7.0%. Unlike for ticket resale where it is optimal to price higher initially with resellers (Cui et al., 2014), we find that for resale of apparel it is optimal to price lower initially with resellers. Even when pricing optimally, however, the presence of a resale market for our firm results in an average negative effect on profit. But the effects are not uniform across SKUs, and may range from -11.4% to 14.6% based on the relative size of inventory compared to market size. Thus, for some retailers banning or promoting resale may be optimal, whereas the conclusion may be different for other firms. Understanding how to price effectively and how to best respond to resellers are empirical questions that our model can help managers answer in their own context.

Our empirical application focused on product drops, where retailers release limited-edition product lines on a specific date for a short period of time. Product drop strategies continue to gain traction with large apparel brands (Paton, 2016), and the resale markets that evolve from product drops continue to grow (Griffith, 2019). We provide an empirical study that examines how firms using product drops are impacted by resellers, exposing a research context that is not well-studied. One area for future analytical research would be to formalize how resellers respond to product drops, or how resellers respond in other fashion contexts that experience markdown pricing.

While our results are specific to our partner retailer, the insights generalize to other apparel contexts. An interesting area for future research would be to examine other contexts with resellers outside of tickets and apparel. Further, we expect other empirical or behavioral questions on how resellers respond to firm behavior to exist that have not been examined outside analytical research.

Finally, in our counterfactuals we explored strategies that retailers may consider when responding to resale markets. Similar to other resale papers, we considered the ability of the firm to change resale transaction costs. However, how exactly firms can change these transaction costs remains an open question. Changing product characteristics to discourage resale (Cui et al., 2014; Deng, 2018), pursuing legal action against resale markets (Cui et al., 2014), and taking a more active role in managing resale markets (Courty and Davey, 2020) have all been mentioned as ways for firms to change resale transaction costs. The effectiveness of each lever to changing resale transaction costs is yet to be explored. Field studies that shine light on how resellers respond to various approaches to changing resale transaction costs would better enable firms to respond to resellers. Using a model like ours, a firm can understand how their resellers behave to inform the best way to engage with resellers.

CHAPTER 3: LOCAL FULFILLMENT IN E-COMMERCE: STRUCTURAL ESTIMATION OF FULFILLING DEMAND SENSITIVE TO DELIVERY SPEED

3.1 Introduction

The explosion of e-commerce in retail has heightened the importance of effective e-commerce operations (Caro et al., 2020). While the general importance of e-commerce has been projected over the last couple decades (Swaminathan and Tayur, 2003), the effective implementations in-place today resulted from revolutionary operational practices from the leading e-commerce players of Amazon, JD.com, and Alibaba (Caro et al., 2020). Logistics, in particular, has gained significant attention as shipping speeds to customers have reduced to a matter of hours in some major cities for best-selling products (Fiegerman, 2018) and two-day shipping has become the norm (Winkler, 2021). To incorporate such rapid delivery requires investment in last-mile logistics, but last-mile logistics may account for a high portion of total fulfillment costs (Caro et al., 2020). Thus retailers need to understand the benefits of last-mile delivery to improving demand in order to justify the costs in such investment.

Yet the operations management (OM) literature has provided little empirical guidance on the benefits of last-mile delivery when managers take these costs into consideration. Empirical papers have documented the demand benefits of improved delivery time from quasi-experiments (Cui et al., 2019; Fisher et al., 2020) and leveraging customer satisfaction scores (Deshpande and Pendem, 2022; Bray, 2020), but these works do not incorporate the managerial decision-making of considering the costs of achieving improved delivery – costs that are known to hamper last-mile delivery implementations in e-commerce (Kaplan, 2017; Swaminathan and Tayur, 2003). Despite these papers documenting demand impacts from improved delivery speed, the existing OM models that do incorporate the managerial decision of considering delivery costs assume that the underlying demand distribution is unaffected when fulfillment decisions result in differing delivery times

(Chen and Graves, 2021; Perakis et al., 2020). Similarly, the highly useful newsvendor model from OM that has gained wide adoption from practitioners to help consider setting inventory levels when facing stochastic demand (Choi, 2012; Van Mieghem and Rudi, 2002; Bertsimas and Thiele, 2005) is limited because it assumes the demand distribution is exogenous to the inventory decision. In this paper we seek to close these gaps by empirically examining the benefits of improved delivery speed while incorporating fulfillment costs that impact managerial decisions in practice.

Our key empirical challenge results from the fact that managerial decisions result from both demand benefits and costs, neither of which we know precisely based on the data. Whereas the quasi-experiments of Cui et al. (2019) and Fisher et al. (2020) can leverage exogenous variation in delivery speed to isolate the benefits to sales, simultaneously studying both the benefits and costs of delivery speed requires the ability to disentangle the cost-side determinants from the demand-side determinants. To accomplish this, we build and estimate a structural model where we specify the primitives of the behavior in the system both on the demand-side and the cost-side that are not endogenous to the outcomes of the system. Based on these primitives, we can then examine counterfactual scenarios to understand the benefits of improving delivery speed options to managers in practice (Reiss and Wolak, 2007).

To estimate our structural model, we leverage data from one of the leading e-commerce retailers JD.com, provided in the 2020 MSOM data competition. To fulfill online orders, JD.com leverages a multi-warehouse distribution network consisting of regional DCs that have large storage capacity but are fewer in number and front DCs which are close to the customers but have limited storage capacity (Ma et al., 2018). Each front DC has a specified regional DC to use for backup fulfillment (Shen et al., 2020). The closest front DC to the customer attempts to fulfill demand directly, but when the closest DC does not have the required inventory it uses backup fulfillment by requesting assistance from its regional DC (Shen et al., 2020). Since backup fulfillment requires shipping from a DC further from the customer, the promised delivery time increases. As a result, JD.com faces a central problem: how to best fulfill local demand in each DC in order to minimize delivery speed to maximize sales, but balance the costs of local fulfillment compared to backup fulfillment.

Specifically, we seek to answer the following research questions in the context of JD.com's use of front DCs: 1) To what extent does use of front DCs impact operational outcomes, and which front

DCs should be considered first for investment to reduce local fulfillment costs? 2) To what extent does incorporating delivery speed differences from local and backup fulfillment into the inventory decision impact operational outcomes?

The JD.com dataset has several novel features important to answering our research questions of interest. First, the data provides transactional data of customer orders marking the closest DC for fulfillment and the actual DC that fulfilled the order. This provides us information on when local fulfillment and backup fulfillment options are chosen, as well as the closest DC to the customer for each order. Second, the data provides promised delivery times to the customer to allow us to estimate the demand response to delivery time and observe how promised delivery times vary based on the inventory decision. Third, the JD.com dataset has variation in local fulfillment rates where only 30% of orders on average are filled locally from front DCs. These low fulfillment rates from front DCs are despite the fact that the data suggest a clear improvement to both delivery time and sales when orders are filled locally by front DCs, providing evidence that managerial costs impact local fulfillment decisions. Fourth, the inventory data provides information on end-of-day inventory that we can incorporate into our likelihood functions to validly estimate our parameters.

Our results are as follows. We find that JD.com's current utilization of front DCs improves average promised delivery time by 28.3%, resulting in a 10.7% improvement in average profit. Front DCs provide the largest benefits by allowing the manager to capture sales from high-margin SKUs with high demand where backup fulfillment results in much longer promised delivery time. We identify the five best front DCs for reducing holding costs, which are marked by long backup delivery speed or large estimated local demand more so than large holding costs. If the loss in demand from backup fulfillment due to delivery time is ignored in the inventory decision, average promised delivery time worsens by 14.8% leading to an average profit reduction of 6.8%. The manager under-utilizes local inventory, missing out on benefits of front DCs to improve demand.

We make the following contributions. First, we build a model that can be applied to local fulfillment decisions in e-commerce when the inventory decision changes promised delivery time. We add to the rich history of OM models for inventory decisions by allowing the demand distribution to be endogenous to the inventory decision. Our model is also parsimonious and can be used by practitioners. Second, we use structural estimation to disentangle the determinants of manager fulfillment decisions across demand-side and cost-side determinants. While the costs are often taken as given in optimization-based approaches in the OM literature (Perakis et al., 2020), generally these costs are unobserved to researchers. A framework to estimate these parameters allows for use of our model in conjunction with other approaches. Third, we empirically quantify the benefits of improved delivery when incorporated into managerial decisions that consider the costs of using these improvements. Our results suggest that investment in improved delivery to improve demand provides a meaningful return to profit.

3.2 Related Work

Our work studies the benefits of front distribution centers by improving customer waiting times, building on prior literature of inventory management in e-commerce, the value of improving delivery times, and relevant structural models.

3.2.1 Inventory Management in E-Commerce

OM literature has studied the expansion of operational strategies to support the recent booming of e-commerce (Caro et al., 2020; Swaminathan and Tayur, 2003). Some of these include inventory management through a network of distribution centers (Acimovic and Graves, 2015; Xu et al., 2009; Van Roy et al., 1997), dynamic pricing based on inventory availability or demand shifts (Caro and Gallien, 2012; Ferreira et al., 2016; Dong et al., 2009), and omnichannel fulfillment where both online and offline channels are leveraged (Gallino and Moreno, 2014; Gao and Su, 2017; Gallino et al., 2017). Our work is most similar to the stream of literature on inventory management in a network of distribution centers.

OM literature on inventory management in a distribution network has a rich history in optimal inventory allocation more generally. Papers on optimal inventory allocation date back to seminal papers of Veinott (1965), Clark and Scarf (1960), and Arrow et al. (1951), where Clark and Scarf (1960) start a stream of literature considering multi-echelon distribution networks where the lowest echelon (e.g., the brick-and-mortar retail location) fulfills demand but faces lead times from receiving inventory from higher echelons (e.g., the warehouses) (de Kok and Graves, 2003). When demand cannot be fulfilled by the lowest echelon, these models impose either backordering costs due to expediting inventory or costs for lost sales. Unlike the multi-echelon context, in e-commerce, multi-warehouse fulfillment allows for demand to be fulfilled even if the local distribution center does not have inventory as another distribution center can ship inventory directly to the customer (Chen and Graves, 2021).[1] Our work focuses on inventory management in a distribution network that leverages multi-warehouse fulfillment.

OM papers that consider multi-warehouse fulfillment adopt a similar convention in considering backordering costs (Chen and Graves, 2021; Li et al., 2019). Backordering costs may result from increased shipping costs to get the product to the customer at the promised delivery speed from a distribution center that is further from the customer. Thus the trade-off to the manager revolves around increased costs to fulfill the demand but the underlying demand distribution is exogenous to the inventory decision. Instead, in our approach we allow for the underlying demand distribution to differ according to longer promised delivery speeds when backup fulfillment is used.

OM literature has also stressed the importance of last-mile logistics in the effectiveness of distribution in e-commerce (Swaminathan and Tayur, 2003). Yet many retailers have struggled with the implementation of e-commerce due to lack of understanding of the logistics required for last-mile delivery, often grossly estimating the costs (Swaminathan and Tayur, 2003; Kaplan, 2017). In fact, OM literature has recently documented that last-mile logistics are responsible for a high portion of fulfillment costs (Caro et al., 2020). Our work estimates these logistics costs and incorporates them into a framework to inform the value of improving delivery speeds to improve operational outcomes.

3.2.2 Value of Improving Delivery Times

The value of improving delivery times has its roots in the OM literature through the importance of reducing lead times. Traditionally, OM literature has focused on the supply-chain benefits of reduced lead times, showing that reducing lead times can reduce volatility in the orders throughout the supply chain (Lee et al., 1997), reduce inventory holding costs (Fisher and Raman, 1996; Krishnan et al., 2010), improve forecasting (Fisher and Raman, 1996; Krishnan et al., 2010), or

[1] Drop-shipping is similar to multi-warehouse fulfillment and has received attention in the literature (Netessine and Rudi, 2006; Randall et al., 2006), but differs in that a third-party generally manages backup fulfillment.

allow for reordering of products with short selling seasons (Iyer and Bergen, 1997). In particular, quick response gained attention for the ability to directly improve lead times to improve supply chain performance (Iyer and Bergen, 1997). In our specific context, however, we focus on the demand-side benefits from improved delivery times increasing sales.

More recently, OM literature has started to incorporate the demand-side effects of improving lead times. For example, in the stream of strategic consumer behavior, Cachon and Swinney (2009) show that quick response benefits the retailer by allowing to manipulate matching supply with demand. Many of these papers are analytical which provide directional insights, but we wish to empirically quantify the benefits to sales from improving lead time based on fulfillment in an e-commerce distribution network.

A few recent OM empirical studies have demonstrated that consumers respond positively to reduced delivery time in e-commerce. Cui et al. (2019) and Fisher et al. (2020) document the demand benefits of improved delivery time through quasi-experiments whereas Deshpande and Pendem (2022) and Bray (2020) leverage customer satisfaction scores. As an example, using a quasi-experiment in an omnichannel retail environment, Fisher et al. (2020) show that on average sales increase by 1.45% per business-day reduction in delivery time. Similarly, in a quasi-experiment at Alibaba, Cui et al. (2019) show that the removal of high-quality delivery partner SF Express negatively impacted sales by 14.56%. We complement these papers by estimating customer sensitivity to delivery time in JD.com's context, and leverage this to inform managerial decisions in making inventory decisions.

3.2.3 Relevant Structural Models

Structural models for consumer and firm behavior have gained prominence in the OM community (Terwiesch et al., 2020) with a variety of applications to such industries as call centers (Aksin et al., 2013), retail (Bray et al., 2019; Moon et al., 2018), air-travel (Li et al., 2014), and healthcare (Olivares et al., 2008). Our approach is most similar to Bray et al. (2019) in that we consider non-stationary base-stock polices of the (s_t, S_t) class. Bray et al. (2019) cite Aguirregabiria (1999), Erdem et al. (2003), and Hendel and Nevo (2006) as other previous structural papers that consider (s_t, S_t) policies. Unlike these papers, we consider an e-commerce context with multi-warehouse fulfillment.

A few OM structural papers present contexts with some rough similarities to that of JD.com. Aksin et al. (2013) model caller sensitivity to delay in call centers, similar to customer sensitivity to delivery times at JD.com. Allon et al. (2011) model fast-food restaurants to show that customers have a high cost to waiting for service. Both papers suggest that the firm should incorporate customer reaction to waiting times into operational decisions. Musalem et al. (2010) estimate the effect of lost sales of stockouts, similar to the negative effect on sales of increased delivery times from stockouts in a local DC. In this sense, the effect of stockouts for JD.com is different: increased delivery times mitigate the full effect of a stockout when another distribution center can provide backup fulfillment. While these structural papers provide insights that could be relevant to JD.com, none of these insights directly translate to a context where the distribution center manager considers local fulfillment in a multi-warehouse distribution network.

3.3 Research Context and Data

3.3.1 Research Context

We examine our research questions in the context of JD.com, one of the most prominent e-commerce retailers (Caro et al., 2020). JD.com distinguishes itself in the Chinese e-commerce market with its superior logistics. JD.com's self-operated nationwide logistics network provides a key competitive advantage in its ability to offer 90% same-or-next-day delivery as a standard service, while still maintaining low distribution costs. As stated by Sidney Huang, CFO of JD.com, "Mainly, our quick delivery is a result of our warehouse network, which means the products can be extremely close to our customers" (Zhu and Sun, 2019).

One key component from JD.com's logistics network is the setup of distribution centers in order to minimize the number of times goods move around, typically reduced from four to five movements in traditional logistics, to one or two movements maximum (see Zhu and Sun (2019) for more details). Based on the data we are provided, we focus on considering JD.com's logistics as a multi-warehouse fulfillment network following how JD.com describes its own DC network (Ma et al., 2018), and how the DC network is described in the 2020 MSOM data competition (Shen et al., 2020). Figure 3.1 presents an example of the DC layout in a given region with one regional

DC and multiple front DCs (Ma et al., 2018). Regional DCs have large storage capacity but are

Figure 3.1: JD.com's Multi-Warehouse Fulfillment Network

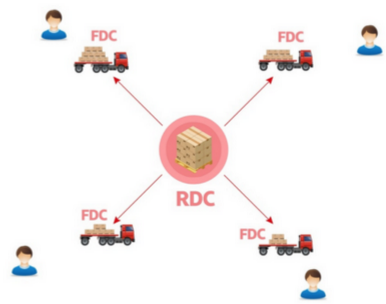


Figure copied from Ma et al. (2018)

fewer in number; front DCs can reach customers in surrounding areas directly but have less storage capacity.

The closest front DC to the customer attempts to fulfill demand directly. When the closest front DC does not have the required inventory to meet its local demand, it leverages backup fulfillment by requesting assistance from the regional DC (Shen et al., 2020).

Since backup fulfillment requires shipping from a DC further from the customer, the promised delivery time increases. But capturing faster delivery times from local fulfillment comes at a cost. Local fulfillment costs may include logistics costs of frequent replenishment or administrative warehouse costs of holding inventory, whereas backup fulfillment costs may include increased shipping costs. Furthermore, demand is realized after the point of inventory replenishment, so JD.com makes its inventory decisions with uncertain demand for each product. Thus, JD.com faces a central problem: how to best leverage inventory in front DCs to minimize delivery speed to maximize sales, but balance the costs of local fulfillment compared to backup fulfillment.

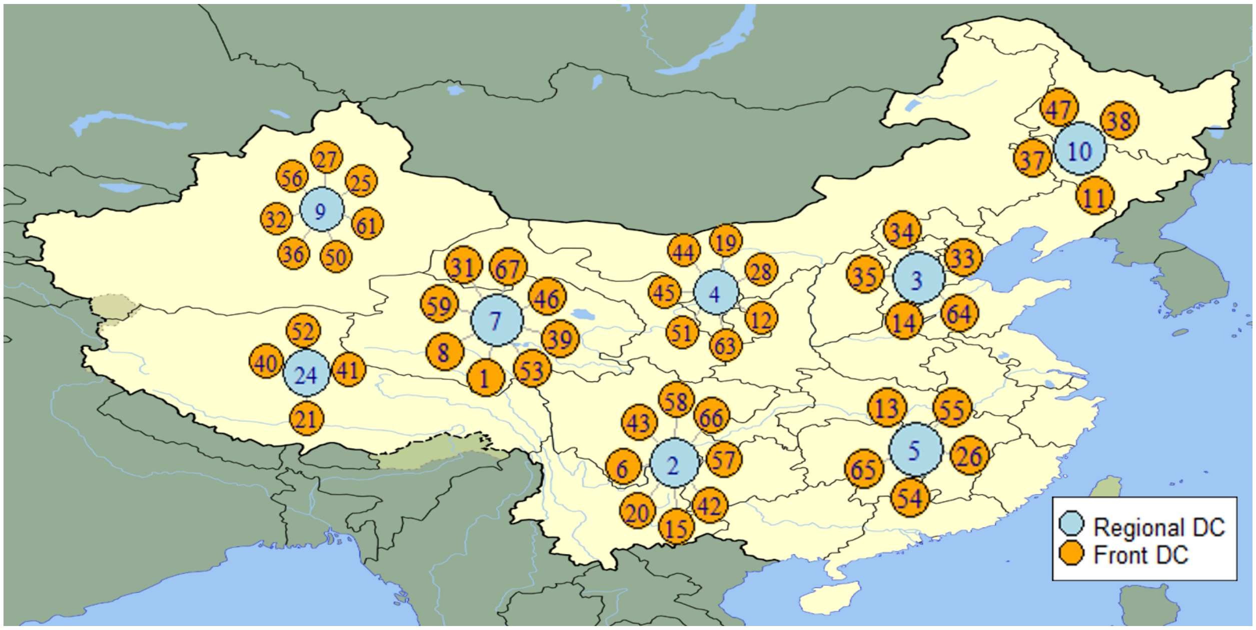
3.3.2 Data

We leverage data provided by JD.com in the 2020 MSOM data competition. We focus on data from three data tables: network, orders, and inventory.

The network table shows the region of each front DC and its corresponding regional DC. Figure 3.2 provides an illustration of JD.com's multi-warehouse fulfillment network.[2] We can see that

[2]Since JD.com does not provide actual locations of the DCs, our graphic is fictional and purely for illustration.

Figure 3.2: Illustration of JD.com's Multi-Warehouse Fulfillment Network



there are eight regions and each regional DC supports four to eight front DCs.

The orders table includes 549,989 sales transactions from March 1 to March 31 of 2018, with relevant features that we now describe. Quantity provides us the number of sales transactions. Order date provides us which day of the month the order was placed. SKU type describes the ownership of the inventory of the SKU, where Type 1 SKU inventory is managed directly by JD.com. Promised delivery time is how long the customer should expect to receive the product. As discussed in Appendix B.3, the customer is presented a single promise time when making the decision to purchase the product. Price is what the customer pays for the order in RMB. Finally, the order data marks the closest DC to the customer ("dc_des") and the actual DC that fulfilled the order ("dc_ori"). We refer to "dc_des" as the locality for where demand occurs.

When "dc_des" and "dc_ori" are not equal, the order is fulfilled by another warehouse in the district. As described in Shen et al. (2020), in theory any warehouse in the network can provide backup fulfillment. However, in practice backup fulfillment is primarily provided by the regional DC (Shen et al., 2020). This is supported empirically from the data. 93% of orders in a region are fulfilled by DCs within that region. Within a given region, 97% of orders are fulfilled either by the front DC of the locality or its regional DC.

The inventory data provides information on whether a given SKU is on-hand in each warehouse in the data at the end of the day. As discussed in Appendix B.1, there is empirical evidence that inventory replenishment occurs daily as 56% of SKUs that stock out are replenished the next day. While the data does not provide the amount of inventory, the inventory data remains useful for our analysis when combined with the orders data.

Since the number of observations is large, we reduce our data set for analysis. First, we focus on Type 1 SKUs as JD.com has discretion over managing the inventory of these SKUs (Shen et al., 2020). As a result, 89% of of the inventory data provided is for Type 1 SKUs. Second, to reduce the number of SKUs, we focus on SKUs that had some sales in each period across the entire network, representing 79% of Type 1 sales in the data. Third, we focus on sales transactions at front DCs only. As expected since regional DCs provide backup fulfillment, they exhibit very high service levels of 95% local orders fulfilled. On the other hand, front DCs can only fulfill 30% of orders locally, motivating our focus on these DCs in our research questions. Our working data set then involves 71,735 sales across 61 SKUs and 41 front DCs.

To examine the daily inventory decision in our model, we then combine our three data sets and aggregate data to the day-SKU-locality level, resulting in 77,531 observations. Table 3.1 provides summary statistics across our observations. We see that for an average observation sales are 0.93.

Table 3.1: Summary Statistics by Observation

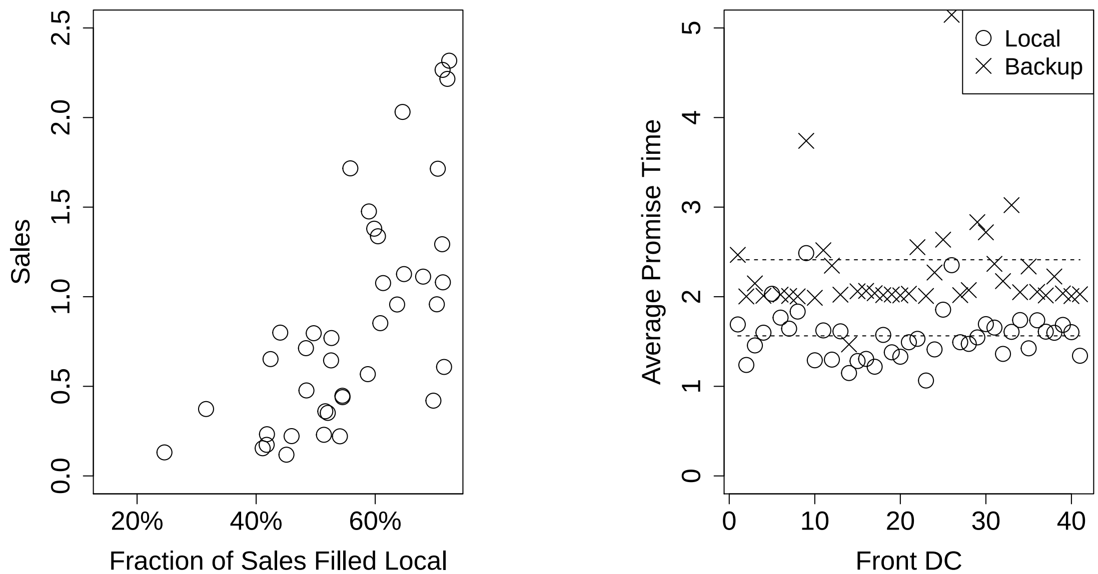
Summary Measure	Mean	StDev	Min	Max
Sales	0.93	2.53	0.00	74.00
Local Sales	0.54	1.95	0.00	69.00
Price (in RMB)	99.78	62.39	1.90	297.00
Promise Time (Local)	1.56	0.28	1.06	2.49
Promise Time (Backup)	2.41	0.97	1.47	7.34

We also see that the local service level is higher for Type 1 SKUs than on average, at 58% local fulfillment. Further, price is on average 99.78 RMB. On average the promise time when fulfilled by the closest local DC is 1.56, whereas the promise time fulfilled by the backup DC is 2.41. Thus, on average backup fulfillment results in increased promise times for JD.com.

3.3.3 Model-free Evidence Demand Impacted by Local Fulfillment

Now we explore model-free evidence that demand is impacted by local inventory positioning decisions. From before, Table 3.1 gives evidence that promise time is impacted by JD.com's local fulfillment decisions as promise time increases for backup fulfillment. Panel (a) of Figure 3.3 plots the fraction of DC sales filled locally relative to the average sales for the DC. This provides model-free evidence that increased local fulfillment aligns with increased sales.

Figure 3.3: Model-free Evidence of Importance of Front DCs



(a) Increased local fullillment aligns with increased sales

(b) All DCs experience increased delivery time from backup fulfilllment

Panel (b) of Figure 3.3 plots the average promise time when fulfilled locally and the average promise time when backup fulfillment is used, by DC. As expected, we see all DCs experience increased average promise times from backup fulfillment. Further, we see heterogeneity across DCs both in local promise time and backup promise time that may impact the local fulfillment decision.

It is possible that larger front DCs are strategically positioned in areas of high demand. This muddies the model-free analysis because high service levels may be due to low local fulfillment costs or due to benefits from improving delivery speed. Disentangling the demand-side and cost-side effects that influence the front DC inventory decision motivates the use of our structural model.

3.4 Model

3.4.1 Preliminaries

We consider a warehouse network that leverages multi-warehouse fulfillment, where the front DC fulfills demand with its available inventory and the regional DC provides backup fulfillment for additional demand. The large regional warehouse has infinite capacity[3] whereas the front DC faces limited capacity resulting in additional inventory handling costs. Front DCs provide faster delivery times that may result in increased sales. Unlike the classical newsvendor model with recourse (Bertsimas and Thiele, 2005) and other newsvendor models that have been applied in brick-and-mortar settings (de Kok and Graves, 2003), backup fulfillment in an e-commerce context may result in reduced demand in addition to increased costs. As inventory decisions in e-commerce often occur daily (Chen and Graves, 2021), the central planner faces a trade-off in determining how much inventory to place in the front DC for a given SKU each day.

On a given day, customers arrive one-by-one throughout the day. Since demand is stochastic at the time of determining the inventory to place in the front DC, the central planner leverages a forecast of future demand to inform the inventory to place in the front DC. Following Li et al. (2019), we refer to the decision for how much inventory to place in the front DC as "Predictive Shipping", where the manager considers how much to Pre-Ship in each period based on the forecast of demand. Our model for the Pre-Ship decision falls in the class of (s, S) base-stock policies where the Pre-Ship quantity aligns with the order-up-to level S so that the planner replenishes up to S each period. We allow the demand forecast in each period to change, resulting in volatility in the Pre-Ship quantity so that our model becomes a non-stationary base-stock policy in the class of (s_t, S_t) policies (Bray et al., 2019). Appendix B.2 provides additional discussion on why an (s_t, S_t) policy is appropriate in our context.

In the following sections we outline the key details of the model. In Section 3.4.2 we outline our model for demand. In Section 3.4.3 we outline our model for the managerial decision-making for the optimal Pre-Ship quantity.

---

[3]Assuming the highest-level facility in the process has infinite capacity is an assumption adopted by other OM papers for tractability (Alfredsson and Verrijdt, 1999)

3.4.2 Demand Model

In this section we outline our demand model for how customers respond to delivery speed and how this results in sales based on a chosen Pre-Ship quantity.

Similar to other OM papers considering multi-warehouse fulfillment (e.g., Bertsimas and Thiele, 2005; Li et al., 2019), we model aggregate demand on a given day t for SKU j in front DC locality i. We consider demand for SKU j independently of SKU $k \neq j$, similar to other structural papers for tractability (Aguirregabiria, 1999; Nair, 2007). Customers are sensitive to price p_{ijt} according to α. Customers also value faster delivery, and are sensitive to promised delivery time according to γ. Let v_{ijt}^L be the promised delivery speed when the order is sent from the front DC in the locality. We also incorporate fixed effects to capture heterogeneity in demand across SKUs, front DC localities, and given time periods. Let β represent a column vector of relevant fixed effects of dimension $N + M + T$, and Z be a matrix of dimension $(NMT) \times (N + M + T)$ with rows Z_{ijt} as indicators for each relevant fixed effect. Then, we specify demand when fulfillment occurs locally through the front DC in the locality i on a given day t for SKU j as

$$D_{ijt}^L = -\alpha p_{ijt} - \gamma v_{ijt}^L + \vec{Z_{ijt}}\vec{\beta} + \epsilon_{ijt}$$

where ϵ_{ijt} are idiosyncratic shocks to demand for each observation distributed as iid mean-zero normal random variables with standard deviation σ_ϵ.

When the local DC does not have inventory so that the order is sent from the regional DC for backup fulfillment, the customer receives a potentially longer promised delivery speed $v_{ijt}^B \geq v_{ijt}^L$. As a result, demand shifts according to the increased promise time of $v_{ijt}^B - v_{ijt}^L$. Since the other variables remain unchanged, the only change to demand results from increased promised delivery time. Then, we can describe the demand for backup fulfillment in the locality i on a given day t for SKU j as

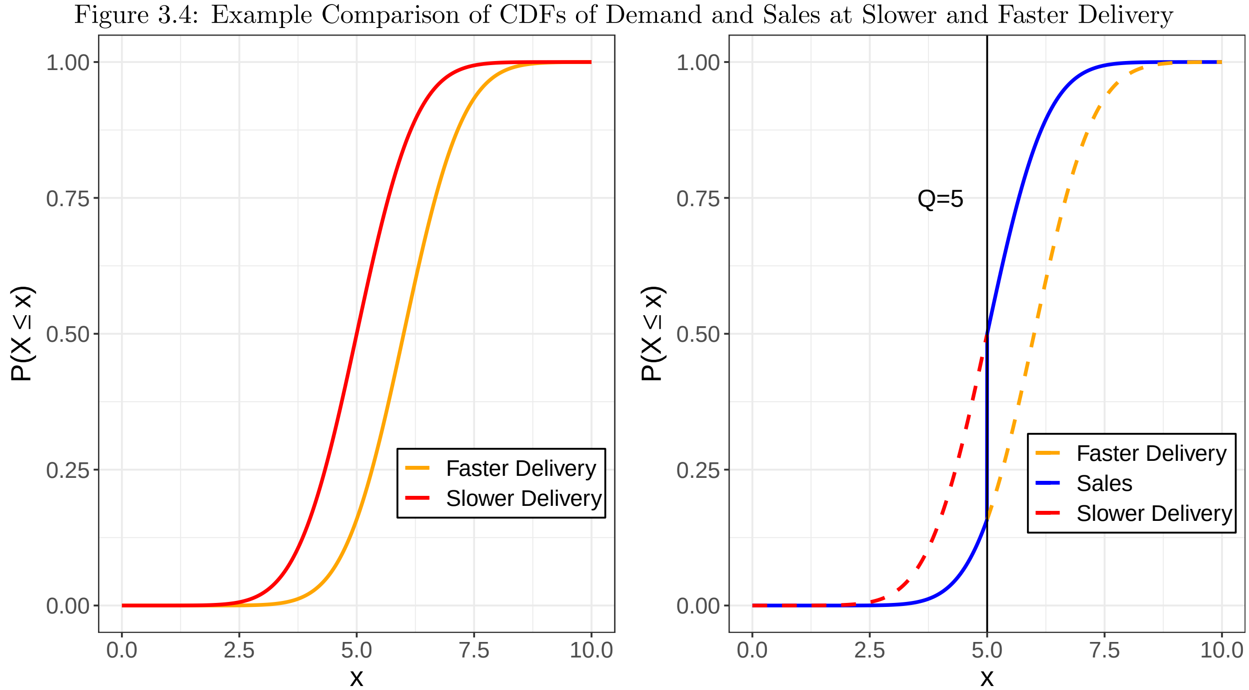
$$D_{ijt}^B = D_{ijt}^L - \gamma(v_{ijt}^B - v_{ijt}^L)$$

or $D_{ijt}^B = D_{ijt}^L - \Gamma$ where $\Gamma = \gamma(v_{ijt}^B - v_{ijt}^L)$.

Notice that we can consider D^L_{ijt} and D^B_{ijt} as counterfactual distributions when applying to the data.[4] Since a given customer only observes one promise time (see Appendix B.3 for a discussion), demand for a given promised delivery time is observed whereas demand for the alternative promised delivery time is not. Similarly, the manager only observes sales at the chosen inventory in the front DC.

To see how the demand model leads to sales under a chosen local inventory level, consider the example presented in Figure 3.4. Panel (a) of Figure 3.4 shows an example comparison of

Figure 3.4: Example Comparison of CDFs of Demand and Sales at Slower and Faster Delivery



(a) Example CDFs of Demand From Faster and Slower Delivery

(b) Example CDF of Sales When Q=5 is Chosen

the cumulative distribution functions of D^L and D^B, where $D^L \sim N(6,1)$ and $D^L \sim N(5,1)$. Notice that demand for faster delivery stochastically dominates demand for slower delivery as $P(D^L \geq x) \geq P(D^B \geq x)$ with strict inequality for finite x. Panel (b) of Figure 3.4 presents how a choice of local inventory $Q = 5$ impacts sales. To the left of $Q = 5$, additional sales are captured through faster delivery; to the right of $Q = 5$, sales are lost due to slower delivery. One

[4]We can consider D^L and D^B as being related through the copula $C = \min\{F(d^L), G(d^B)\}$ (Dhaene et al., 2002), where copulas have been applied successfully in the OM literature (e.g. Clemen and Reilly, 1999; Jouini and Clemen, 1996). Specifically this copula defines comonotonic random variables that can be represented as non-decreasing functions of a common random variable Z (Dhaene et al., 2002), which can be seen by $D^L = \sigma Z + \mu$ and $D^B = \sigma Z + \mu - K$ for $K \geq 0$. The comonotonic relationship aligns with an interpretation of counterfactual distributions.

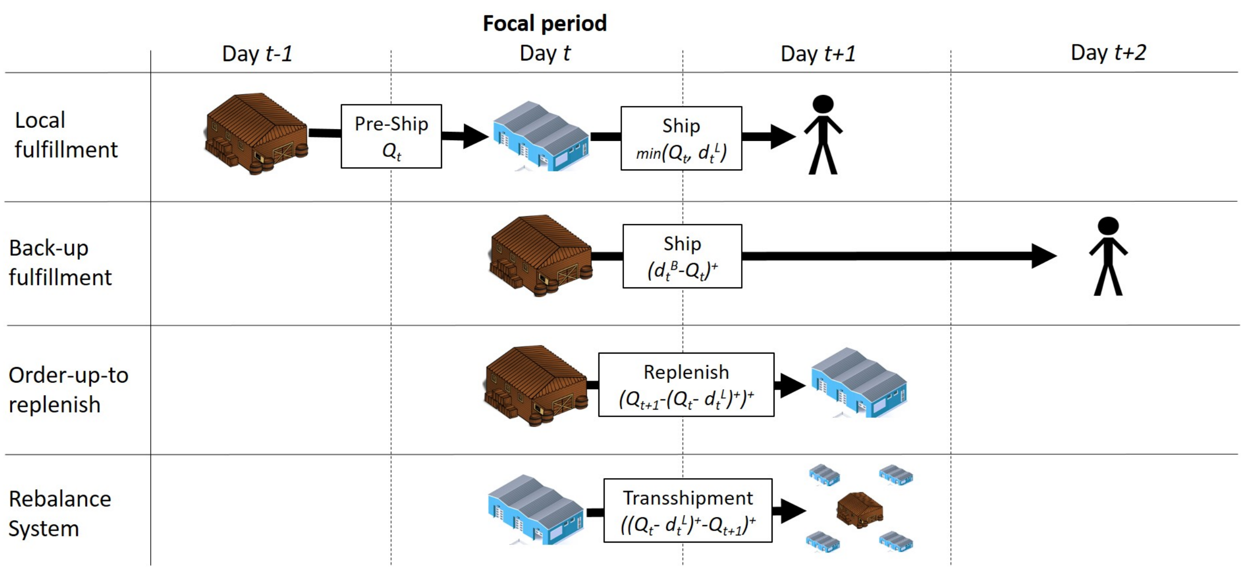
interpretation to the mechanics in Figure 3.4 is an ordering of customers according to idiosyncratic valuations for delivery speed, where customers that highly value delivery speed arrive first under efficient rationing (Su, 2010). Faster delivery speed allows to capture customers that highly value delivery speed and customers that do not value delivery speed are also captured through backup fulfilment. Those customers with intermediate valuation for delivery speed do not purchase. Our demand distributions aggregate the idiosyncratic utilities of the customers (Mas-Colell et al., 1995).

3.4.3 Model for Pre-Ship Quantities

In this section we outline how the central planner determines the Pre-Ship quantity to each front DC on a given day. The manager maximizes expected profit in its decision of the Pre-Ship quantity according to forecasted demand and fulfillment costs.

Figure 3.5 provides an example of the system dynamics that the manager considers when making the Pre-Ship decision, as described in what follows. For a given SKU and front DC, let Q_t be the

Figure 3.5: Multi-Warehouse Fulfillment Process Flow



Pre-Ship quantity for day t. To Pre-Ship Q_t incurs per-unit costs c. Sales locally resolve from $\min(Q_t, d_t^L)$ and provide per-unit revenue with price p_t, where d_t^L resolves from D_t^L. If $Q_t > d_t^L$, per-unit holding costs of h are incurred. If $d_t^B > Q_t$, the regional DC provides backup fulfillment of $(d_t^B - Q_t)^+$ that ships to the customer at per-unit cost b. In the next period $t + 1$, the Pre-Ship amount Q_{t+1} again incurs per-unit costs c where some portion will be used from on-hand inventory[5] from period t and some portion will be replenished as $(Q_{t+1} - (Q_t - D_t)^+)^+$. If remaining inventory from period t is larger than the next-period Pre-Ship amount Q_{t+1}, then the central planner will rebalance the system through transshipment of inventory to other DCs in the network at per-unit cost r, an approach discussed as common for e-commerce retailers to consider daily (Chen and Graves, 2021). Thus, costs will be incurred for rebalancing inventory of $((Q_t - D_t)^+ - Q_{t+1})^+$. We abstract beyond the mechanics of how transshipment occurs as it is beyond the scope of this work, but note its relevance for study as done in other research (e.g., Rudi et al., 2001; Zhao et al., 2005, 2008). Finally, we assume the cost of production is sunk at the time of the Pre-Ship decision, as DCs are generally purposed for distributing inventory for fulfillment.[6]

Now that we have described the mechanics of the system, we are ready to formulate the manager's profit function. To ease exposition we drop the t subscripts in considering profit for a given SKU. Let $Q^{(+1)} \equiv Q_{t+1}$, which the manager strategically considers in making the Pre-Ship decision Q in period t. Based on the realization of D^L and D^B, the manager receives profit given the chosen Pre-Ship quantity Q according to

$$\pi(Q) = \begin{cases} pd^L - cQ - h(Q - d^L) - r(Q - Q^{(+1)} - d^L) & \text{if } 0 \leq d^L \leq Q - Q^{(+1)} \\ pd^L - cQ - h(Q - d^L) & \text{if } Q - Q^{(+1)} < d^L \leq Q \\ pd^B - cQ - b(d^B - Q) & \text{if } d^B > Q \\ pQ - cQ & \text{if } d^L > Q \text{ but } d^B \leq Q \end{cases}$$

We can then formulate the managers expected profit $\pi(Q)$ for a given Q. Since sales must be non-negative, to formulate expected profit we normalize the demand distributions described previously through the truncated normal distribution,[7] a technique that can be done without loss

[5]The per-unit cost c for remaining inventory from period t can be thought of as processing costs for inventory separate from that replenished. Our model can be extended to incorporate different costs, such as no cost to using inventory on-hand, but we maintain this modeling choice for parsimony.

[6]Production costs could also be considered as included in c and b but incorporating production decisions may incur a different timeline than Pre-Ship decisions which is outside of the scope of this work.

[7]Specifically, let $\underset{\sim}{D}^L$ be distributed as a left-truncated normal at zero according to the parameters of D^L, and let $\underset{\sim}{D}^B$ = $\underset{\sim}{D}^L$ - Γ.

of generality (Perakis et al., 2020). With a slight abuse of notation, whenever the distributions are considered in the Pre-Ship decision, the truncated normal distribution is used. Then,

$$\begin{aligned}E\pi(Q) =& pE\min(D^L, Q) - hE[Q - D^L]^+ - rE[Q - Q^{(+1)} - D^L]^+ \\ &+ (p - b)E[D^B - Q]^+ - cQ\end{aligned}$$

Now we describe how the manager solves for the optimal Pre-Ship quantity Q^e that maximizes expected profit. Let $[x]^+$ denote an operator for $\max(0, x)$. Leveraging $\min(a, b) = a - [a - b]^+$ (Dong and Rudi, 2004), we can rewrite the expected profit as

$$E\pi(Q) = (p - c)Q - (p + h)E[Q - D^L]^+ - rE[Q - Q^{(+1)} - D^L]^+ + (p - b)E[D^B - Q]^+$$

Let F describe the cumulative distribution function for the left-censored truncated normal for D^L. Leveraging the Lerner rule (Choi, 2012), the first and second derivatives with respect to Q are

$$\begin{aligned}\frac{dE\pi(Q)}{dQ} =& (p - c) - (p + h)P(D^L \leq Q) - rP(D^L \leq Q - Q^{(+1)}) - (p - b)P(D^B > Q) \\ =& (b - c) - (p + h)F(Q) - rF(Q - Q^{(+1)}) + (p - b)F(Q + \Gamma) \\ \frac{d^2E\pi(Q)}{dQ^2} =& -(p + h)f(Q) - rf(Q - Q^{(+1)}) + (p - b)f(Q + \Gamma)\end{aligned}$$

Notice that the first-order condition does not allow for a closed-form solution as in the classical newsvendor model. Still, we see that $dE\pi(0)/dQ \geq b - c$ when $p \geq b$[8] and $dE\pi(\infty)/dQ = -c - h - r$ as F is strictly increasing and bounded by [0,1]. We will assume $b - c > 0$ as in Bertsimas and Thiele (2005) and that all cost parameters are nonzero for sensibility. So by the intermediate value theorem, there exists a root where the first derivative in Q equals zero. Unfortunately the second-order condition for concavity is not met without either $\Gamma = 0$ or $b > p$, which are assumptions we do not want to make. Yet, it turns out that the expected profit function is quasiconcave in Q, which provides a unique global maximizer Q^e (Mas-Colell et al., 1995). Appendix B.4 provides more details regarding quasiconcavity of the expected profit function. Using these conditions, we

[8]In scenarios where the first derivative is negative at $Q = 0$, we let $Q = 0$ as then expected profit decreases in Q.

can then solve for the optimal Pre-Ship quantity by leveraging the first-order condition where the gradient equals zero. We leverage gradient ascent, which increases computation relative to a closed form solution.

We also consider the local shipment as having unobserved shocks to the optimal expected Pre-Ship quantity the manager chooses. Specifically, we consider the local shipment as having random deviations to the orders, such as due to variations in truck sizes or other logistics, that the manager observes after making the order decision but we as researchers do not. We will assume these random deviations ξ are iid across observations and occur according to a mean-zero normal distribution with standard deviation σ_ξ. The realized order quantity is then

$$Q^* = Q^e + \xi$$

3.5 Estimation

3.5.1 Overview

We now provide an overview of the steps required to estimate the demand and cost parameters. We assume that customers and the central planner behave optimally according to the model so that primitives of behavior can be revealed from the actions in the data. When forecasting demand in making the Pre-Ship decision, like other structural papers (e.g., Nair, 2007) we assume the central planner forms rational expectations on future outcomes according to the equilibrium observed in the data. Since customers do not observe the quantity decisions from the central planner, we can validly estimate demand conditional on promise time separately from the decisions of the central planner. To allow for estimation of the shift in demand for the counterfactual demand distribution of backup demand compared to local demand, we assume that managers prioritize fulfilling orders with front DC inventory before using backup fulfillment.[9] Similar to DeHoratius et al. (2008), our assumption allows for sales data to reveal information on inventory. Then, we can leverage different conditions based on sales data and whether inventory is on hand at the end of the day to formulate our likelihood functions to allow for valid estimation that accounts for the censored inventory data.

[9] This assumption is supported in the data, as 91% of backup fulfillment occurs when no inventory is on-hand at the end of the day

Given these conditions, we can estimate our parameters in two-steps, as has been done in other structural papers (Nair, 2007). Our two-step approach is as follows:

Step 1: Estimate demand parameters

- Estimate the demand primitives through a likelihood function that accounts for the counterfactual demand distribution and censoring based on sales and whether inventory is on hand at the end of the day.

Step 2: Estimate supply parameters

- Compute the optimal Pre-Ship quantity based on the choice of cost parameters, conditional on the expected demand response from the first stage.
- Leveraging a likelihood function that accounts for censored inventory, estimate the cost parameters by maximizing the likelihood of Pre-Ship quantity decisions observed in the data.

3.5.2 Demand Estimation

In this section we describe our approach to estimating the demand primitives defined in our model, $\theta_d = \{\alpha, \gamma, \vec{\beta}, \sigma_\epsilon\}$.

To estimate our parameters, we seek to maximize a likelihood function of the form

$$L(\theta_d) = \prod_{i=1}^{N} \prod_{j=1}^{M} \prod_{t=1}^{T} f(s_{ijt}; \theta_d)$$

where $f(s_{ijt}; \theta_d)$ is the likelihood contribution at a given parameter θ_d from observing sales s_{ijt} for observation of locality i, SKU j, on day t. To simplify exposition, we drop the subscripts for a given observation. As mentioned previously, to derive our likelihood function we formulate five conditions based on what we observe in the data given that the manager prioritizes filling demand locally.

For a given observation we observe sales $s = s^L + s^B$, where $s^L \geq 0$ are fulfilled locally and $s^B \geq 0$ are fulfilled through backup fulfillment. Note this implies $s \geq s^L$. Since the manager prioritizes filling demand locally, $Q \geq s^L$, and when inventory is on hand at the end of the day $Q > s$. Let $T \in \{0, 1\}$ be an indicator for whether inventory is on-hand at the end of the day.

Recall also that local demand stochastically dominates backup demand due to faster delivery time, so that $D^L \geq D^B$. Now we can formulate our five conditions:

1. Local demand non-positive ($D^L \leq 0$). $s = 0$ and $T = 1$, implying $Q > 0$: no sales occurred with inventory on hand.

2. Backup demand non-positive ($D^B \leq 0$). $s = 0$ and $T = 0$, implying $Q = 0$: no sales occurred with no inventory on hand.

3. Local demand equals sales ($D^L = s$). $s = s^L > 0$ and $T = 1$, implying $Q > s = s^L$: all sales occurred locally with inventory on hand.

4. Backup demand equals sales ($D^B = s$). $s > s^L$ and $T = 0$, implying $s > Q = s^L$: some sales occurred through backup fulfillment.

5. Local inventory used, no additional backup demand ($D^L \geq s \geq D^B$). $s = s^L$ and $T = 0$, implying $s = Q$: all sales occurred locally without backup sales and no end of day inventory.

Using these conditions, we can now formulate our likelihood contribution for a given observation. For a given observation, the likelihood of observing s given Q is given by

$$f(s|Q;\theta_d) = \begin{cases} F(0;\theta_d) \text{ if } s = 0 \text{ and } Q > 0 \\ F(\gamma;\theta_d) \text{ if } s = 0 \text{ and } Q = 0 \\ f(s;\theta_d) \text{ if } 0 < s < Q \\ f(s+\gamma;\theta_d) \text{ if } s > Q \\ F(Q+\gamma;\theta_d) - F(Q;\theta_d) \text{ if } s = Q \text{ and } Q > 0 \end{cases}$$

Examining our likelihood function, we can see that conditions 1 and 2 account for the requirement of observing non-negative sales. Condition 5 accounts for the fact that when local inventory is used, no additional sales could result from a reduction in demand from longer delivery times. Similar to other censored likelihood functions like the Tobit model (Wooldridge, 2002), conditions 3 and 4 provide point identification for our parameters while the other conditions provide partial identification. Observations satisfying the conditions with partial identification should still be included as they provide useful information about the underlying parameters (Bajari et al., 2007).

In the language of method of moments, conditions 3 and 4 provide moment equalities, whereas conditions 1, 2, and 5 provide moment inequalities (Bajari et al., 2007).

3.5.3 Supply Estimation

In this section we describe how we estimate the cost parameters $\theta_c = \{c, b, h, r, \sigma_\xi\}$ for a given region. We estimate these parameters according to the local fulfillment decisions in the data, based on the likelihood of the observations according to our model. As in demand estimation, our goal is to formulate a likelihood function of the form

$$L(\theta_c) = \prod_{i=1}^{N}\prod_{j=1}^{M}\prod_{t=1}^{T} h(Q_{ijt}|s_{ijt};\theta_c)$$

where $h(Q_{ijt}|s_{ijt};\theta_c)$ is the likelihood contribution at a given parameter θ_c for Q_{ijt} with sales s_{ijt} for observation of DC i, SKU j, on day t. To simplify exposition, we again drop the subscripts for a given observation. As in demand estimation, we similarly formulate the likelihood function to account for the fact that Q is censored.

We now formulate each likelihood contribution $h(Q|s;\theta_c)$. First, if $Q = 0$ in the data then we will need to consider left-censored data as the Pre-Ship quantity cannot be negative. These will be observations satisfying condition 2 in Section 3.5.2. Second, when observations satisfy conditions 4 and 5, sales reveal local inventory providing point identification. Finally, when observations satisfy conditions 1 and 3, the Pre-Ship quantity is censored because inventory is larger than sales, providing partial identification.

Let $Q^e_{\theta_c}$ be the optimal Pre-Ship quantity according to the model based on parameters θ_c for a given observation. We specify the idiosyncratic shocks to the observed Pre-Ship quantity to be $\xi \sim N(0, \sigma_\xi)$. Using the criteria in the prior paragraph, the likelihood of observing Q based on sales s for a chosen parameter θ_c is then

$$h(Q|s;\theta_c) = \begin{cases} \Phi(-Q^e_{\theta_c}/\sigma_\xi) & \text{if } Q = 0 \text{ and } s = 0 \\ \phi((Q - Q^e_{\theta_c})/\sigma_\xi) & \text{if } 0 < Q \leq s \\ 1 - \Phi((s - Q^e_{\theta_c})/\sigma_\xi) & \text{if } Q > s \end{cases}$$

where $\Phi(\cdot)$ represents the standard normal cumulative distribution and $\phi(\cdot)$ represents the standard normal probability density function.

One additional challenge we must overcome in estimating the supply parameters is computation. Since we do not have a closed form solution for the optimal Pre-Ship quantity (see Section 3.4.3 for more details), we have to solve for it through multiple evaluations through gradient ascent which is costly. Furthermore, like other two-step estimators (Olivares et al., 2008), we need to leverage bootstrapping to compute the standard errors, further increasing computation. Finally, across 41 front DCs there are a large number of potential parameters to estimate.

To ease computation we estimate the parameters separately within each of the eight regions, utilizing the fact that the front DC and backup regional DC are always within the same region. To retain parsimony while capturing heterogeneity across front DCs, we estimate h for each front DC and one of each of c, b, r, and σ_ξ per region. Similar to Bray and Stamatopoulos (2021), we perform the estimation routine in parallel on the university research computing cluster.

Another challenge we must overcome in estimation is how the manager strategically considers Pre-Ship quantities in the future as they impact the rebalancing costs. Like other structural papers (e.g., Nair, 2007), we will assume that the manager has rational expectations on future outcomes according to the equilibrium observed in the data. Specifically, the manager has rational expectations on future Pre-Ship quantities, which results from rational expectations on forecasted demand that is observed from the equilibrium in the data.[10] For next-period observations where the sales are informative on the Pre-Ship decision (i.e., conditions 2, 4, and 5 from Section 3.5.2), we can use the Pre-Ship decision observed in the data. Otherwise, we do not directly observe the next-period Pre-Ship decision due to censored inventory. To overcome this difficulty when the next-period Pre-Ship observation is censored, we leverage backward induction to compute the next-period Pre-Ship decision according to the chosen parameters.

[10]For tractability in the final period we set the next-period Pre-Ship quantity to be large, following similar approaches in other OM papers to resolve inventory in the final period (Veinott, 1965).

3.5.4 Identification

In this section we discuss identification of the parameters for demand and Pre-Ship fulfillment costs, using informal arguments similar to other works (Nair, 2007; Bray and Stamatopoulos, 2021).

We start with how we identify the demand parameters. According to the conditions discussed in Section 3.5.2, some observations provide point identification and other observations provide partial identification. The waiting senstivity parameter γ is identified by variation in local and backup promised delivery times, for observations with similar demand conditions but differing sales. Outside of the waiting sensitivity parameter γ, parameter identification follows similar arguments to in other structural works (e.g., Nair, 2007; Ishihara and Ching, 2019). The variation in prices identify price sensitivity α; the mean sales within SKU, locality, and day identify the fixed effects composing $\vec{\beta}$ for SKU, locality, and day respectively; and the scale parameter of the idiosyncratic shock σ_ϵ is identified by variation in sales from the model prediction.

Next we discuss how we identify the cost parameters. Similar to identification of the demand parameters, according to the conditions discussed in Section 3.5.3, some observations provide point identification and other observations provide partial identification. We have four sources of variation to identify the four parameters c, b, h, and r: variation in prices, variation in delivery speed differences of local and backup fulfillment, variation in next-period Pre-Ship quantity, and average local FDC sales. Variation in next-period Pre-ship quantity identifies rebalancing costs r. Pre-Ship replenishment costs c are identified by variation in delivery speed differences of local and backup fulfillment; Pre-Ship replenishment costs must be high if Pre-Ship inventory is low when delivery speed differences are large. Backup fulfillment costs are identified by the variation in prices that determine the margins lost when backup fulfillment is used; backup fulfillment costs must be high if Pre-Ship inventory is low resulting in high-priced lost sales. For a given local FDC, holding costs h are identified by shifts in mean local sales. Table 3.4 in Section 3.5.5.2 shows how observables explain variation in the parameters, additional evidence for the identification arguments. Finally, the standard deviation of the idiosyncratic error to the Pre-Ship quantity is captured by the deviations from the Pre-Ship quantity that maximizes expected profit. Smaller variation in the observed Pre-Ship quantity relative to the theoretical Pre-Ship quantity implies smaller values of σ_ξ.

3.5.5 Estimation Results

3.5.5.1 Estimated Demand Parameters

Table 3.2 presents the estimated demand primitives $\hat{\theta}_d$. We include SKU, day, and locality fixed effects that allow for a rich demand model across key dimensions in the data. The intercept represents the base case and the model provides good fit with a Pseudo-R^2 value of .23 (McFadden, 1979).

Table 3.2: Estimated Demand Parameters

Parameter	Estimate
Intercept	1.470***
$\hat{\beta}_0$	(0.330)
Price Sensitivity	0.026***
$\hat{\alpha}$	(0.003)
Waiting Sensitivity	1.201***
$\hat{\gamma}$	(0.012)
Standard Deviation	4.847***
$\hat{\sigma}_\epsilon$	(0.079)
SKU Fixed Effects	Yes
Date Fixed Effects	Yes
Locality Fixed Effects	Yes

Notes. The sample includes 77,531 observations. Standard errors are computed using the Fisher information matrix. The Pseudo-R^2 is 0.23, defined by McFadden's R^2 where McFadden (1979) describe values between 0.2 and 0.4 as providing excellent fit. Coefficients with *** are significant at the .01 level.

The parameters support our intuition. Price sensitivity $\hat{\alpha}$ has the expected sign and is significant, meaning that increasing price reduces quantity demanded. Waiting sensitivity $\hat{\gamma}$ has the expected sign and is significant, meaning that longer promised delivery times reduce quantity demanded.

3.5.5.2 Estimated Cost Parameters

Our discussion of the estimated cost parameters leverages similar tables and figures to Bray and Stamatopoulos (2021). We estimate our parameters in each region, with eight parameters for each of $\hat{c}$, $\hat{b}$, $\hat{r}$, $\hat{\sigma}_\xi$ and 41 parameters for $\hat{h}$. Given our two-step estimator, we bootstrap the standard error for each parameter. 86% of the coefficients are significant at the .05 level and the Pseudo-R^2 ranges from 0.10 to 0.68, with a median of 0.39.

Table 3.3 presents the quartiles of the estimated cost parameters for each of the eight regions and Figure 3.6 provides the distribution of the parameters and their respective t-statistics.

Table 3.3: Estimated Supply Parameter Quartiles

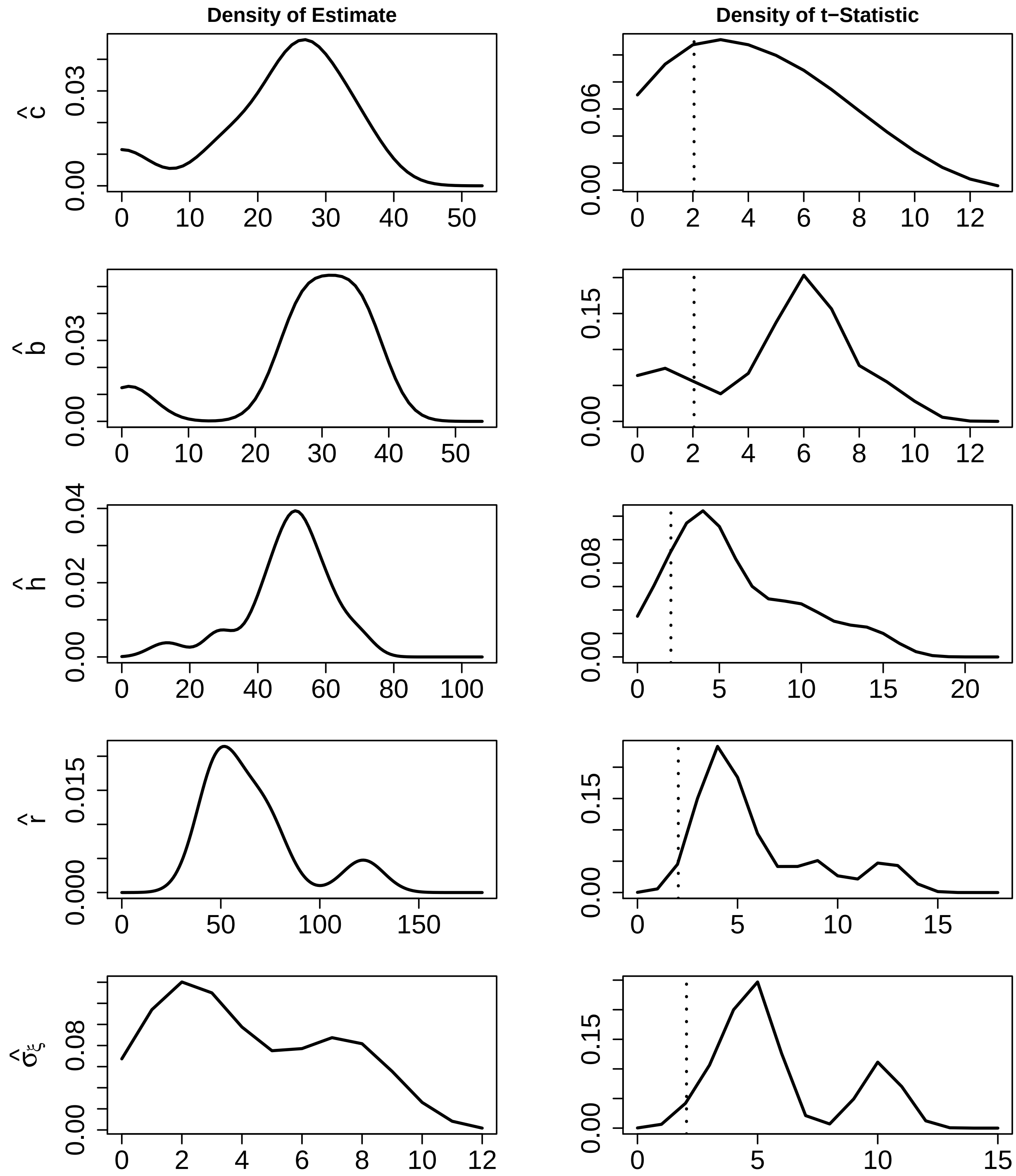
Quartile	$\hat{c}$	$\hat{b}$	$\hat{h}$	$\hat{r}$	$\hat{\sigma}_\xi$
Q1	19.6	26.8	44.5	48.3	2.1
Q2	25.7	29.6	50.9	57.6	3.1
Q3	28.7	34.7	55.9	72.5	6.6

Notes. Each column presents the quartile for each parameter for estimation in each of 8 regions, similar to the table in Bray and Stamatopoulos (2021). A given region has one respective parameter for b, c, r, σ_ξ and each front DC has its own h. As in Bray and Stamatopoulos (2021) we compute standard errors with 30 bootstrap samples. 86% of the coefficients are significant at the .05 level and the Pseudo-R^2 ranges from 0.10 to 0.68, with a median of 0.39.

Based on the quartiles, we can see that generally $\hat{c} < \hat{b} < \hat{h} < \hat{r}$. Given that backup delivery requires shipping directly to the customer, it is reasonable that $\hat{c} < \hat{b}$. Given that FDCs have limited space, it is reasonable that holding costs $\hat{h}$ are relatively high. Given the logistics to tranship inventory, it is reasonable that these costs are high.

In addition we consider two industry benchmarks. One benchmark for the delivery costs of $\hat{c}$ and $\hat{b}$ comes from Cui et al. (2019) who note that SF charges 23 RMB per package on average with an industry average of 12.38 RMB. Notably JD.com likely has lower shipping costs than the prices faced by consumers and these benchmarks are averages across all package types, so the type of products in the product category provided by JD.com (which is not provided with the data) could have higher or lower shipping costs. Still, these benchmarks show that our estimates are reasonable given industry benchmarks. Another benchmark for the estimated parameters comes from Perakis et al. (2020) who note an industry average of 3.0 underage-to-overage ratio. While this cost ratio is not directly applicable in our setting due to the impact of delivery time on demand and our consideration of strategic inventory considerations, we could consider a comparable simplified model that only considers underage costs $p - b$ and overage costs h with $\gamma = 0$. With an average price of $p = 100$, median backup fulfillment costs $b = 30$, and median overage costs of $h = 50$, the median underage-to-overage ratio would be roughly 1.5. Thus, relative to another industry

Figure 3.6: Distribution of Cost Parameter Estimates and Corresponding t-Statistics



Notes. As in Bray and Stamatopoulos (2021), we create these plots by estimating the distributions with a kernel density estimator. The dashed lines in the t-statistic plots mark the $p = .0.05$ statistical threshold; anything to the right of these lines is significantly greater than zero.

benchmark our parameter estimates are reasonable.

Last, through Table 3.4 we inspect how variation in the observables in the data explain variations in our cost parameters. We compute relative ratios $\hat{c}/\hat{r}$, $\hat{b}/\hat{r}$, and $\hat{h}/\hat{r}$, to examine how the parameters vary within region for a fixed $\hat{r}$.

Table 3.4: Explanation of Variation in Cost Parameter Estimates

	$\hat{c}/\hat{r}$	$\hat{b}/\hat{r}$	$\hat{h}/\hat{r}$	$\hat{r}$
Intercept	14.21	15.64*	19.44	39.28***
	(9.02)	(8.38)	(12.02)	(13.81)
Percent Sales Local	-0.25	-0.21	-0.97***	
	(0.25)	(0.23)	(0.33)	
Speed Local - Speed Backup	-0.08*	-0.06	-0.07	
	(0.04)	(0.04)	(0.05)	
Average Price	-0.14	-0.15*	-0.18	
	(0.09)	(0.08)	(0.12)	
Percent Sales Local +1				73.56**
				29.31
Standard Deviation of Local Sales +1				-12.44**
				(5.82)

Notes. For each column in the table, we regress the estimated parameter ratio on the observed operational statistics in the data. ***,**,* denote significance at the .01, .05, .10 significance level, respectively.

We see that statistically, relative replenishment costs decrease with increases in backup delivery speed; relative backup fulfillment costs decrease with price; and relative holding costs decrease as local sales percentages increase. Finally, replenishment costs increase as next period local sales increase and decrease when volatility in next period local sales increases.

3.6 Counterfactual Results

We now examine our research questions of interest through counterfactual analyses. Here are our key takeaways:

1. *To what extent does use of front DCs impact operational outcomes?* We find that JD.com's current utilization of front DCs improves average promised delivery time by 28.3%, resulting in 10.7% improved average profit. Front DCs provide the largest benefits by allowing managers to capture sales for high-margin SKUs with high demand where backup fulfillment results in

much longer promised delivery time.

2. *To what extent does ignoring backup delivery speed impact operational outcomes?* If the loss in demand from backup fulfillment is ignored in the Pre-Ship decision, average promised delivery time increases by 14.8% leading to an average profit reduction of 6.8%. Because the manager overestimates demand at a given Pre-Ship quantity, large negative profit impacts result from the manager under-ordering.

3. *Which front DCs should receive investment to reduce local fulfillment costs?* FDCs 41, 27, 12, 50, and 52 are the five best FDCs to target with reducing holding costs. These improvements align with DCs with long backup delivery speed and large estimated local demand, more so than the magnitude of the holding costs.

In the following sections we describe how we reach these insights. First, we compare the operational outcomes in our predicted equilibrium to a counterfactual setting without FDCs. Next, examine a counterfactual setting where the manager ignores the reduction in demand from backup fulfillment in the Pre-Ship decision. Then, we examine a counterfactual setting with reduced holding costs to identify those last-mile DCs that would most benefit from investment to improve local fulfillment.

Appendix B.5 describes how we estimate the equilibrium for a given set of parameters. Appendix B.6 describes our predicted equilibrium's fit to the data. Our predicted equilibrium fits the data well across a variety of operational metrics, as all metrics are within 15% of what we observe in the data.

3.6.1 Value of Front DCs in Practice

In this section we examine the value of Front DCs in practice. Our approach to simulating a scenario without Front DCs involves generating an optimal Pre-Ship policy of $Q = 0$ for all observations. This policy can be achieved in a number of ways by perturbing our parameters, such as setting $c \to \infty$, $h \to \infty$, or $r \to \infty$. We choose to set $c \to \infty$. Given this policy, we generate a new equilibrium to compare to the equilibrium our model predicts in the data.

Table 3.5 summarizes the operational impacts of all of our counterfactuals. Examining the first

Table 3.5: Average Impact to Outcomes from Counterfactuals Relative to Predicted Equilibrium

Counterfactual	Profit	Revenue	Delivery Time	Pre-Ship Quantity
Remove Front DCs ($c \to \infty$)	-10.7%	-10.6%	+28.3%	-100.0%
Ignore Demand Shift ($Q^e_{D^B = D^L}$)	-6.8%	-8.4%	+14.8%	-69.8%
Half Holding Costs ($h = .5\hat{h}$)	+3.5%	+2.6%	-3.0%	+38.3%

Notes. Impacts for each outcome measured relative to the predicted equilibrium for what is observed in the data. To generate the equilibrium, expected Pre-Ship quantities are computed according to rational expectations of demand behavior, solved through backward induction. Demand is simulated using 100 Halton draws, which have been known to perform as well ten times the number of random samples (Train, 2000).

row as it aligns with our current counterfactual, we see that JD.com's utilization of front DCs improves average promised delivery time by 28.3%, resulting in 10.7% improved average profit.

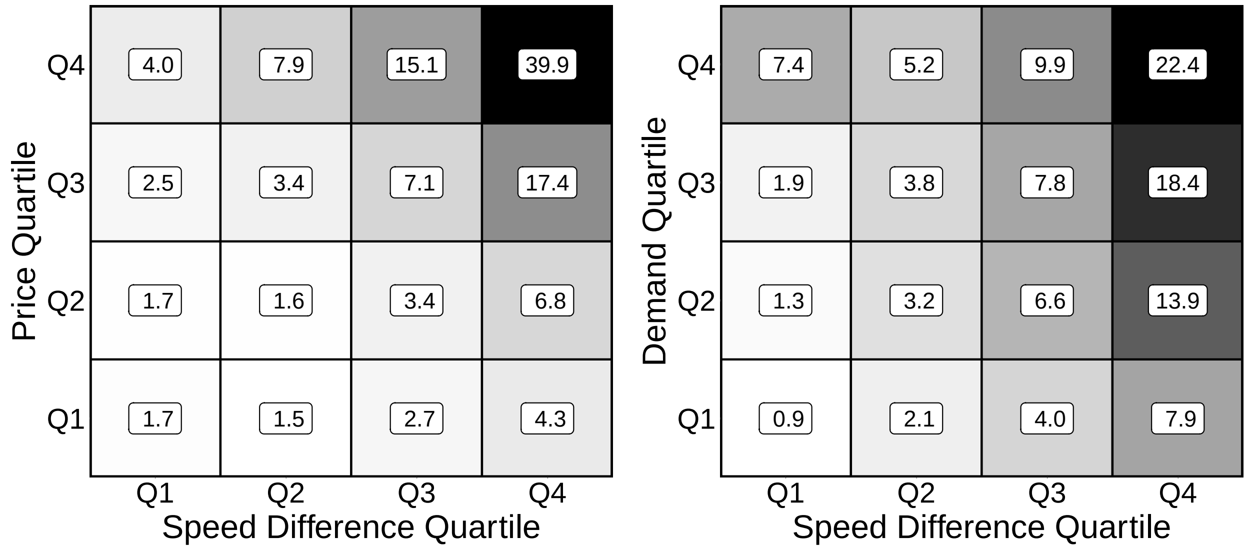
We now explore how these impacts differ across observations. A natural starting point is to see how the profit impacts align with the estimated cost parameters. Intuitively, front DCs should have less impacts for DCs with high local fulfillment costs. From a regression of the cost parameters on the profit impact, we return an R^2 of 0.18 with all parameters significant. Thus, while the cost parameters do explain a meaningful portion of variation in the benefits of front DCs to profit, they do not tell the whole story.

We additionally investigate how the demand-side impacts influence the Pre-Ship decision. Recall that the observed data that are exogenous to our supply-side model include the difference in delivery speed for local and backup fulfillment (denoted "Speed Difference"), price, and estimated demand for local fulfillment (denoted "Demand").[11] We consider the variation of these features according to the quartiles in the data when ranked from lowest to highest, denoted by Q1, Q2, Q3, and Q4. Figure 3.7 provides two plots of the average profit benefits in RMB of front DCs in practice relative to the described quartiles.

Panel (a) of Figure 3.7 focuses on the quartiles of Speed Difference and Price. We can see that profit benefits of FDCs are minimal in the bottom-left quadrant where Price and Speed Difference are small in magnitude, whereas the profit benefits of FDCs are large in the top-right quadrant. In other words, the central planner is able to leverage Pre-Ship inventory to capture additional demand

[11] The counterfactual estimated demand for backup fulfillment is directly related to the difference in delivery speed through γ.

Figure 3.7: Profit Gains From Front DCs by Quartiles of Observables



(a) Front DCs provide largest benefits to observations with high price, large speed difference

(b) Front DCs provide largest benefits to observations with high demand, large speed difference

for high-priced SKUs with greater opportunity in improving promised delivery time through local fulfillment.

Panel (b) of Figure 3.7 focuses on the quartiles of Speed Difference and Demand. Similar to Panel (a), we see that profit benefits of FDCs are minimal in the bottom-left quadrant where Demand and Speed Difference are small in magnitude, whereas the profit benefits of FDCs are large in the top-right quadrant.

Combining the insights from Figure 3.7, we can see that in both scenarios the benefits of front DCs depend on the ability to capture additional demand through improved delivery speed. While the cost-based approach is common in the multi-warehouse fulfillment models in the OM literature (e.g., Perakis et al., 2020; Chen and Graves, 2021), we provide evidence that both the trade-offs of delivery costs and demand impacts of local fulfillment are important in the manager's local fulfillment decision.

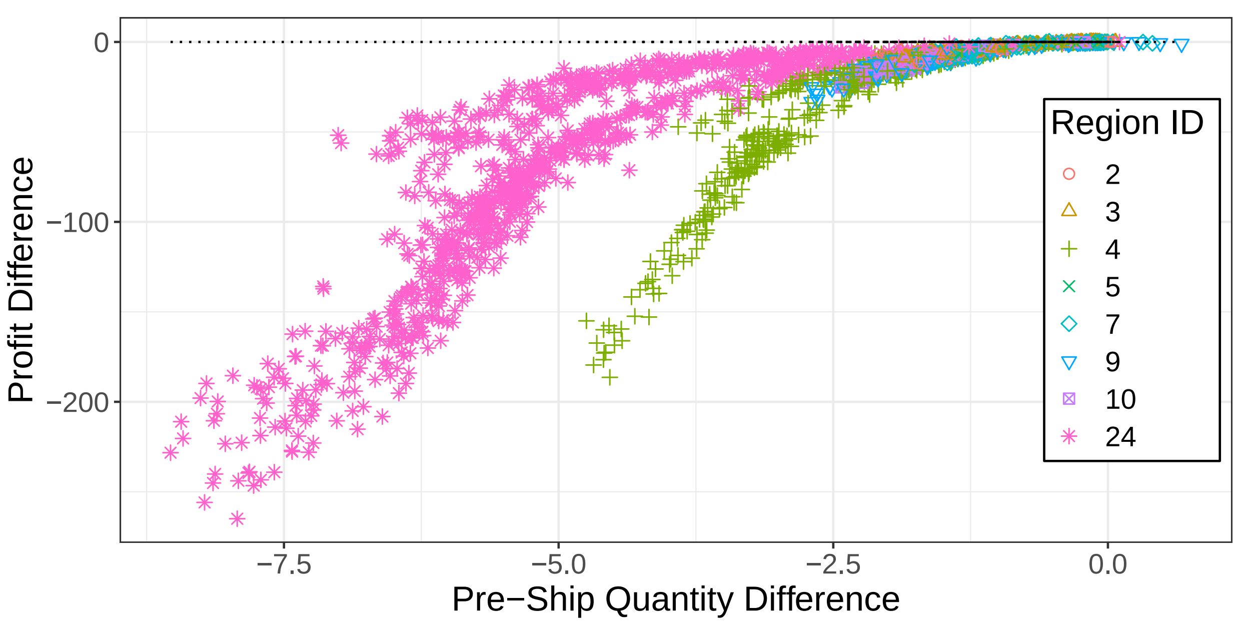
3.6.2 Ignoring Demand Shift for Backup Fulfillment

Prior OM literature generally assumes that the demand distribution is not impacted by backup fulfillment which is tied to the inventory decision (see Choi, 2012; de Kok and Graves, 2003, for reviews). In this counterfactual we investigate the importance of incorporating the shift in demand from backup fulfillment into the Pre-Ship decision. For comparison, we simulate a scenario where the central planner ignores the demand shift from backup fulfillment. To simulate this scenario, we consider a policy where the central planner assumes the demand for backup fulfillment is equal to the demand for local fulfillment, or $D^B = D^L$. Thus, the planner follows the policy $Q^e_{D^B=D^L}$ despite the fact that $D^B < D^L$ according to the data. We then compare the outcomes of the equilibrium generated according to $Q^e_{D^B=D^L}$ to that predicted from the data.

Examining the second row of Table 3.5, we can see that on average ignoring the demand shift from backup fulfillment results in a 6.8% reduction in profit. In particular, we can see that on average $Q^e_{D^B=D^L} < Q^e$ where Q^e is the optimal Pre-Ship quantity. Because the Pre-Ship quantity is lower, fewer orders are fulfilled through local fulfillment, thus increasing the promised delivery time, resulting in less revenue and reducing profit.

We now explore the impact of ignoring the demand shift from backup fulfillment across observations. Figure 3.8 plots the Pre-Ship quantity difference relative to the profit difference for each observation when the demand shift is ignored in the Pre-Ship decision. We immediately see that

Figure 3.8: Profit Impacts of Ignoring Demand Shift for Backup Fulfillment



large profit differences align with when the suboptimal Pre-Ship quantity is much smaller than the optimal Pre-Ship quantity. Given that $D^B < D^L$ results in less overall demand, we may intuitively think instead that the optimal Pre-Ship quantity should be smaller so that $Q^e_{D^B=D^L} > Q^e$. But since the price is generally larger than the local fulfillment costs in our data, the manager will optimally increase the Pre-Ship quantity when made aware of a demand shift from backup fulfillment to capture more demand locally for observations in the quadrants discussed in the counterfactual from Section 3.6.1. When price is not larger than local fulfillment costs, the manager will not adjust the Pre-Ship quantity, thus resulting in little profit impact when ignoring the demand shift from backup fulfillment.

We also see in Figure 3.8 that large profit differences generally align with certain regions, where regions 24, 4, and 9 have observations with the largest profit differences. In the next section we explore DC-level impacts to better understand which regions are impacted by the ability to leverage front DCs.

3.6.3 Identifying DCs for Investment

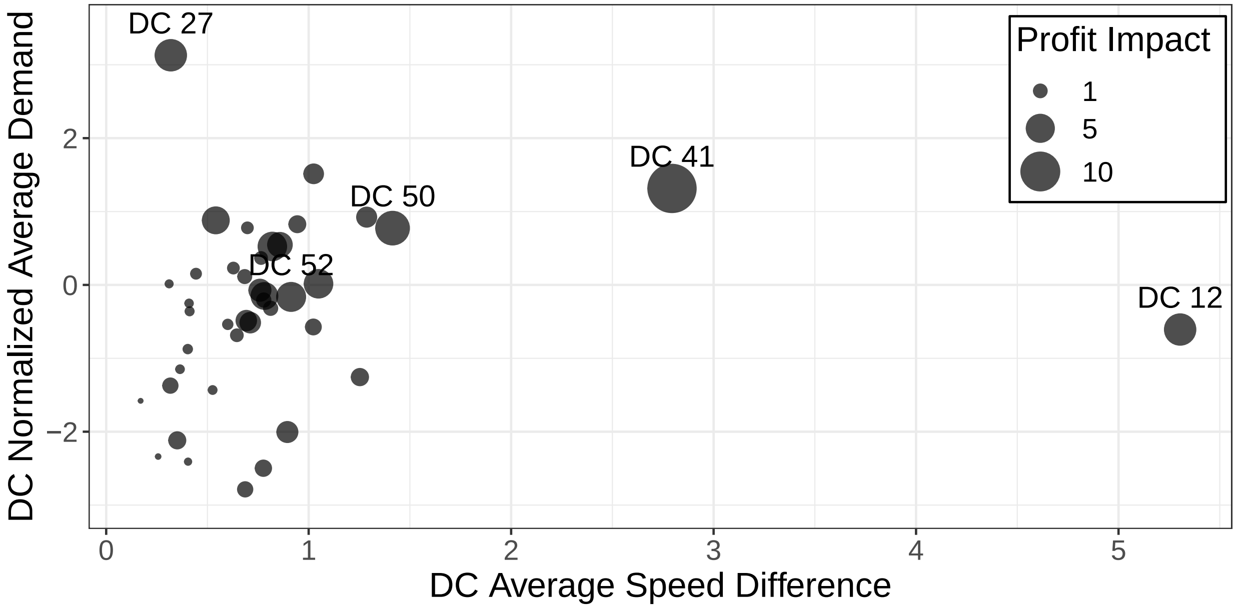
In this section we leverage our model to help identify the best DCs for investment to improve local fulfillment. We consider a scenario where JD.com may consider reducing holding costs through such improvements as capacity expansions, or state-of-the-art additions such as installing robots to automate warehouse inventory handling (Azadeh et al., 2019). Specifically, we examine the operational implications if JD.com were able to halve the holding costs observed in the data of certain DCs. Thus, we simulate a counterfactual equilibrium with $h = .5\hat{h}$ to compare to the equilibrium predicted in the data.

Examining the third row in Table 3.5, we can see that on average reducing holding costs by half results in a 38.3% increase in Pre-Ship quantity, leading to a 3.0% reduction in average promised delivery time and a 3.5% increase in average profit. Thus, reducing holding costs leads to meaningful operational benefits in general.

We now turn to investigating the impacts to specific front DCs from halving holding costs. Figure 3.9 presents the average profit impact per front DC resulting from halving holding costs, relative to the front DC's average Speed Difference and average normalized Demand, according to the labels presented in Section 3.6.1.[12] The largest bubbles identify DCs 41, 27, 12, 50, and 52 as

[12]To normalize demand we use the standard formula $v = (x - \bar{x})/s$, where x is the value of Demand, $\bar{x}$ is the average

Figure 3.9: Average DC Profit Impacts by Estimated Demand and Speed Difference



the DCs with the largest opportunity to improve profit. In general, we can see that the best DCs for investment involve DCs with large opportunities to improve differences between backup and local promise delivery speed, as well as those DCs with large local demand to capture more sales by improving delivery speed. As the correlation between holding costs and the profit impact is 0.25, again we can see investment in front DCs should consider the demand-side benefits to revenue of local fulfillment in addition to reducing expenses from local fulfillment costs.

3.7 Robustness Checks

We now run a set of robustness checks.

First, it is possible that normalizing unobserved next-period Pre-Ship inventory to be large in the final period overstates profit. Instead, we exaggerate the impact of the last period and set next-period Pre-Ship inventory to zero and re-compute the predicted equilibrium. The average Pre-Ship quantity reduces relative to the predicted equilibrium from 1.22 to 1.16 and average profit reduces from 69.02 RMB to 68.87 RMB. Since this impact only occurs in the final period, the overall impacts are minimal.

value of Demand across DCs, and s is the standard deviation of Demand across DCs.

Second, in our counterfactual regarding ignoring delivery speed differences, we considered a scenario where the manager considers the backup speed to be the same as the local delivery speed. Alternatively, we could set both speeds according to the average across local and backup delivery speeds. We find the average Pre-Ship quantity impact changes from a reduction of 69.8% to a reduction of 71.3% and the profit impact changes from a reduction of 6.8% to a reduction of 6.9%. Thus the impacts are minimal. Note the manager does slightly better assuming faster delivery because negative impacts result from under-utilizing faster delivery speeds of front DCs, as discussed in Section 3.6.2.

Third, in our counterfactual to identify front DCs for investment we halved holding costs. Since reducing holding costs by a factor of $K = .5$ reduces costs more for front DCs with high holding costs, we could alternatively adjust holding costs by some constant L so that $h = \hat{h} - L$. We choose $L = 10$. We find the average Pre-Ship quantity impact changes from an increase of 38.3% to an increase of 25.8% and the profit impact changes from an increase of 3.5% to an increase of 1.9%. Thus the magnitude of the impacts may differ based on whether investments reduce holding costs by a factor or a constant. Related to our research question for identifying DCs for investment, DC 41 remains the best front DC for investment, and the top 5 DCs for investment all remain in the top 10.

Fourth, we inspect the importance of incorporating rebalancing costs into the model through a counterfactual analysis and simulations, since rebalancing costs are not included in the Pre-Ship model of Li et al. (2019). Based on analysis in Appendix B.7, we see that on average ignoring rebalancing costs does not have a large impact on profit, but these costs should be included in the model generally to account for observations where rebalancing costs may be important.

3.8 Conclusion

Improving delivery time to improve sales through distribution centers closer to the customer has been a source of competitive advantage for the most successful e-commerce companies (Zhu and Sun, 2019; Caro et al., 2020). Yet quantifying the benefits of managers leveraging these front DCs in practice remains under-explored. Further, the extant models for inventory decisions assume demand is exogenous to the inventory decision, despite acknowledging faster delivery speed impacts demand (Perakis et al., 2020). In this work we built and estimated a structural model in the context of JD.com that addresses these nuances to answer our research questions.

Based on our estimated primitives, customers are sensitive to promised delivery time which the central planner attempts to capitalize on through inventory in front DCs. In practice, we find that the use of front DCs allows the manager to improve average promised delivery time by 28.3%, resulting in more than 10.7% increased average profit. The largest gains come from high-margin, high-demand SKUs where front DCs dramatically improve delivery speed. When delivery speed differences between the front DC and regional DC are ignored, the planner places too little inventory in the front DC from under-utilizing the benefits of front DCs. Our model also shows that considering these delivery speed differences provides insight into which front DCs are best for investing in increasing capacity, beyond focusing on front DCs with the highest inventory costs. These insights supplement the existing OM literature that discusses the importance of service level on impacting demand (Craig et al., 2016), where in e-commerce improved service level allows for improving delivery speed to better capture demand.

To the best of our knowledge, this is the first work to empirically examine the managerial decision of fulfilling demand locally or leveraging backup fulfillment as it shifts demand according to increased delivery time in a multi-warehouse fulfilment context. A few extensions could be considered for future research. Our model focused on the daily inventory decisions, but could be extended to work in conjunction with models with decisions at a lower frequency such as monthly inventory allocation decisions or at a higher frequency such as minute-to-minute fulfillment decisions (Chen and Graves, 2021). Additionally, incorporating inventory constraints on SKU availability or DC capacity is an extension to the model that could capture tensions across stocking DCs in the entire network (Perakis et al., 2020). In principle the extension is straightforward through Lagrangian duality to use approaches that leverage the gradient such as simulation-based gradient ascent (Van Mieghem and Rudi, 2002), log-barrier methods (Ouorou et al., 2000; Wright, 2005), or directly using the Karush-Kuhn-Tucker conditions (Perakis et al., 2020). Since our work requires estimating the parameters in addition to solving the model, the increased computation makes the extension outside of the scope of this work under current computational resources. Last, the strategic decision of where to place front DCs also seems promising. One notable structural paper, Holmes (2011), examines where to place Walmart distribution centers for brick-and-mortar fulfillment, but we note that the fulfillment impacts are different for brick-and-mortar and online retailers. Our model can help inform e-commerce practitioners and future researchers on both tactical and strategic decisions on how to best leverage front DCs to improve operational outcomes.

CHAPTER 4: INCENTIVIZING RECYCLING TO IMPROVE SUSTAINABILITY: EVIDENCE FROM FIELD EXPERIMENTS

4.1 Introduction

Corporate social responsibility (CSR) initiatives continue to grow in importance for retailers (McKinsey, 2021), but the impact to customer choices remains an open question (Caro et al., 2020). One specific area of focus for CSR initiatives is the circular economy, which has been an increasing area of focus for retailers (McKinsey, 2021; Walmart, 2017; Agrawal et al., 2021) due to the economic potential of trillions of dollars (*McKinsey Quarterly*, 2017; Accenture, 2017; Agrawal et al., 2019). While study of the supply-side of the circular economy such as developing industrial systems, designing circular processes, and transitioning to circular business models has gained recent attention in the operations management (OM) literature (Agrawal et al., 2019; Atasu et al., 2008; Savaskan et al., 2004; Agrawal et al., 2021), the demand-side of attracting customers to participate in the circular economy has received little attention.

Yet the need to understand how to encourage customers to participate has become increasingly important as companies begin programs to incentivize customers to return their products. Some companies offer incentives for the customer to return the product in an attempt to extract value directly from the return through means such as reuse, refurbishing, remanufacturing, recycling, or resale. A few examples include Patagonia WornWear, Nike Reuse-a-Shoe, and Apple Trade-in (Leighton, 2020; Martin, 2019). Other companies partner with non-profit recycling organizations and incentivize customer returns to achieve sustainability goals, meet regulatory requirements, or improve brand reputation. Examples of these include North Face Clothes-the-Loop and The Body Shop Return-Reycle-Repeat (Leighton, 2020; Martin, 2019). In this paper, we attempt to empirically quantify customer sensitivity to incentives when engaging in sustainable returns programs.

We partner with Logitech, a consumer electronics company interested in improving its corporate sustainability goals (Logitech, 2021) by understanding how its customers respond to incentives to return products to be recycled. As a consumer electronics company, Logitech is specifically interested in recycling behavior of end-of-life electrical and electronic equipment (e-waste) (Atasu and Subramanian, 2012). This category has gained attention recently following the WEEE Directive adopted in the European Union in 2012, and numerous academic studies have documented large variance in recycling rates resulting from household reluctance to recycle e-waste (Shevchenko et al., 2019; Delcea et al., 2020; Litchfield et al., 2018; Ongondo and Williams, 2011). While recycling generally incurs a handoff cost (Bourne et al., 2021; Shevchenko et al., 2019), reluctance to recycle e-waste is heightened by hibernation (Wilson et al., 2017; Bourne et al., 2021), where consumers may retain old products due to perceived residual value or lack of knowledge of how to recycle electronic devices. In particular, customers that perceive economic residual value of the item may require an incentive to induce return behavior. Through an academic partnership, Logitech hoped to gain understanding of the effectiveness of incentives in attracting participation of recycling of e-waste.

Prior academic literature has been limited in providing guidance. E-waste recycling literature has primarily used observational studies to demonstrate that customers respond to value-based incentives (e.g. monetary, environmental, and societal) and convenience-based incentives (e.g. ease of access in recycling) (Viscusi et al., 2011; Shevchenko et al., 2019; Barile et al., 2015). Where recycling behavior determinants are studied, the effect sizes are often captured by intentions from survey-based work (e.g., Delcea et al., 2020; Yin et al., 2014; Dixit and Vaish, 2015) instead of measuring the behavior directly. In general, observational studies may invalidly support conclusions that result from unknown variables, leading to misleading insights for organizations like Logitech that wish to implement recycling programs. On the other hand, randomized field experiments are the "gold standard" to allow for insight into how a manipulation causes a change in behavior, with valid inference for causality (Fisher et al., 2020; Wu and Hamada, 2011). Furthermore, existing studies focus on interactions between an individual and a recycling organization, with little guiding evidence for businesses like Logitech that want to build recycling programs into sustainability efforts. Thus, through field experiments our study provides needed empirical evidence of the causal impacts of a business using different incentives to improve recycling behavior, to inform which incentives are most appropriate.

Specifically, we seek to answer the following research questions in our study: 1) To what extent do incentives impact customer e-waste recycling behavior? 2) Between value-based and convenience-based incentives, which should be considered in an e-waste recycling program?

Like many field experiments, our key challenges involved designing an experiment that could be executed within Logitech's business constraints while ensuring valid experimentation. First, Logitech did not have an existing return process for recyclable e-waste, and did not want to add on to existing in-store return processes at retailers due to the complications from COVID-19. Instead, we help build a mail-based return process where the customer receives an initial email with details regarding the incentive provided if they return the product for recycling, then the customer chooses to proceed (or not) by filling out an online survey, and then the customer receives a prepaid shipping label with instructions to mail the return to a partner recycling facility. The initial email is displayed randomly based on an industry standard of A/B testing, where a different version of the email is randomly presented to customers depending on the treatment (Mullin, 2020). Second, it was unclear which electronics products should be considered, as accepting all types of electronics product would be prohibitively costly for a pilot experimental study. Given the program would leverage mail-based returns, the electronics item would need to be relatively light to reduce shipping costs. This led us to focus on returns of headphones, a category that has not been well-studied relative to other types of electronic waste such as mobile phones (Litchfield et al., 2018; Ongondo and Williams, 2011). Third, it was unclear who to target for the email campaign. In the first experiment, Logitech targeted an email list of past customers, similar to other email-based promotions (Sahni et al., 2017), but developed concerns that many of these customers either may not consider recycling or may not have products to recycle. To overcome this concern, in the second experiment we help design a process for Logitech to collect a list of emails through a survey on social media that initially does not mention recycling. Logitech only targets those customers that explicitly state interest in recycling and have end-of-life headsets to recycle. Last, feasibility for Logitech to execute the experiment guided our choices of number of treatments (limited sample size) as well as the type and value of incentives (limited budget).

The key results are as follows. In our first experiment, we are unable to induce recycling behavior when providing a modest value-based (environmental) incentive of planting trees if the customer returns the end-of-life headset by dropping off at a FedEx location. In the second experiment, when we introduce a convenience-based incentive to offer to pay for a FedEx pick-up, again we are unable to induce recycling behavior. Thus, we conclude that either the environmental incentive would need to be increased, the environmental incentive may need to be used in conjunction with the convenience-based incentive, or monetary incentives should be explored over non-monetary incentives (Singh et al., 2019; Shevchenko et al., 2019; Stern, 1999).

Our study makes the following contributions. First, we take an operational approach to bolster insights from the existing recycling literature by documenting the difficulty of driving recycling behavior in the field. Even when we observe a large number of participants that explicitly state the desire to recycle, it may not translate to recycling behavior. Further, despite the literature documenting value-based and convenience-based incentives as driving reycling intention (Shevchenko et al., 2019), these incentives may not induce the recycling behavior as expected. These insights add to the known difficulties in the OM literature of implementing reverse logistics (Fleischmann et al., 1997; Savaskan et al., 2004) by shedding light on the difficulty to facilitate consumer participation. Second, our results suggest that organizations offering programs to encourage e-waste recycling behavior can be a costly endeavor. Examining the monetary costs of Logitech's recycling program, shipping costs for a package up to one pound through FedEx costs roughly \$3 per returned electronic (FedEx, 2022) and planting 10 trees costs up to \$10 per returned electronic (National Forest Foundation, 2022). Inducing recycling behavior would require an even costlier incentive. These funds could be redirected to encouraging other promising models in the circular economy outside of recycling such as servicizing and leasing (Agrawal et al., 2021). Third, our study examines a recycling program promoted by a business, a context that has received little attention in the literature relative to recycling programs promoted by recycling organizations. Our study provides insights to other companies considering implementation of recycling programs to improve sustainability goals.

4.2 Relevant Literature

Our work studies how consumers respond to incentives offered by a business to recycle end-of-life electrical and electronic equipment (e-waste), building on prior literature of the circular economy, recycling behavior of e-waste, and recycling behavior response to incentives.

4.2.1 Circular Economy

The circular economy is defined by the European Union (European Parliament, 2015) as:

> *a model of production and consumption, which involves sharing, leasing, resusing, repairing, refurbishing, and recycling existing materials and products as long as possible.*

Recent OM literature suggests that transition to the circular economy can be better achieved through circular product design, such as making products more durable or more recyclable, and circular business models, such as leasing or servicizing products (Agrawal et al., 2021). Improving economic and environmental outcomes through circular design (Savaskan et al., 2004; Ferrer and Swaminathan, 2006; Debo et al., 2005) and circular business models (Agrawal and Bellos, 2017; Guide Jr and Van Wassenhove, 2009; Girotra and Netessine, 2013) has a rich history in the OM literature. While the rich theories proposed have started to gain traction in industry, in practice companies largely still operate on a take-make-dispose basis (McKinsey, 2016). Explanations for prevalence of the take-make-dispose mentality include customer adverse selection and/or low valuations of used products (Hendel and Lizzeri, 1999; Waldman, 2003) and costly enhancements required to implement circular design (Waldman, 2003; McKinsey, 2016).

Although recycling is often seen as a last resort in circular economy principles (McKinsey, 2016), recycling allows for a take-make-dispose mentality when changing consumer behavior to engage in new circular business models is a tall order (Agrawal et al., 2017). Curbside recycling has become mainstream in the United States (The Recycling Partnership, 2020), and e-waste recycling rates have increased internationally, particularly in Europe (Delcea et al., 2020). Still, e-waste recycling rates remain underwhelming and academics have started to recognize the need to increase customer participation in recycling schemes since the customer serves a special role both as consumer and waste holder (Shevchenko et al., 2019). In this paper, we focus on providing empirical evidence for how to encourage customer participation in the circular economy through e-waste recycling behavior.

4.2.2 Recycling Behavior of E-Waste

Recycling of e-waste has received recent attention in the recycling literature (Shevchenko et al., 2019). One key element of e-waste recycling is hibernation (Wilson et al., 2017; Bourne et al., 2021), where consumers may retain old products due to perceived residual value or lack of knowledge of how to recycle electronic devices. This leads to lower recycling rates compared to products such as aluminum cans with more transparent degradation in residual value (Bourne et al., 2021), despite the fact that production of products generating e-waste continues to increase rapidly (Shevchenko et al., 2019). Understanding how to overcome the additional challenge of hibernation when developing recycling programs remains an area of interest (Bourne et al., 2021) that we seek to understand empirically.

Empirical papers in the recycling literature interested in determinants of household recycling of e-waste have been primarily observational. The review by Shevchenko et al. (2019) presents 27 research studies of determinants of e-waste recycling behavior. Most of these studies are survey-based (e.g., Yin et al., 2014; Delcea et al., 2020; Thi Thu Nguyen et al., 2019; Wagner, 2013) or involve field studies primarily focusing on mobile phones (e.g., Litchfield et al., 2018; Ongondo and Williams, 2011). These studies document that key determinants of e-waste recycling behavior include awareness, convenience, pro-environmental intrinsic value, and monetary reward. But the documented determinants are not tested in the field to be leveraged directly for policy implementation. We leverage field experimentation to test which determinants most drive e-waste recycling behavior.

Existing OM literature on e-waste recycling is generally related to understanding the impact of recent law and regulation implementations (e.g., Atasu and Subramanian, 2012; Esenduran et al., 2019; Dhanorkar and Muthulingam, 2020). For example, Atasu and Subramanian (2012) examine the implications to firm behavior of product take-back laws that are designed to reduce the environmental impacts of e-waste products. Since these papers are focused on how companies respond to regulation, these papers do not give insight into how a business can encourage its customers to recycle e-waste products. To fill this gap, we seek to understand how a business can encourage its customer to recycle e-waste by offering incentives.

4.2.3 Recycling Behavior Response to Incentives

How consumers respond to incentives to engage in prosocial behavior has been studied in both the OM literature (Gneezy et al., 2012) and the economics literature (Barile et al., 2015; Stern, 1999; Ariely et al., 2009). There is also a stream of literature specifically examining the impact of incentives to recycling behavior, a type of prosocial behavior. Several of the nudges discussed in the e-waste category have been examined in other recycling categories such as monetary incentives in garbage collection (Thogerson, 2003) and aluminum can collection (Allen et al., 1993), and convenience-based importance in curbside recycling programs (Best and Kneip, 2011). Since e-waste recycling behavior is inherently different due to hibernation (Wilson et al., 2017), our study provides empirical evidence on how customers specifically respond to incentives when recycling e-waste.

Within the recycling literature outside of e-waste, the majority of work is either observational (e.g., Viscusi et al., 2011; Best and Kneip, 2011) or analytical (e.g., Stern, 1999; Thogerson, 2003). We have only found one study that leverages a randomized field experiment, related to aluminum can collection (Allen et al., 1993). Thus, our work adds to the greater recycling literature by providing empirical evidence through field experiments of how customers respond to incentives to recycle.

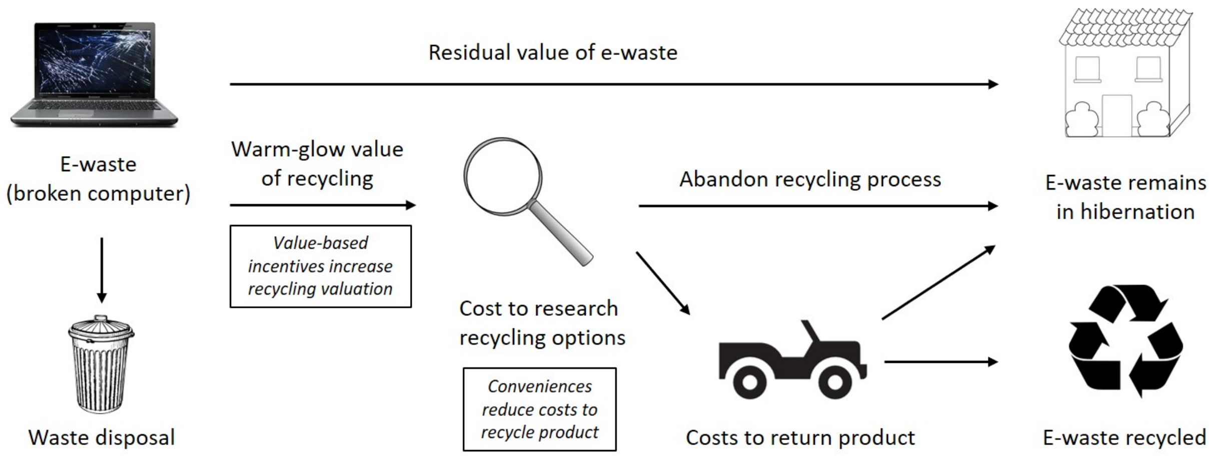
4.3 Theory for the Recycling Decision and Hypothesis Development

We first present a theory for how consumers make a decision in whether to engage in e-waste recycling behavior when provided a recycling program. Then we develop our hypotheses to test empirically.

Our discussion of the recycling decision in the e-waste context is motivated by discussion from Viscusi et al. (2013)[1] in the general context of household recycling behavior. Figure 4.1 provides an overview of the discussion that follows. The recycling decision depends on the mix of consumer purchases, where disposal through recycling is conditional on items in the consumer's household

[1]As mentioned in Viscusi et al. (2013), the discussion is similar in other environmental economics papers that focus on the recycling stage decision such as Kinnaman and Fullerton (2000), Jenkins et al. (2003), and Beatty et al. (2007).

Figure 4.1: Consumer E-waste Recycling Decision



inventory that can be returned. In the e-waste context, household inventory of items that can be returned are hibernating end-of-life items that are not actively being used (Bourne et al., 2021). These e-waste products have some perceived residual valuation to prevent the customer from disposing through a waste channel.

Assuming the customer has an e-waste product in household inventory for recycling, the customer has an inherent "warm-glow" valuation for recycling the product instead of disposing through waste disposal (Viscusi et al., 2013). To capture the warm-glow valuation incurs costs to the customer by engaging in the recycling process. To commence in the recycling process requires the customer to incur time commitment costs of gaining awareness of the options for recycling to forecast the additional time costs to complete the recycling process (Shevchenko et al., 2019; Viscusi et al., 2013). These initial informational costs may be larger than the warm-glow benefits so that the customer ends the recycling process upon new information (Stern, 1999). Once the customer is aware of the costs to recycle the product, the customer then incurs additional time commitment costs and receives the warm-glow benefit following completion of the recycling process (Viscusi et al., 2013). In other words, we distinguish recycling behavior as two pieces: commencing the process to understand how to recycle the e-waste product, and completing the recycling process by returning the e-waste product. The customer's intention to recycle aligns with the warm-glow benefit and can be revealed by consumer actions that do not incur costs from engaging in the recycling process. Self-reported recycling valuations through surveys would align with recycling intention as the customer does not engage in the recycling porcess (Delcea et al., 2020). Our study captures measures of recycling intention and recycling behavior. Experimentally we focus on impacts to recycling behavior as recycling intention has been studied extensively in the literature.

Note that in the e-waste context, in order for the customer to commence the recycling process, the warm-glow valuation must be greater than the costs to recycle the product in addition to the perceived residual value of the product. Otherwise, the customer will retain the electronic in household inventory, similar to how the customer avoided using waste disposal channels previously. As discussed in household recycling contexts, the warm-glow benefit may not be sufficient to induce recycling behavior so the organization managing the recycling program may offer incentives to drive customers to recycle (Viscusi et al., 2011). Value-based incentives (e.g., monetary, environmental, societal) provide additional benefit to completing the recycling process and convenience-based incentives reduce the costs of completing the recycling process (Viscusi et al., 2011; Shevchenko et al., 2019). Providing these incentives upfront may also increase the propensity of the customer to commence in the recycling process.

To summarize, the customer's recycling decision progresses for e-waste as: 1) an acknowledgment of intrinsic warm-glow valuation to recycle a relevant e-waste product, 2) commencing the recycling process by incurring costs to gain awareness of the costs to recycle (which may shift when presented conveniences and value-based incentives), and 3) completing the recycling process through return of the product, incurring additional time commitment costs (potentially reduced through conveniences) while capturing the benefit of the warm-glow valuation (potentialy increased with value-based incentives).

4.3.1 Hypothesized Impact of Incentives to Recycling Behavior

In this section we present hypotheses for how we expect customers to respond to incentives to participate in Logitech's recycling program. We specifically examine the impact of environmental incentives and convenience-based incentives.

Our first hypothesis explores the impact of an environmental incentive on recycling behavior. Dixit and Vaish (2015) document environmental incentives such as offering to plant trees and donating to charity as incentives that would promote recycling behavior. Literature has also documented that customers have a "warm-glow" benefit when engaging in a prosocial behavior (Barile et al., 2015), which should be heightened when the customer's recycling behavior contributes to additional proenvironmental outcomes. Thus, we expect offering to plant trees should promote recycling behavior, leading to our first hypothesis:

Hypothesis 1. *The propensity for customers to participate in e-waste recycling increases when an environmental incentive is provided.*

Our next hypothesis examines the impact of offering a more convenient option. The importance of convenience in recycling has been well-documented (Viscusi et al., 2011; Wagner, 2013; Dixit and Vaish, 2015; Shevchenko et al., 2019). Since customers realize a time and effort cost to recycle (Viscusi et al., 2011), the type of access to recycle could reduce effort costs leading to increased recycling behavior. Further, Best and Kneip (2011) argues that curbside recycling schemes have lower behavioral costs to recycling than a drop-off system which may result in higher recycling rates. Thus, we expect that providing a convenience-based incentive should promote recycling behavior, leading to our second hypothesis:

Hypothesis 2. *The propensity for customers to participate in e-waste recycling increases when the return option is more convenient.*

We note that it is possible for our empirical study to support conclusions contrary to our hypotheses supported by theory in the literature, implying that answering these hypotheses is necessarily an empirical question. First, it is possible for the chosen incentives to be ineffective at driving recycling behavior. Viscusi et al. (2011) describe the distribution of household recycling behavior by corner solutions in which people tend either not to recycle at all or to be diligent recyclers. The incentives offered must increase value or reduce effort costs enough for consumer recycling utility to pass an unobserved threshold – but reaching this threshold may not be feasible due to constraints of our study in the field. Second, some treatment effects may be returned negative. While our sense is this would not occur given prior studies in the e-waste literature documenting the positive effects of incentives to recycling behavior (Shevchenko et al., 2019), it is possible that consumers perceive "nudges" negatively due to such factors as "green-washing" where the customers believe the nudge is not altruistic but instead firm-benefiting (Lyon and Maxwell, 2011). Or customers may experience a "crowding out" demotivation where the value to behave altruistically is diminished by the receipt of a reward (Frey, 1994; Frey and Oberholzer-Gee, 1997). Last, it is also possible that an informational effect occurs in the way that information is presented to the customer that dominates the anticipated effects of the incentives (Stern, 1999).

4.4 Empirical Setting and Data

4.4.1 Empirical Setting

We partner with Logitech, a large company that sells consumer electronics products. Since Logitech sells direct-to-consumer online, we focus on the retail-side of Logitech in how it interacts directly with its customers. Logitech was specifically interested in improving its corporate sustainability goals (Logitech, 2021) by understanding how its customers respond to incentives to return products to be recycled. As a consumer electronics company, Logitech was specifically interested in recycling behavior of end-of-life electrical and electronic equipment (e-waste) (Shevchenko et al., 2019). Logitech hoped to gain understanding of the effectiveness of incentives in attracting participation of recycling of e-waste.

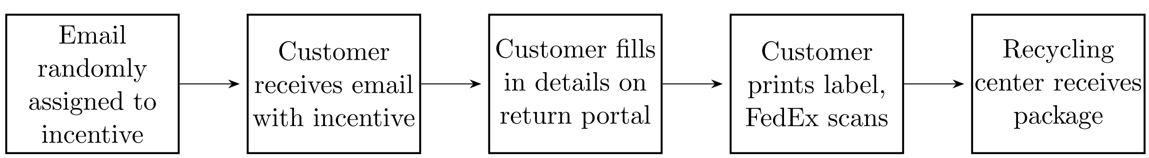
We focus on one specific product line, headsets. Logitech sells a variety of headsets with prices ranging from \$50 to \$300 (Logitech, 2022). Prior to working with us, however, a recycling program for headphones was not in place to collect old headsets to recycle. To test whether incentives impact recycling behavior, we first helped our partner retailer develop a workflow of how a returns process would work, with more details in Section 4.4.2. To implement the returns process workflow, our retailer had to set up partnerships with a returns provider (i.e. FedEx) and a recycling organization (i.e. MRM) to facilitate the workflow. Once the workflow was established, we needed to decide who would be eligible for the program to determine scope of the number of returns and cost of incentives offered. In one experiment, we leverage a sample of prior customers, whereas in the other experiment we leverage social media to narrow down the participant list to those who have headsets to recycle. More details are in Section 4.4.3. We then design a set of experiments to test the hypothesis presented earlier in Section 4.3.1, with more details in Section 4.4.4. Last, in Section 4.4.5 we describe the data provided to us both before and after the experiments. Throughout the experiment all customer information was de-identified from the research team, and we received approval from UNC IRB and INSEAD IRB for the study.

4.4.2 Returns Process

In this section we outline the returns process. We leverage a mail-based return process where Logitech pays for the carrier fee to mail the product to a recycling center. The mail-based return process has two key advantages. First, a mail-based return process can be implemented easily without setting up infrastructure in retail locations to allow for pilot experiments like ours. Second, a mail-based process allows for initiating the process electronically via email where the shipping label provides transactional information on whether or not the customer returned a product for recycling, without requiring another step from the recycling center.[2]

The steps in the returns process occur as follows. Figure 4.2 outlines the returns process that was put in place for the purposes of the experiments. First, we randomly assign customers to

Figure 4.2: Diagram of Returns Process



treatments according to the design in each experiment (Section 4.4.3 outlines how participants are chosen). Next, the customer receives an email from our partner retailer informing them of the ability to recycle the product by mailing it in (see Section 4.4.4 for more details). Our partner retailer pays the shipping costs of the return on behalf of the participant and allows returns of any end-of-life headphones in any condition. Next, if the customer chooses to return a headset, then the customer clicks a link to enter a returns portal hosted by our partner retailer. The customer fills out required information to generate the shipping label such as US Zip Code, as well as additional information for analysis such as what brands are being returned and prior recycling experience (the specifics of the survey are outlined in more detail in Appendix C.3). After completing the

[2]While manual data collection can occur by reviewing received packages at the recycling center, we preferred the in-place automation of transactions tracked through FedEx.

questionnaire in the returns portal, the customer receives a shipping label with instructions on how to return the product (see Appendix C.4 for more detail on the instructions). Once the customer follows the directions for the return, the carrier scans the shipping label provided. Finally, the recycling center receives the package and recycles it.

4.4.3 Selecting Sample of Participants

In this section we outline how we select participants to be eligible for the recycling program.

In the first experiment, we leverage an email distribution list from Logitech including prior customers. We choose prior customers as a starting point following other literature that has investigated email-based promotions (Sahni et al., 2017). The email distribution list has approximately 50,000 customers, but due to costs from incentives and shipping we limit the potential sample to 1,000 customers for our pilot experiment.

In the second experiment, concerned that the sample might be composed of customers who either do not want to recycle (Allen et al., 1993) or may not have hibernating end-of-life devices (Wilson et al., 2017), we send out a social media announcement to solicit responses through a new headset giveaway. Importantly, the social media announcement makes no statement regarding recycling, whereas the survey that the customers are directed to includes questions regarding whether the customer has a headset to recycle and whether the customer would potentially consider recycling their headset. Figure C.1 in Appendix C.1 shows the questions asked in the survey.

The survey received 435 responses. We focus on only those customers who have headsets to recycle (62%), have interest in potentially recycling (91%), live in the United States to be eligible for the FedEx mail-back program (70%), and opt-in to future communications (90%). In total, this gives a total sample of 172 participants (40%).

4.4.4 Experiment Design

The customer's exposure to treatment occurs at the point of receiving an initial email, where the email offers a randomly selected invective to recycle. Practitioners often refer to this as A/B testing (Mullin, 2020). We now outline the design of each experiment.

4.4.4.1 First Experiment Testing Environmental Incentive

Our pilot experiment tests the impact of an environmental incentive relative to receiving no incentive. Using the 1,000 emails as outlined in Section 4.4.3, we randomly divide into 500 emails in the no incentive treatment (control group) and 500 emails in the environmental incentive treatment. Due to the fact that a recycling returns process had not been set previously, we did not have information on the approximate effect sizes of different treatments to choose the sample size required for appropriate power. Appendix C.5 provides details on our preliminary power analysis for why we believed our sample size was sufficient prior to the experiment.

Our partner chooses the environmental incentive to be 10 trees planted. One benchmark of how customers might perceive the economic value of 10 trees planted is the National Forest Foundation, who plant one tree for one dollar (National Forest Foundation, 2022).

For brevity, we present here the initial email for the environmental incentive and provide the initial email for no incentive in Appendix C.2. Figure 4.3 shows the email customers received when offered the environmental incentive. A few key elements can be noticed within the email. First, the trees are only planted when the customer returns a headset to be recycled, within two weeks of receiving the email. Next, headsets from any brand in any condition can be returned. Finally, preliminary instructions are provided for how the customer returns the headset. Given the nature of the pilot study we did not pre-register the design, but we do pre-register the design of the second experiment.

4.4.4.2 Second Experiment Introducing Convenience-based Incentive

The second experiment tests the impact of a convenience-based incentive in addition to the other treatments of offering an environmental incentive and offering no incentive. Using the 172 emails as outlined in Section 4.4.3, we randomly divide into 58 emails in the no incentive treatment (control group), 57 emails in the environmental incentive treatment, and 57 emails in the convenience-based incentive treatment. We set the control group to receive overflow when the sample cannot exactly be divided equally (Athey and Imbens, 2017).

Once again, the environmental incentive of 10 trees planted is provided along with the control group, using the same emails described previously. This time, however, a convenience-based option

Figure 4.3: Initial Email Offering Environmental Incentive

is offered in addition. The customer is provided the option to drop off the package themselves (as provided in the other treatments) or schedule a pickup of the package from their house. While pickup options have been described as being more convenient to the customer (Dixit and Vaish, 2015), we wanted to offer convenience in the form of flexibility in case the drop-off option was in fact more convenient for certain customers. Appendix C.2 additionally provides the initial email for the convenience-based incentive. Our pre-registered design can be found at: `https:`

//aspredicted.org/VMH_NQW. Since we were unable to receive purchase data (as detailed in Section 4.4.5), the discussion on those potential analyses is removed from the paper.

4.4.5 Data

Our partner provides the following information prior to and after the experiment.

Prior to the experiment, we receive data related to each customer. For the first experiment, additional information related to email distribution, including the number of emails the customer opened, the number of clicks within emails opened, and the number of days since the customer opened an email. While these metrics are not purchase metrics, in terms of brand engagement, they resemble recency, frequency, and value information that have been documented as observable indicators for future customer behavior (Sahni et al., 2017; Simester et al., 2009). In Appendix C.6, we leverage these observable characteristics to provide confidence that proper randomization occurred. For the second experiment, additional information was provided from Qualtrics including the time to complete the pre-survey, the time to start the survey since receiving it, and the zip code of the respondent.[3] Similar to in the first experiment, in Appendix C.6 we leverage these observable characteristics to provide confidence that proper randomization occurred.

Following the experiments our partner provides the following data. First, we receive aggregated click data for how many clicks occurred for each treatment email. Next, we receive data from the return portal for those customers that choose to recycle headsets. We also receive the scan data from FedEx when the return occurred, which we leverage as the response variable for whether the customer recycled the product. Due to internal concerns of data privacy of consumer financial information, we are not provided sales data following the experiments for the participants in the study.[4]

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[3] We leverage census data to assign zip codes to four US regional locations.

[4] Specifically we request purchase quantity and purchase value for 30 and 60 days following the initial email. Purchase information could be useful to see if positive branding effects resulted from the recycling program beyond the recycling behavior, and could provide business justification for incurring costs in the recycling program.

4.5 Empirical Approach

4.5.1 Measuring Impacts to Recycling Behavior

We now outline how we estimate the impact of each incentive to recycling behavior. Our goal is to estimate the average treatment effect for a given incentive j based on our response variables of interest. We choose two sets of response variables to gauge whether the incentive induces recycling behavior.

First, we measure whether the participant i commences in recycling behavior. We measure commencing in recycling behavior based on whether the customer clicks the initial email or not to reach the returns portal ($Click_i$), after opening the email. Since the same subject line is sent regardless of the incentive, the impact of the treatment does not occur until the email is opened. Importantly we distinguish this from inherent intention to recycle, which we capture before the incentives are offered. For both experiments we can measure intention to recycle based on the number that open the email (as the incentive has not yet been presented). In the second experiment, we can additionally measure intention to recycle based on the initial survey response.

Second, we measure whether the participant completes the recycling process. We measure completed recycling behavior based on whether or not the participant returns a package that is scanned by FedEx ($Return_i$).

Now we formalize how we measure the treatment effects. Suppose customer i can either receive treatment $j \in \{1, \ldots, J\}$ or receive no treatment denoted $j = 0$ (i.e. in the control group). In general, for a response variable Y_i, our goal is to causally estimate the average treatment effect:

$$\theta_j = E[Y_{ij} - Y_{i0}] \text{ for } j = 1, \ldots, J$$
$$\text{and } Y \in \{Click, Return\}$$

Under randomization, we can provide model-free evidence by examining the average difference between categories that received treatment and those that did not, e.g. $\theta_j = \bar{Y}_j - \bar{Y}_0$ (Athey and Imbens, 2017). We supplement model-free evidence with model specifications to test statistical significance for each hypothesis. Section 4.6 provides the results.

4.5.2 Model Characterization

For each dependent variable, we leverage a linear-in-parameters binary choice model which follows from the models for reycling behavior where customers only choose to engage in prosocial behavior if a certain unobserved threshold in utility is reached (Viscusi et al., 2011; Wooldridge, 2002). We leverage a linear probability model for ease of interpretation, and test the robustness of our results to a probit model (Viscusi et al., 2011).

4.5.2.1 Propensity to Commence in Recycling Behavior

We first model the propensity of customer i to commence in the process to recycle their end-of-life electronic.

Let k denote the experiment under study, where $k \in \{1, 2\}$ for experiment one and experiment two respectively. For the first experiment with covariates $x_i^{(1)}$, let $\alpha_{E10}^{(1)}$ denote the environmental treatment effect to the participant to commence in recycling observed in the first experiment, and let $\mathbb{1}[E_{10}]$ be an indicator function to denote whether the participant was offered an environmental incentive of 10 trees. For the second experiment, let $\alpha_{E10}^{(2)}$ similarly denote the environmental treatment effect observed in the second experiment. Additionally, let $\alpha_{pickup}^{(2)}$ denote the treatment effect of the convenience-based incentive observed in the second experiment, and let $\mathbb{1}[pickup]$ be an indicator function denoting whether the participant was offered the convenience-based incentive of additional flexibility through a pickup option. Then, our model specifications for consumer intention to recycle in experiment one and experiment two ($k = 1, 2$ respectively) become:

$$
\begin{aligned}
P(Click_i^{(1)} = 1|x_i^{(1)}) &= \alpha_0^{(1)} + \alpha_{E10}^{(1)}\mathbb{1}[E_{10}] + \epsilon_i^{(1)} \text{ for } k = 1 \\
P(Click_i^{(2)} = 1|x_i^{(2)}) &= \alpha_0^{(2)} + \alpha_{E10}^{(2)}\mathbb{1}[E_{10}] + \alpha_{pickup}^{(2)}\mathbb{1}[pickup] + \epsilon_i^{(2)} \text{ for } k = 2
\end{aligned}
$$

where the intercept $\alpha_0^{(k)}$ represents the average participant's baseline propensity to commence in recycling (based on the control group) and $\alpha_j^{(k)}$ denotes the additional propensity to commence in recycling when offered incentive $j \in \{E_{10}, pickup\}$, in experiment k. Idiosyncratic errors that our model cannot capture through observed covariates are represented by $\epsilon_i^{(k)}$. The specification preserves the benefits of the randomized experimental design, thus providing an explicit control for unobserved factors that may occur through $\epsilon_i^{(k)}$.

4.5.2.2 Propensity to Complete the Recycling Process

Our specification of consumer propensity to complete the recycling process follows a similar form to the prior section as a binary choice model. Let $\beta_{E10}^{(1)}$ denote the environmental treatment effect to consumer propensity to complete the recycling process observed in the first experiment, and let $\mathbb{1}[E_{10}]$ be an indicator function to denote whether the participant was offered an environmental incentive of 10 trees. For the second experiment, let $\beta_{E10}^{(2)}$ similarly denote the environmental treatment effect observed in the second experiment. Additionally, let $\beta_{pickup}^{(2)}$ denote the treatment effect of the convenience-based incentive, and let $\mathbb{1}[pickup]$ be an indicator function denoting whether the participant was offered the convenience-based incentive of additional flexibility through a pickup option. Then, we specify the propensity to complete the recycling process for consumer i faced with incentive j in experiment k as

$$
\begin{aligned}
P(Return_i^{(1)} = 1|x_i^{(1)}) &= \beta_0^{(1)} + \beta_{E10}^{(1)}\mathbb{1}[E_{10}] + \eta_i^{(1)} \text{ for } k = 1 \\
P(Return_i^{(2)} = 1|x_i^{(2)}) &= \beta_0^{(2)} + \beta_{E10}^{(2)}\mathbb{1}[E_{10}] + \beta_{pickup}^{(2)}\mathbb{1}[pickup] + \eta_i^{(2)} \text{ for } k = 2
\end{aligned}
$$

where $\beta_0^{(k)}$ represents the average participant's baseline propensity to complete the recycling process (based on the control group) and $\beta_j^{(k)}$ denotes the additional propensity to complete the recycling process when offered incentive $j \in \{E_{10}, pickup\}$, in experiment k. Idiosyncratic errors that our model cannot capture through observed covariates are represented by $\eta_i^{(k)}$. As before, the specification preserves the benefits of the randomized experimental design, thus providing an explicit control for unobserved factors that may occur through $\eta_i^{(k)}$.

4.6 Results

4.6.1 Model-Free Evidence

In this section we present model-free evidence for the treatment effects of interest. Table 4.1 shows the outcomes from each experiment. As can be seen across all treatments, a large percentage of participants open the initial email, but the number that click within the email drops

Table 4.1: Model-free Evidence of Impact of Incentives to Recycling Behavior

Treatment	Number Sent[a]	Percent Opened[b]	Percent Clicked[c]	Percent Returned
Experiment 1				
No incentive	500	31.6%	0.7%	0.0%
Environmental	500	26.0%	1.6%	0.0%
Experiment 2				
No incentive	58	55.3%	3.1%	0.0%
Environmental	57	42.5%	0.0%	0.0%
Pickup	57	46.8%	7.4%	0.0%

[a] While 1000 are sent in experiment 1, 20 emails bounce in each category, so we use the number after bounced emails for calculating Percent Opened.

[b] The email subject line is the same across all treatments, so the impact of treatment does not occur until opening the email.

[c] We calculate Percent Clicked based on the number that opened, as the process does not differ across treatments until the email is opened.

off dramatically, and ultimately none of the participants return the product to be recycled. A small percentage of customers commence the recycling process by clicking to the returns portal whereas none complete the recycling process by returning an e-waste product. Thus, this supports the idea that customers want to recycle, but the actual behavior does not align with their intentions.

Regarding our treatment effects, differences across Percent Clicked and Percent Returned by treatment in Table 4.1 provides model-free evidence of our treatment effects. In the first experiment the environmental incentive leads to a slight increase in click percentage, whereas in the second experiment the click percentage is less than the control. Thus, the results of the first experiment support our first hypothesis, whereas the results of the second experiment do not. In the second experiment, the convenience-based incentive of a pickup option increases the click percentage by more than double. This supports our second hypothesis. In both experiments, no effect occurs toward completing the recycling process, contrary to the effects for commencing the recycling process. To properly make conclusions regarding these effects, we investigate these effects statistically through our model.

4.6.2 Impact of Incentives to Recycling Behavior

Now we statistically examine the impact of the incentives to recycling behavior. Recall we examine the impacts towards recycling behavior in two ways: first the impact to customers commencing the recycling process (clicking forward to understand the process) and second the impact to customers completing the recycling process (returning the e-waste product).

We start with examining the impact of the incentives to customers commencing the recycling process. Table 4.2 presents the regression results from our model specifications of the impact of incentives to commencing the recycling process. Columns (1) and (2) present the linear probability

Table 4.2: Regression Results for Impact to Clicks

	Dependent variable:			
	Clicks			
	OLS		*probit*	
	(1)	(2)	(3)	(4)
$\alpha_0^{(k)}$	0.007	0.031	-2.479^{***}	-1.863^{***}
(intercept)	(0.008)	(0.033)	(0.355)	(0.437)
$\alpha_{E10}^{(k)}$	0.009	-0.031	0.335	-4.056
(environmental)	(0.013)	(0.051)	(0.453)	(16.544)
$\alpha_{pickup}^{(k)}$		0.043		0.417
(pickup)		(0.049)		(0.566)
Observations	277	83	277	83
R^2	0.002	0.025		
Log Likelihood			-16.275	-11.579
Note:				*p<0.1; **p<0.05; ***p<0.01

model for experiment one and experiment two, respectively; columns (3) and columns (4) present the specifications as a probit model as a robustness check. We can see that none of the treatment coefficients are significant in the linear probability models, which is supported in the probit models.

While Section 4.6.1 suggested mixed results from the environmental incentive, we see that the treatment effects are insignificant meaning that the environmental incentive does not drive customers to commence in recycling behavior. Similarly, the impact of the convenience-based incentive is insignificant despite Section 4.6.1 suggesting a positive impact. Thus, across both experiments we conclude that the environmental incentives and convenience-based incentives under consideration do not drive recycling behavior.

Next we consider the impact of the incentives to customers completing the recycling process by returning an e-waste product. Based on the model-free evidence, there are no returns in the data so we do not need to leverage our model to determine that all of our hypotheses are rejected. As there is no variation in recycling outcomes as a result of the incentives being introduced, mathematically our model cannot conclude that incentives lead to changes in recycling return behavior.

4.6.3 Discussion

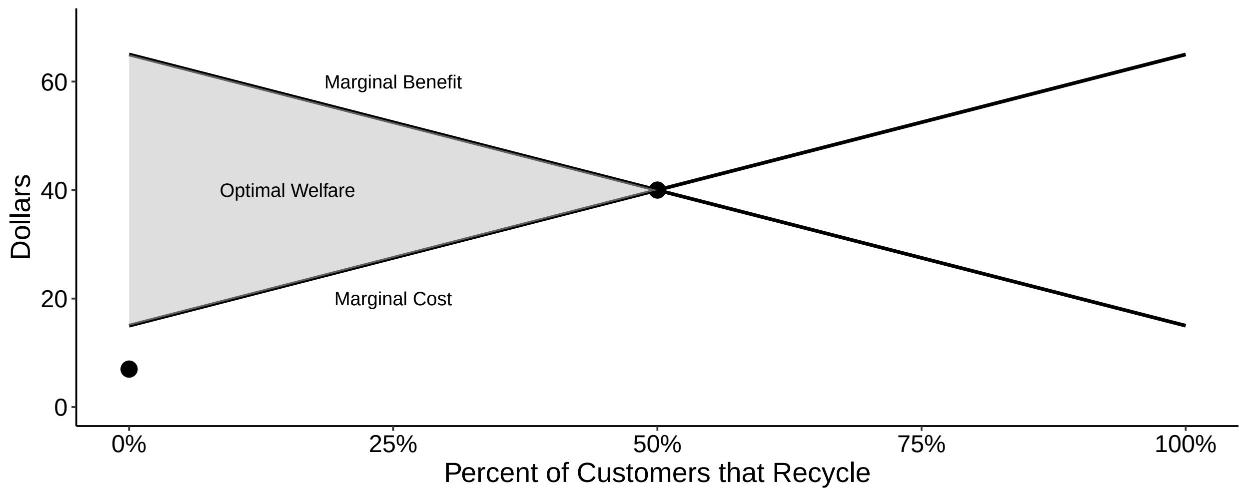
The prior section presented evidence suggesting which incentives induce changes in behavior. In our study the incentives under consideration were ineffective in driving recycling behavior. These results are despite the fact that customers have a clear intention to want to recycle, as across both experiments 25-55% of customers opened the initial email. Further, in collecting participants in the second sample, 91% of Logitech customers explicitly state a desire to recycle, and 62% of the customers have a headset to recycle. As stated in the existing literature, it is clear that customers have a desire to recycle and there is clear evidence of hibernation. But our study shows these intentions do not translate into action for e-waste through a company's recycling program.

Following Viscusi et al. (2011), recycling behavior can be characterized by corner solutions in which people tend either not to recycle at all or to be diligent recyclers. The incentives offered must increase value or reduce effort costs enough for consumer recycling utility to pass an unobserved threshold – but reaching this threshold may not be feasible in our study in the field. Within the limitations of our field experiment, these threshold were unable to be met. Future research may be able to increase the incentives offered to induce recycling behavior.

We now present a simple cost-benefit comparison of how a company like Logitech may consider the benefits of the recycling program if larger incentives were considered. Fullerton and Kinnaman (1996) use a figure similar to our Figure 4.4 to represent a simple cost-benefit analysis.

As in Fullerton and Kinnaman (1996), suppose the firm has reducing marginal benefit from

Figure 4.4: Marginal Benefit and Marginal Cost of Recycling Program



consumers returning recycled products as the number of customers that recycle increases. Decreasing marginal benefits may result from the fact that achieving sustainability goals have decreasing marginal benefits to the company once the goal is achieved. Similarly, some returning the product allows to claim the benefits of the recycling program in external reports such as the Annual Sustainability Report (Logitech, 2021), but with diminishing returns. We also consider an increasing marginal cost to collecting recycled products. As customers have differing valuations to return the product as discussed previously, higher-cost incentives will need to be explored to capture customers with lower benefits from recycling. By increasing the value of the incentive, the company can potentially receive optimal welfare benefit at the point of intersection marked in the middle of the figure, resulting in total benefit according to the shaded region.

We have learned that the costs faced by Logitech in the experiment did not induce recycling behavior. Thus, the y-intercept in Figure 4.4 for where recycling behavior begins must be at least as large as the costs faced in our experiment, marked by the point in the bottom-left. The cost for our partner to pay for free shipping to the customer is approximately \$3.00 using standard parcel delivery via FedEx (FedEx, 2022). The additional cost for pick-up is approximately \$4.00 (FedEx, 2022). Based on a partnership with a tree-planting organization, our partner could internally plant the trees for \$0.35 per tree, cheaper than the benchmark of \$1.00 per tree that some companies may face instead (National Forest Foundation, 2022). Since the costs of the environmental incentive and the convenience-based incentive are the same, we can conclude that at least $7 per recycled product is required for Logitech to induce recycling behavior. Logitech internal stakeholders need to evaluate the benefits of the recycling outcomes to formulate the marginal benefit curve and whether it can generate a shaded region of benefit as described in Figure 4.4. How much larger of an incentive is required to achieve the desired recycling outcome is a topic for future study that could leverage the methodology presented in this work.

4.7 Conclusion

With the growing focus of sustainability initiatives for businesses to promote a circular economy, understanding how to encourage customers to participate has become important. Yet academic literature is largely silent on addressing how customers respond to incentives provided by companies to engage in recycling behavior. In this paper we partnered with Logitech to empirically examine how consumers respond to incentives to recycle when offered by a business. We helped design a mail-back returns process necessary to perform the experiments, helped design a process to collect a sample of participants, and designed two field experiments to test the existing theories from literature in an e-waste context.

In the first experiment we tested the impact of an environmental incentive (plant trees) offered as a proenvironmental reward in conjunction with the customer's intrinsic benefit from recycling. In the second experiment we additionally tested the impact of a convenience-based incentive (flexibility for residential pickup). In both cases, we found that the incentives considered are ineffective in isolation in driving recycling behavior, despite importance of these incentives toward recycling intentions reported in the literature (Shevchenko et al., 2019).

While our results do not support our hypotheses, our study highlights the difficulty of inducing customer recycling behavior in the field. Future researchers may be able to examine different incentives or larger incentives to induce behavior to provide a better understanding of how customers respond to incentives to recycle. As the circular economy becomes an increasing focus in practice and in OM literature, studies like ours that quantify how consumers respond to operational strategies proposed in literature can help better understand the feasibility of implementing these strategies in practice.

CHAPTER 5: CONCLUDING REMARKS AND FUTURE RESEARCH

In this dissertation we empirically investigated three recent operational process innovations at retailers. We leveraged the methodologies of structural estimation and field experimentation to allow to investigate the impacts of these innovations with limited historical data. In Chapter 2 we learned that resellers are important to incorporate into the pricing decision, and our model can help inform decisions regarding interactions with resellers. In Chapter 3 we learned that in practice e-commerce retailers capture sizable benefits to profit from utilizing distribution centers closer to the customer to improve delivery speed. Our model can help inform inventory decisions when delivery time based on inventory placement impacts demand. In Chapter 4 we learned in the field that producing recycling behavior through incentives is less straightforward than expected despite customer intentions to recycle. Our study can help other retailers focused on improving sustainable operations to invest in sustainable programs in a financially responsible way.

This dissertation merely scratches the surface for the opportunities on the horizon for study of innovations in retail. As stated in Caro et al. (2020), "the retail sector is perhaps among the first to grasp [technological advances], leading to innovative business practices worth studying." In addition to the areas for research discussed in Caro et al. (2020), other important areas for study include how retailers can better incorporate innovations from machine learning into operations or better incorporate innovations in payment methods such as cryptocurrency. Retail is also uniquely positioned as a bridge at the interface of operations management and marketing because retailers make decisions based on understanding how their customers respond (Caro et al., 2020). Since companies will always need to maintain a competitive advantage in interacting with customers, the study of how retailers can leverage operational innovations will continue to provide for relevant and impactful research.

APPENDICES

APPENDIX A: INTERTEMPORAL PRICING WITH RESELLERS: AN EMPIRICAL STUDY OF PRODUCT DROPS

A.1 Inverting Resale Demand

Recall that the quantity demanded in the resale market is $q^D_{T+1} = M_{T+1}s^R(S_{T+1}, r_{T+1})$. Using the logit form, $s^R(S_{T+1}, r_{T+1}) = \exp(\gamma - \alpha r_{T+1})/(1 + \exp(\gamma - \alpha r_{T+1}))$. The market clearing price occurs where $q^D_{T+1} = q^S_{T+1}$. Inverting this relation for r_{T+1}, we have:

$$
\begin{aligned}
q^S_{T+1} &= M_{T+1}\exp(\gamma - \alpha r_{T+1})/(1 + \exp(\gamma - \alpha r_{T+1})) \\
&\Leftrightarrow \\
q^S_{T+1}/(M_{T+1} - q_{T+1}) &= \exp(\gamma - \alpha r_{T+1}) \\
&\Leftrightarrow \\
r_{T+1} &= \frac{\gamma - \log(\frac{q^S_{T+1}}{M_{T+1} - q^S_{T+1}})}{\alpha}
\end{aligned}
$$

A.2 Specification for Consumer Beliefs

Recall from earlier that we need to specify consumer beliefs to solve the contraction mappings for $W(S_t, p_t)$ in Equation 2.1 and $E[\tilde{r}_t|S_t, p_t]$ in Equation 2.2 from the Model section.

The contraction mappings have four components that are related to consumer beliefs: 1) beliefs on whether the next period is the primary market or the resale market, 2) beliefs on what the next-period inventory will be if the next period is the primary market, 3) beliefs on what the next-period price will be if the next period is the primary market, and 4) beliefs on what the next-period resale price will be if the next period is the resale market.

We start by specifying beliefs on whether the next period is the primary market or the resale market and what inventory will be if the next period is the primary market. In our model, the former is a consequence of the latter: if the firm has nonzero inventory in the next period, then the next period is the primary market; if the firm has zero inventory in the next period, then the next period is the resale market. Thus, to capture both required pieces we define $f(I_{t+1}|S_t, p_t)$ as the consumer's belief on the probability of next-period inventory I_{t+1} given the current state S_t, composed of market size M_t and inventory I_t, and price p_t. Given that inventory and prices are the only pay-off relevant variables that enter the consumer utility function, and that the firm sets prices endogenously to the market size, we assume that the consumer only sets future beliefs based on inventory and price. Thus, the belief for the probability of next-period inventory becomes $f(I_{t+1}|I_t, p_t)$. We specify the belief for next-period inventory as a linear relation based on the current value of inventory, similar to how other works set expectations on a future variable conditional on a one-period lag of the variable (Nair, 2007; Gowrisankaran and Rysman, 2012). Since the majority of consumer purchases at the retailer occur during the "hype" period, we also specify that consumers condition their beliefs on whether the current period is a hype period, represented by the indicator variable $\mathbb{1}_{t=0}$. Then, next-period inventory beliefs can be characterized by an AR process as follows:

$$I_{t+1} = a_0 \mathbb{1}_{t=0} + a_1 I_t + \nu_{t+1}, \nu_{t+1} \overset{\text{iid}}{\sim} \mathrm{N}(0, \sigma_I)$$

We use a left-censored Type I Tobit regression to estimate the parameters for beliefs of inventory transitions, as inventory can never be negative (Wooldridge, 2002). We solve the Tobit regression through maximum likelihood estimation. Once we have estimated the parameters $\hat{a}_0$, $\hat{a}_1$ and $\hat{\sigma}_I$, we can describe the belief for the probability of next-period inventory I_{t+1} as induced by ν_{t+1}, which is distributed as an iid normal random variable. When ν_{t+1} induces a positive value of next-period inventory, $I_{t+1} > 0$, the consumer sets their belief according to the value of induced next-period inventory. So, the pdf of a standard normal random variable, ϕ, captures the belief for the point-mass probability of $I_{t+1} > 0$. When ν_{t+1} induces a negative value of next-period inventory, $I_{t+1} < 0$, the consumer sets their belief to zero because inventory cannot be negative. So, the cdf of a standard normal random variable, Φ, captures the belief for the cumulative probability of all possible $I_{t+1} \leq 0$ induced by ν_{t+1}. Then, the customer's belief on the probability of next-period inventory is

$$f(I_{t+1}|I_t) = \begin{cases} \phi((I_{t+1} - \hat{a}_0 \mathbb{1}_{t=0} - \hat{a}_1 I_t)/\hat{\sigma}_I) & \text{if } I_{t+1} > 0 \\ \Phi((\hat{a}_0 \mathbb{1}_{t=0} - \hat{a}_1 I_t)/\hat{\sigma}_I) & \text{if } I_{t+1} = 0 \end{cases}$$

Now we specify the last two needed components of beliefs on what the next-period price will be if the next period is the primary market and what the next-period resale price will be if the next period is the resale market. As in the case of inventory, we assume that the consumer only sets future beliefs based on inventory and price. We define the consumer's belief of the probability of the next-period price conditional on the current price p_t and whether the next-period inventory is nonzero as $f(p_{t+1}|, p_t, I_{t+1} > 0)$; similarly we define the consumer's belief of the probability of next-period resale price conditional on the current price p_t and whether the next-period inventory is zero as $f(r_{t+1}|, p_t, I_{t+1} = 0)$. We assume that the customer uses a linear relation on both prices and resale prices to condition on whether the current period is a hype period and the current period price. Then, we can characterize our two components of interest as:

$$\{p_{t+1}|I_{t+1} > 0\} = b_0 \mathbb{1}_{t=0} + b_1 p_t + \eta_{t+1}, \eta_{t+1} \overset{\text{iid}}{\sim} \text{N}(0, \sigma_p)$$
$$\{r_{+1}|I_{t+1} = 0\} = c_0 \mathbb{1}_{t=0} + c_1 p_t + \omega_{t+1}, \omega_{t+1} \overset{\text{iid}}{\sim} \text{N}(0, \sigma_r)$$

We estimate the parameters for the beliefs for price and resale price transitions separately using maximum likelihood estimation.[1] Again, we can describe next-period primary market prices p_{t+1} and next-period resale-market prices r_{t+1} as induced by η_{t+1} and ω_{t+1} respectively which are both iid normal random variables. Then, the customer's beliefs on the probability of next-period prices conditional on whether the next period is the primary market are described as

$$f(p_{t+1}|, p_t, I_{t+1} > 0) = \phi((p_{t+1} - \hat{b}_0 \mathbb{1}_{t=0} - \hat{b}_1 p_t)/\hat{\sigma}_p)$$
$$f(r_{t+1}|p_t, I_{t+1} = 0) = \phi((r_{t+1} - \hat{c}_0 \mathbb{1}_{t=0} - \hat{c}_1 p_t)/\hat{\sigma}_r)$$

[1] These specifications are both linear with normally distributed errors. Thus, an ordinary least squares (OLS) regression will return the same estimated parameters, aside from the estimated standard deviation on the error term. We use maximum likelihood estimation to get an estimate for the standard error of the standard deviation of the error term.

Table A.1 presents the estimated values of $\theta_d^b = \{\hat{a}_0, \hat{a}_1, \hat{b}_0, \hat{b}_1, \hat{c}_0, \hat{c}_1, \hat{\sigma}_I, \hat{\sigma}_p, \hat{\sigma}_r\}$ for each product category. The values of $\hat{a}_0$ show that next-period inventory declines significantly more during the hype period, as expected since the majority of sales occur in the hype period. The values of $\hat{a}_1$ show that inventory gradually declines each period by about 1/4 of the prior-period value, conditional on the hype period variable. The values of $\hat{b}_0$ demonstrate that Rompers and Sets are less likely to be marked down following the hype period than Dresses. The values of $\hat{b}_1$ show that prices are expected to remain close to the prior-period value, as expected since 88% of prices remain at the prior-period values. The values of $\hat{c}_0$ show that resale prices are expected to be higher when a stock-out occurs in the hype period. The values of $\hat{c}_1$ show that the expected resale price is about 20% higher than in the primary market, as we would expect from the Data section.

Table A.1: Consumer Belief Parameters by Product Category

		Rompers[a]	Sets[a]	Dresses[a]
Inventory	a_0	-62.133 (2.354)***	-47.361 (2.799)***	-38.626 (2.104)***
	a_1	0.758 (0.015)***	0.722 (0.025)***	0.76 (0.022)***
	σ_I	24.947 (0.593)	16.841 (0.641)	11.787 (0.42)
	Observations	1151	447	479
	LR Index[b]	0.12	0.12	0.151
Price	b_0	1.237 (0.332)***	1.131 (0.474)*	0.812 (0.451)*
	b_1	0.959 (0.005)***	0.964 (0.007)***	0.972 (0.006)***
	σ_p	3.756 (0.088)	3.434 (0.129)	3.184 (0.112)
	Observations	913	353	403
	LR Index[b]	0.424	0.447	0.459
Resale Price	c_0	2.925 (1.384)**	3.949 (2.75)	4.168 (2.614)
	c_1	1.262 (0.028)***	1.2 (0.047)***	1.173 (0.049)***
	σ_r	9.673 (0.443)	9.914 (0.746)	9.155 (0.73)
	Observations	238	94	76
	LR Index[b]	0.265	0.262	0.265

[a] The estimated parameters are presented with their respective (standard errors). Standard errors are computed using the Fisher information matrix.

[b] The LR (Likelihood Ratio) Index is a measure of goodness of fit defined as 1 - (log $\hat{L}$/ log L_0), where log $\hat{L}$ is the log-likelihood of the estimated model, and log L_0 is the log-likelihood under the null hypothesis that all parameters except σ are equal to zero (as presented in Aguirregabiria and Alonso-Borrego (2014)).

[c] ***,**,* denote significance at the .01, .05, .10 significance level, respectively.

A.2.1 Identification of Consumer Belief Parameters

The beliefs parameters for future inventory, price, and resale price are identified by variation in their respective future values. In each regression for beliefs on inventory, price, and resale price, there are $k = 3$ parameters. Since inventory can be censored, there must be at least three observations that stock out in $t > 1$ to identify the inventory belief parameters. For the belief parameters for price there must be at least three observations that do not stock out in the first period, a weaker requirement than identifying the inventory parameters. For the belief parameters for resale price, there must be at least three products with resale prices. Thus, our data easily meets the requirements for identification of the beliefs parameters as our sample has 408 SKUs with resale data, with 65% of SKUs having observations after $t = 1$.

A.3 Derivation of Demand Likelihood Function

In this section we derive the likelihood function presented in Section 2.5.2.2.

We start with deriving the likelihood component for primary market purchases, $f_{q|p,I}$. Recall that purchases in the primary market can come from either consumption decisions or speculation decisions, which we denote q^F_{jt} and q^S_{jt} respectively. However, we do not observe q^F_{jt} and q^S_{jt} directly in the data, but we do observe the total q_{jt}. Therefore, we need a way to formulate the likelihood component using the model's predictions of q^F_{jt} and q^S_{jt}, despite only observing q_{jt}. Our approach is to bundle the model's predictions for consumption and speculation since $q_{jt} = q^F_{jt} + q^S_{jt}$ in the primary market.

From the Model section, the probability of a consumer taking a given action in the primary market is expressed as s^a_{jt}, $a \in \{F, S, W\}$. Thus, we can formulate the probability of purchase as the sum of probability of consumption or speculation actions, $s^F_{jt} + s^S_{jt}$, and the probability of no purchase as the probability of waiting, s^W_{jt}. Since each customer has iid shocks to their utility for each action, the probability of a consumer purchasing is a bernoulli random variable with purchase probability $s^F_{jt} + s^S_{jt}$. Since the shocks are also independent across all customers, the distribution of quantity demanded is a binomial random variable with success parameter $s^F_{jt} + s^S_{jt}$ and number of observations M_{jt} for the market size of customers considering the product. In the final period of the primary market, when the firm stocks out of inventory, demand will be censored so that a simple binomial distribution cannot be used. For the final period in the primary market, we calculate the cumulative probability that the quantity demanded is greater than or equal to the firm's inventory.

This can be computed easily using the cumulative binomial distribution. Hence,

$$f_{q|p,I}(q_{jt}|p_{jt}, I_{jt} > 0; \hat{\theta}_d^b, \theta_d^p) = \begin{cases} \sum_{i=I_{jt}}^{M_{jt}} \binom{M_{jt}}{i}(s_{jt}^S + s_{jt}^F)^i (s_{jt}^W)^{M_{jt}-i} & \text{if } q_{jt} = I_{jt} \\ \binom{M_{jt}}{q_{jt}}(s_{jt}^S + s_{jt}^F)^{q_{jt}} (s_{jt}^W)^{M_{jt}-q_{jt}} & \text{if } q_{jt} \in \{0, 1, \dots, I_{jt} - 1\} \\ 0 & \text{otherwise} \end{cases}$$

Given that our data has potentially large market sizes, the binomial coefficient can be costly to compute. To account for this, we use the well-known and efficient saddle-point approximation for computing probabilities from the binomial distribution (Daniels, 1954).

Now we derive the likelihood component for resale market purchases, $f_{q|r,I}$. Unlike in the primary market, purchases in the resale market come from consumption decisions only, represented by q_{jTj+1}^R. The probability of a consumer taking a given action in the resale market is expressed as s_{jt}^a, $a \in \{R, E\}$. Also, recall from our model that all speculators sell at the market-clearing price so that $q_{jT_j+1} = \sum_{t=1}^T q_{jt}^S = q_{jTj+1}^R$. Because the market-clearing price requires the joint realization of quantity supplied and quantity demanded, we can use conditional probability to separate the joint distribution into the probability of the observed total speculation quantity and the probability of the observed resale demand conditional on the total speculation quantity. The probability of the observed resale demand can leverage the same arguments from the primary market to use the binomial distribution, and censoring is not incorporated because the price clears at the quantity demanded. The probability of the observed total speculation can be specified as $T_j + 1$ convolutions of the pdfs g_{jt} for speculation purchases q_{jt}^S in each period of the primary market $t = 0, 1, \dots, T_j$. However, g_{jt} cannot be simply calculated from a binomial distribution using s_{jt}^S as the probability of success and M_{jt} as the number of trials because censoring in the final period implies that the number of speculation purchases in the final period is dependent on the number of consumption purchases. Instead, we can think of g_{jt} as a *conditional* distribution on the quantity observed, q_{jt}. It turns out that we can express g_{jt} using a "reparameterized" binomial distribution with success probability $s_{jt}^S/(s_{jt}^S + s_{jt}^F)$ and number of trials q_{jt}. For $t < T_j$, $q_{jt} < I_{jt}$ so that censoring is not an issue and Bayes rule can be leveraged to derive the result, which we show in Appendix A.4. For $t = T_j$ we assume that arrivals to the primary market are arbitrary and that purchases deplete inventory based on arrival. In other words, the allocation between consumers that purchase to consume and purchase to speculate is arbitrarily assigned. Then, the conditional distribution of speculation decisions once again follows the same form of a reparameterized binomial. Then,

$$f_{q|r,I}(q_{jT_j+1}|r_{jT_j+1}, I_{jT_j+1} = 0; \hat{\theta}^b_d, \theta^p_d) = \binom{M_{jTj+1}}{q_{jT_j+1}} (s^R_{jTj+1})^{q_{jT_j+1}} (s^E_{jTj+1})^{M_{jTj+1}-q_{jT_j+1}}$$
$$\times (g_{j1} * \cdots * g_{jT_j})(q_{jT_j+1})$$

where $(f_1 {*} f_2)$ denotes the convolution of functions f_1 and f_2, and $g_{jt}(k; q_{jt}, s^S_{jt}, s^F_{jt}) = \binom{q_{jt}}{k}[s^S_{jt}/(s^S_{jt} + s^F_{jt})]^k[s^F_{jt}/(s^S_{jt} + s^F_{jt})]^{q_{jt}-k}$ follows from a binomial with success parameter $s^S_{jt}/(s^S_{jt} + s^F_{jt})$ and number of trials q_{jt}. Since each pdf of speculation decisions in the primary market is binomial, we can use efficient and accurate approximations to the convolution of binomials to improve computation (Butler and Stephens, 2017). We use a second-order saddlepoint approximation (see Eisinga et al., 2013). In our application we found the approximation performs on the order of 100 times faster than exact computation while maintaining very high accuracy.

Now that we have all pieces of our likelihood function, we combine all products, using $\log(\cdot)$ as it preserves monotonicity, to solve the joint log likelihood problem for θ_d

$$\max_{\theta_d} l(\theta_d) = \sum_j \log(L(\boldsymbol{q_j}|\boldsymbol{I_j}, \boldsymbol{p_j}, r_j; \hat{\theta}^b_d, \theta_d))$$

Our likelihood function requires computing market shares in the primary market s^a_{jt}, $a \in \{F, S, W\}$, which incorporate strategic behavior for beliefs on the expected resale price and the value of waiting. The value of waiting, $W(S_t, p_t)$, will change at each guess of the primitives because the value of future consumption changes. To account for this, we estimate consumer primitives through a Nested Fixed Point Algorithm (NFXP) (Rust, 1987) where the inner loop solves a contraction mapping for the value function for waiting - conditional on consumer beliefs, the expected resale price, and the choice of the primitives - and the outer loop solves for the primitives that maximize the likelihood of purchase decisions in the data. Appendix A.5 outlines the computational procedure used to estimate the primitives $\theta_d = \{\gamma, \gamma^0, \alpha, \tau\}$.

A.4 Derivation of conditional distribution of speculation purchases as reparameterized binomial when $T < T_j$

In this section we show that the distribution of the quantity of speculation purchases given the total quantity purchased in a given period is a reparameterized binomial when $T < T_j$ with success probability $s^S_{jt}/(s^S_{jt} + s^F_{jt})$ and number of trials q_{jt}. Recall that when $T < T_j$, $q_{jt} < I_{jt}$ so that censoring is not an issue and we can simply examine the quantity demanded for each action to purchase for consumption, purchase for speculation, or wait. Also recall that purchases come from the sum of quantity demanded for consumption and speculation, so that $q_{jt} = q^F_{jt} + q^S_{jt}$, and that consumers that do not purchase wait, so that $q^W_{jt} = M_{jt} - q_{jt}$. Further, recall that the sum of consumption actions and speculation actions is distributed as a binomial random variable with success parameter $s^F_{jt} + s^S_{jt}$ and number of trials M_{jt}. Due to symmetry of a binomial random variable, the sum of waiting actions is distributed as a binomial with success parameter s^W_{jt} and number of trials M_{jt}. Dropping the t, j subscripts, leveraging these relations and using Bayes rule, we have that

$$\begin{aligned}
P(\tilde{Q}^S = q^S|q) &= P(\tilde{Q}^S = q^S, \tilde{Q}^F = q - q^S|q) \\
&= P(\tilde{Q}^S = q^S, \tilde{Q}^F = q - q^S|\tilde{Q}^W = M - q) \\
&= \frac{P(\tilde{Q}^S = q^S, \tilde{Q}^F = q - q^S, \tilde{Q}^W = M - q)}{P(\tilde{Q}^W = M - q)} \\
&= \frac{\frac{M!}{q^S!(q-q^S)!(M-q)!}(s^S)^{q^S}(s^F)^{q-q^S}(s^W)^{M-q}}{\frac{M!}{(M-q)!q!}(s^W)^{M-q}(s^F + s^S)^q} \\
&= \frac{\frac{M!}{q^S!(q-q^S)!(M-q)!}(s^S)^{q^S}(s^F)^{q-q^S}(s^W)^{M-q}}{\frac{M!}{(M-q)!q!}(s^W)^{M-q}(s^F + s^S)^{q^S+q-q^S}} \\
&= \frac{q!}{q^S!(q - q^S)!}\left[\frac{s^S}{s^S + s^F}\right]^{q^S}\left[\frac{s^F}{s^S + s^F}\right]^{q-q^S}
\end{aligned}$$

A.5 Demand Estimation Procedure

We perform the following routine to estimate our demand parameters $\{\theta^b_d, \theta^p_d\}$.

1. Estimate beliefs parameters θ^b_d using OLS and left-censored Type I regressions.

2. Stack $T_j + 1$ observations for each product. Discretize the states for consumer beliefs P, I, R, $\mathbb{1}_{t=0}$ forming $|P| \times (|I| - 1) \times 2 + |R| \times 2$ dimensional vector to represent grid $\mathcal{G}$. Add a no-payoff terminating state to which all resale periods transition with probability 1.
3. Compute transition matrix $\mathcal{T}_\mathcal{G}$ using θ_d^b.
4. Approximate $E[\tilde{r}|S, p]$ at grid points using $(I - \delta_c \mathcal{T}_\mathcal{G})^{-1} c$ where $c(i) = r_i$, $r_i \in R$.[2]
5. Set tolerance $\kappa = .000001$. Guess at preference parameters $\theta_d^{(n)}$.
6. Approximate $W^{(n)}$ through iteration on the contraction mapping:
   (a) Initialize $W_\mathcal{G}^{(n,0)} = 0$ at each point in $\mathcal{G}$
   (b) Compute $W_\mathcal{G}^{(n,k)}$ using $W_\mathcal{G}^{(n,k-1)}$ and transition matrix $\mathcal{T}_\mathcal{G}$
   (c) Iterate (b) until $|W_\mathcal{G}^{(n,k)} - W_\mathcal{G}^{(n,k-1)}| < \kappa$
7. Compute market shares s_t^a where $a \in \{F, S, W, R, E\}$ to compute demand $\tilde{Q}_t^{(n)}$.
8. Compute $l(\theta_d^{p,(n)})$. Repeat steps 5-8 to solve $\hat{\theta}_d^p = \arg\max_{\theta_d^p} l(\theta_d^p)$.

We discretize the state space for consumer beliefs into 30 uniform grid points in each of the price and inventory dimensions based on the minimum and maximum values observed in the data. Appendix A.9 provides details on how to form the transition matrix for consumer beliefs based on a given discretization. This makes $|\mathcal{G}| = 1801$, so that $\mathcal{T}_\mathcal{G}$ has 3.2 million elements. Similar to as discussed in Judd (1998) we approximate the transition matrix by assigning probability mass to intervals defined by our discretization. Probability mass is assigned based on the cumulative density functions for ν, η, ω which are distributed as iid normal random variables with estimated standard deviations. In other words, we can describe next-period variables $I_{t+1}, p_{t+1}, r_{t+1}$ as induced by $\eta_{t+1}, \nu_{t+1}, \omega_{t+1}$ respectively. We approximate the resale price function and waiting function by solving on the grid points and then use functional approximation for values between the grid points. For ease of computation, we use multi-linear interpolation, but other approaches such as Chebychev polynomials or splines could be used (see Judd, 1998). To solve the maximization problem we use the Nelder-Mead method as proposed in other contexts (e.g. Lee, 2013; Judd, 1998, Algorithm 4.3).

[2] We choose to use matrix algebra to solve the contraction mapping for $E[\tilde{r}|S, p]$ as the vector c is fixed from consumer beliefs on resale prices.

A.6 CCP formulation

In this section we provide additional details on our CCP formulation.

We begin with modifying our model to allow for the firm's discrete choice in prices. In discretizing the pricing decision, we select uniformly spaced prices with endpoints from the minimum and maximum prices observed in the data. Let $D = \{p^1, \dots, p^D\}$ be the set of hypothetical price levels in a given period. Define $\xi_t^d \equiv \xi_\beta(p_t^d)$. Now, the firm's one-period payoff function for hypothetical price $p^d \in D$ becomes:

$$\pi(S_t, p_t^d, \xi_t^d) = \pi(S_t, p_t^d)^e + \xi_\beta(p_t^d)$$

where $\{\xi_\beta(p^d) : p^d = 1, \dots, D\}$ are iid location-zero Gumbel random variables with scale parameter $\beta > 0$ that will need to be estimated.

Under the CCP approach, the firm optimally makes a discrete choice in price. Recall from equation 2.4 in the Model section that the firm's pricing policy maximizes profit across a (theoretically) infinite horizon. Through its pricing decision in the current period, the firm impacts the evolution of its future stream of profits. The strategic nature of the firm is captured through a *value function*. We define $v(S_t, p_t; \theta_u)$ as the choice-specific value function that the firm would expect to receive from its pricing decision today, p_t, in state S_t if it priced optimally in the future, prior to the realization of its unobserved private shock. We refer the reader to Aguirregabiria and Mira (2010) for a thorough discussion on deriving $v(S_t, p_t; \theta_u)$ in the CCP framework.

Since the unobserved shocks are Gumbel, we can use the logit form to represent the firm's choice probabilities across pricing decisions. Our conditional choice probabilities for each decision are expressed as

$$P(p_t^d | S_t; \theta_u, \beta) = \frac{\exp(v(S_t, p_t^d; \theta_u)/\beta)}{\sum_j \exp(v(S_t, p_t^j; \theta_u)/\beta)}$$

Using the conditional choice probabilities we can now build a likelihood function for the pricing decisions in the data at a given parameter value. We form the PML (pseudo-maximum likeklihood) estimator from Aguirregabiria and Mira (2010) as:

$$Q(\theta_u, \beta) = \sum_{j=1}^{J} \sum_{t=1}^{T_j} \log P(p_{jt}^d | S_{jt}; \theta_u, \beta)$$

A.7 Supply Estimation Procedure

Our supply-side estimation strategy can be summarized as:

1. Stack $T_j + 1$ observations for each product. Discretize the state-price decisions for the firm M, I, $\mathbb{1}_{t=0}, P_{t-1}$, P forming $|M| \times |I| \times 2 \times |P_{t-1}| \times |P|$ dimensional vector to represent grid $\mathcal{G}$. Add a no-payoff terminating state to which the primary market transitions with probability 1 when $I = 0$.
2. Compute choice-specific value functions conditional on the supply-side parameters $v(S, p; \theta_u)$ (We refer the reader to Aguirregabiria and Mira (2010) for details on computing $\mathbf{\Pi}_{\mathcal{G}}(p^d)$, $\boldsymbol{e}_{\mathcal{G}}(p^d)$, $\boldsymbol{W}_{\boldsymbol{\mathcal{G}}}^{\boldsymbol{P}}$):
   (a) Using the approximated functions for expected resale price and waiting from the demand side, compute expected demand based on pricing decisions. Use expected demand to compute transition matrix $\hat{\boldsymbol{F}}_{\mathcal{G}}(p^d)$.
   (b) Estimate in-sample CCP's, $\hat{\boldsymbol{P}}_{\mathcal{G}}(p^d)$, non-parametrically.
   (c) Compute model-payoff functions $\mathbf{\Pi}_{\mathcal{G}}(p^d)$, $\boldsymbol{e}_{\mathcal{G}}(p^d)$.
   (d) Solve for policy policy operator $\boldsymbol{W}_{\boldsymbol{\mathcal{G}}}^{\boldsymbol{P}}$ to compute $v(S, p^d; \theta_u)$.
3. Guess at supply-side parameters $\{\theta_u^{(n)}, \beta^{(n)}\}$.
4. Compute $Q(\theta_u^{(n)}, \beta^{(n)})$. Repeat steps 3-4 to find $\{\hat{\theta}_u, \hat{\beta}\} = \arg\max_{\theta_u,\beta} Q(\theta_u, \beta)$.

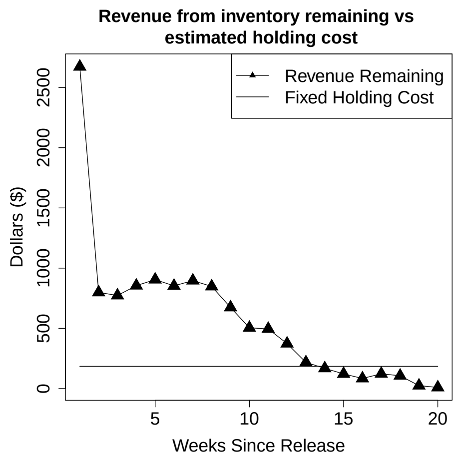
We discretize the state space for inventory, market size, and prices respectively into 12,4,8 uniform grid points based on the minimum and maximum values observed in the data within each product category. The available price decisions are eight to align with the number of grid points for lagged price. This makes $|\mathcal{G}| = 6145$, so that $\mathcal{T}_{\mathcal{G}}$ has 37.8 million elements. We choose fewer grid points in each dimension because the number of dimensions has increased, and will need to increase by an additional state in the equilibrium computation to track the number of resellers to clear the resale market. We choose the highest number of grid points in the states that most affect the estimation routine, noting that additional grid points from what we set do not substantially change the estimated parameters. We obtain consistent estimates of $\hat{\boldsymbol{P}}_{\mathcal{G}}(p^d)$ using nonparametric kernel density estimation using Guassian kernel smoothing with the bandwidth matrix selected from Silverman's rule of thumb. We estimate at the actual data points and then evaluate at the discrete points as suggested in Hotz and Miller (1993) and Aguirregabiria (1999). To solve the maximization problem we use the Nelder-Mead method as in demand estimation.

A.8 Discussion of estimated values of $\hat{\iota}, \hat{\mu}$

We first discuss the estimated value of $\hat{\iota}$. Consider a "usual" markup in retail of 50% (Peacock, 2020) on cost to make and ship the product. Assuming a 50% markup on cost of capital, with an average price of 28.59 from the Data section, the firm's weekly variable holding cost is about 9.8% of cost of capital, which is in-line with estimates in other studies. While the context is different, we compare to the results in Aguirregabiria (1999) since our model builds on that model. The monthly holding cost of his first model is 33.44. Using a 50% markup on cost of capital and converting to weekly by dividing by 4, the holding costs reflect roughly 1.8%., 4.6%, 7.4% of weekly cost of capital, conservatively using the highest price of Diapers (698), Wine Carta de Plata (272), and Maria Bisquits (169) respectively. Using the mean prices instead of the highest prices would make the cost of capital even larger.

Now we discuss the estimated value of $\hat{\mu}$. Considering only fixed holding costs, a rule of thumb for when the firm will need to reduce its price to stockout is when the fixed holding cost becomes larger than the expected revenue from inventory remaining. Figure A.1 plots the average expected revenue from inventory remaining (average price in period times average starting inventory in period) observed in the data against the fixed holding cost estimated in the model. We can see that after period 14 (where recall from the Data section only 10% of SKUs remain in inventory after period 11), fixed holding costs become larger than revenue from inventory remaining in the period. Thus $\hat{\iota} = 185.30$ is a reasonable value for fixed holding costs in this context. The firm faces price adjustment costs that are larger than the fixed holding costs, explaining why some SKUs remain in inventory even when holding costs outweigh revenue gained.

Figure A.1: Comparison of when holding cost outweighs revenue from inventory remaining



A.9 Forming Consumer Beliefs Transition Matrix

In this section we provide the steps to create the transition probability matrix for consumer beliefs to compute $E[\tilde{r}_t|S_t, p_t]$ and $W(S_t, p_t)$ through either iteration or matrix algebra. For expositional convenience we ignore the hype period in this discussion, which could be easily added as the cross-product with a binary variable. We define $p > 0$ if $I > 0$ and $r > 0$ if $I = 0$. Let $(p, I) \in \mathcal{P} \times \mathcal{I} \backslash \{0\}$ be a two-tuple element in the cross product of the supports of prices and nonzero inventory. Let $(r, 0) \in \mathcal{R} \times \{0\}$ be a two-tuple element in the cross product of the support of resale prices and zero inventory. Let $(0, 0)$ be an absorbing two-tuple to which all $(r, 0)$ two-tuples transition to with probability 1. Stack all (p, I) and $(r, 0)$ so that $\mathcal{E} = \{\mathcal{P} \times \mathcal{I} \backslash \{0\} \cup \mathcal{R} \times \{0\} \cup (0, 0)\}$ is the state space of all consumer beliefs of transitions of prices and inventory. Then, we can define a transition matrix

$$\mathcal{T}_{\mathcal{E}} \text{ s.t. } \alpha_{ij} = P(\{x_{t+1}, y_{t+1}\} = j \ |\{x_t, y_t\} = i), \forall (x_t, y_t) \in \mathcal{E}$$

where α_{ij} would be computed from the joint probabilities of either $f(p_{t+1}, I_{t+1}|p_t, I_t, I_{t+1} > 0)$ or $f(r_{t+1}, I_{t+1} = 0|p_t, I_t)$. Using the functional forms of consumer beliefs, defined earlier, we can write

$$\begin{aligned} f(p_{t+1}, I_{t+1}|p_t, I_t, I_{t+1} > 0) &= f(p_{t+1}|p_t, I_{t+1} > 0) f(I_{t+1}|I_t, I_{t+1} > 0) \\ f(r_{t+1}, I_{t+1} = 0|p_t, I_t) &= f(r_{t+1}|p_t, I_{t+1} = 0) f(I_{t+1} = 0|I_t) \end{aligned} \tag{A.1}$$

The transition matrix is currently defined abstractly to allow for continuous supports of $\mathcal{P}, \mathcal{I}, \mathcal{R}$. For estimation we will need to discretize the supports to allow for a matrix of finite dimensions. Suppose that we discretize $\mathcal{E}$ finitely into $\mathcal{G}$ in some fashion. As an example, consider the transition matrix $\mathcal{T}_\mathcal{G}$ below:

$$
\begin{array}{c}
\\
(p_H, I_H) \\
(p_L, I_H) \\
(p_H, I_L) \\
(p_L, I_L) \\
(r_H, 0) \\
(r_L, 0) \\
(0,0)
\end{array}
\begin{array}{c}
\begin{array}{ccccccc}
(p_H, I_H) & (p_L, I_H) & (p_H, I_L) & (p_L, I_L) & (r_H, 0) & (r_L, 0) & (0,0)
\end{array} \\
\begin{pmatrix}
\alpha_{11} & \alpha_{12} & \alpha_{13} & \alpha_{14} & \alpha_{15} & \alpha_{16} & 0 \\
\alpha_{21} & \alpha_{22} & \alpha_{23} & \alpha_{24} & \alpha_{25} & \alpha_{26} & 0 \\
\alpha_{31} & \alpha_{32} & \alpha_{33} & \alpha_{34} & \alpha_{35} & \alpha_{36} & 0 \\
\alpha_{41} & \alpha_{42} & \alpha_{43} & \alpha_{44} & \alpha_{45} & \alpha_{46} & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 1 \\
0 & 0 & 0 & 0 & 0 & 0 & 1 \\
0 & 0 & 0 & 0 & 0 & 0 & 1
\end{pmatrix}
\end{array}
$$

where: $\mathcal{G} = \{(p_H, I_H), (p_L, I_H), (p_H, I_L), (p_L, I_L), (r_H, 0), (r_L, 0), (0, 0)\}$. Now, α_{ij} will be defined as the probability across the interval of discrete points (see Judd, 1998, Chapter 3 for a similar approach). Create an ordering in the grid of $O^K = \{K_1, \ldots, K_N\}$ for each $K \in p, r, I$. For example, let the ordering of prices be $O^p = \{p_1, \ldots, p_N\}$, for $p_i \in \mathcal{P}$. For a given K_i in O^K, define the lower endpoint of the interval as $\underline{K}_i = -\infty$ for $i = 1$ and $\underline{K}_i = K_{i-1}$ for $i = 2, \ldots, N$; define the upper endpoint of the interval[3] as $\bar{K}_i = K_i$ for $i = 1, \ldots, N-1$ and $\bar{K}_i = \infty$ for $i = N$. Thus, we form the transition probability from one point on the grid to another point on the grid as:

$$
\begin{aligned}
f^\mathcal{G}(p_{t+1}, I_{t+1}|p_t, I_t, I_{t+1} > 0) &= f^\mathcal{G}(p_{t+1}|p_t, I_{t+1} > 0) f^\mathcal{G}(I_{t+1}|I_t, I_{t+1} > 0) \\
&= \int_{\underline{p}_{t+1}}^{\bar{p}_{t+1}} f(p_{t+1}|p_t, I_{t+1} > 0) dp \int_{\underline{I}_{t+1}}^{\bar{I}_{t+1}} f(I_{t+1}|I_t, I_{t+1} > 0) dI
\end{aligned} \tag{A.2}
$$

[3]We integrate over the interval endpoints because $I_t = 0$ is economically meaningful whereas $I_t < 0$ is not.

$$f^{\mathcal{G}}(r_{t+1}, I_{t+1} = 0|p_t, I_t) = f^{\mathcal{G}}(r_{t+1}|p_t, I_{t+1} = 0) f^{\mathcal{G}}(I_{t+1} = 0|I_t)$$
$$= \int_{\underline{r}_{t+1}}^{\bar{r}_{t+1}} f(r_{t+1}|p_t, I_{t+1} = 0) dr \int_{-\infty}^{0} f(I_{t+1} = 0|I_t) dI \qquad \text{(A.3)}$$

As an example, consider the first element of the example transition matrix $\mathcal{T}_{\mathcal{G}}$,

$$\alpha_{11} = \int_{p_H}^{\infty} f(p_H|p_H, I_{t+1} > 0) dp \int_{I_H}^{\infty} f(I_H|I_t) dI$$
$$= [1 - \Phi((p_H - \hat{b}_1 p_H)/\hat{\sigma}_p)] \times [1 - \Phi((I_H - \hat{a}_1 I_H)/\hat{\sigma}_I))]$$

A.10 Equilibrium Estimation

We outline how we use the estimated demand parameters and estimated supply parameters to compute the equilibrium. Recall that we assume consumers make purchases based on forming equilibrium expectation functions for future resale prices and the value of waiting, and the firm takes these expectations into account in its pricing decision. The firm also takes into account its expectations of its optimal future pricing behavior when making pricing decisions today. Denote the equilibrium optimal pricing policy $p^*(S)$, the equilibrium expected future resale price $E[\tilde{r}|S, p]$, and the equilibrium waiting function $W(S, p)$. Under logit errors, the pricing policy $p^*(S, p)$ is uniquely determined by the firm's ex-ante choice-specific value function $v(S, p^d)$. Thus, our equilibrium is defined by equilibrium functions $E[\tilde{r}|S, p]$, $W(S, p)$, $v(S, p^d)$. We use a nested fixed point algorithm (e.g. Nair, 2007; Rust, 1987) where the equilibrium resale and waiting functions are nested within the solution of the equilibrium ex ante choice-specific value function.[4] In other words, consumers play a strategic game for a fixed pricing policy, and the firm plays a strategic game for fixed consumer expectations. The Nash equilibrium occurs where the equilibrium functions are consistent with the agents' optimal behavior.

When we change our parameters, the equilibrium changes, so that the equilibrium functions estimated in the data are no longer valid. In particular, up to this point we have only needed to examine the resale market based on the equilibrium observed in the data. The equilibrium will

[4]To reduce computation time, we solve iteratively, updating all three equilibrium functions at once. We find the same results to nesting.

change when the primitives change. We also will now need to compute the equilibrium in the resale market in addition to the equilibrium in the primary market. In deriving the equilibrium of the resale market, we assumed all speculation is sold in period $T+1$. Thus, we have the identity $\sum_{t=1}^{T} q_t^S = q_{T+1}$, which we can invert to find the resale price from $r_{T+1} = q_{T+1}^{-1}$. To account for this, we append an additional state variable in the primary market for the cumulative speculative actions up to time t: $L_t = \sum_{t=1}^{t-1} q_t^S$. The evolution of this state variable can be described as $L_{t+1} = L_t + q_t^S$. While the firm does not observe speculation actions directly, from an initial state in a market path, the firm can develop rational expectations on the evolution of speculation decisions given knowledge of the preference parameters.

Our computational details for generating the equilibrium are presented in Appendix A.10.1. First we compute the equilibrium functions $E[\tilde{r}|S,p]$, $W(S,p)$, $v(S,p^d)$, and then simulate data using these equilibrium functions with inverse transform sampling to account for the errors of the customer and firm pricing decisions. We generate 1000 replications of the equilibrium using the estimated demand and supply parameters, the initial states of market size and inventory for each SKU in the data, and the estimated equilibrium functions. We compute our predicted metrics by averaging across the results of each replication. In our analysis we drop extreme observations that may result from simulation error (bottom and top 10% profit impacts).

Before examining the counterfactuals of interest, we first compute the predicted equilibrium based on the estimated parameters from the data. We refer to the predicted equilibrium as the "base case" as a benchmark for comparison when performing counterfactuals. Our predicted equilibrium matches the equilibrium observed in the data well, across a variety of primary market metrics (e.g. revenue, average price, average time to stockout) and a variety of resale market metrics (e.g. resale market revenue, average resale price, average resale quantity). Appendix A.11 gives a discussion of our predicted equilibrium and the fit to the data.

A.10.1 Equilibrium Estimation Procedure

Using policy iteration, with demand preference parameters and supply-side parameters as the inputs, our equilibrium estimation procedure can be summarized as follows:

1. Discretize the state-price decisions for the firm $M, I, \mathbb{1}_{t=0}, P_{t-1}, L, P$ forming $|M| \times |I| \times 2 \times$

$|P_{t-1}| \times |L| \times |P|$ dimensional vector to represent grid $\mathcal{G}$. Add a no-payoff terminating state to which the primary market transitions with probability 1 when $I = 0$.

2. Take guesses for $v^{(n)}(S,p)$, $W^{(n,k)}(S,p)$, $E^{(n,k,l)}[\tilde{r}|S,p]$. Approximate each function to have continuous support over S. Set tolerance $\kappa = .000001$.

3. Given the guesses, compute $s^{a(n,k,l)}(S,p)$ for $a \in \{F,S,W\}$, $p \in P$.

4. Let prime ($'$) denote next period value. Given $s^{a(n,k,l)}(S,p)$, set up evolution of state variables $S' = \{M'^{(n,k,l)}, I'^{(n,k,l)}, 0, p_{-1}'^{(n,k,l)}, L'^{(n,k,l)}\}$:

   (a) If $I^{(n,k,l)} = 0$: $S' = \{0,0,0,0,0\}$, an absorbing state

   (b) If $I^{(n,k,l)} > 0$: compute $q^{(n,k,l)} = \min\{I^{(n,k,l)}, M^{(n,k,l)}[s^{F(n,k,l)} + s^{S(n,k,l)}]\}$

   - $M'^{(n,k,l)} = M^{(n,k,l)} - q^{(n,k,l)}$
   - $I'^{(n,k,l)} = I^{(n,k,l)} - q^{(n,k,l)}$
   - $L'^{(n,k,l)} = L^{(n,k,l)} + q^{(n,k,l)}[s^{S(n,k,l)}/(s^{F(n,k,l)} + s^{S(n,k,l)})]$
   - $p_{-1}'^{(n,k,l)} = p$

5. Compute optimal pricing[5] for next period: $P^{(n,k,l)}(p'|S') = \frac{\exp(v^{(n)}(S',p')/\beta)}{\sum_{j\in P}\exp(v^{(n)}(S',j)/\beta)}$

6. Based on evolution of state variables compute $E^{(n,k,l+1)}[\tilde{r}|S,p]$:

   (a) $E^{(n,k,l+1)}[\tilde{r}|S,p] = \delta_c \mathbb{1}_{I'^{(n,k,l)}=0}\tilde{Q}^{-1}(S';\Theta)$
   $+\delta_c \mathbb{1}_{I'^{(n,k,l)}>0}\sum_{p'\in P} E^{(n,k,l)}[\tilde{r}|S',p')]P^{(n,k,l)}(p'|S')$

   (b) Iterate on 2-6 until $E^{(n,k,l+1)}[\tilde{r}|S,p]$ converges within κ.

7. Based on guess of equilibrium expected resale price compute $W^{(n,k+1,l+1)}(S,p)$

   (a) $W^{(n,k+1,l+1)}(S,p) = \delta_c \mathbb{1}_{I'^{(n,k,l+1)}=0}\log[\exp(\gamma - \alpha\tilde{Q}^{-1}(S',\Theta)) + 1]$
   $+\delta_c \mathbb{1}_{I'^{(n,k,l+1)}>0}\sum_{p'\in P}\log[\exp(\gamma - \alpha p')$
   $+\exp(E^{(n,k,l+1)}[\tilde{r}|S',p'] - p' - \tau)$
   $+\exp(W^{(n,k,l+1)}(S',p'))]P^{(n,k,l)}(p'|S')$

[5] In searching across the parameter space during estimation, $v(\cdot)$ can be a relatively large number relative to β. For example, if $v = 2000$, which is relevant in our context as single period sales are on average \$2000, then exp(2000) is outside double precision used for standard computing. To account for this in computation, we find the largest choice-specific value conditional on the state, $\bar{v}(S_t) = \max\{v(S_t,p_t^1),\ldots,v(S_t,p_D^1)\}$, and subtract from each choice-specific value function to find "max-shifted" conditional value functions $\bar{v}(S_t,p_t^d) = v(S_t,p_t^d) - \bar{v}(S_t)$. It is easy to see the choice probabilities remain unchanged as $\exp(\bar{v}(S_t,p_t^d)) = \exp(v(S_t,p_t^d))\exp(-\bar{v}(S_t))$. For $\exp(\bar{v}(S_t,p_t^d))$ close to 0, 0 is a decent approximation relative to 1 for the maximum value.

(b) Iterate on 2-6 until $W^{(n,k+1,l+1)}(S,p)$ converges within κ.

8. Given $E^{(n,k+1,l+1)}[\tilde{r}|S,p]$, $W^{(n,k+1,l+1)}(S,p)$, $P^{(n,k,l)}(p'|S')$, solve for firm's choice-specific value function $v^{(n)}(S,p)$:

   (a) $\pi^{(n)}(S,p) = pq^{(n,k+1,l+1)} - \mu - \iota I'^{(n,k+1,l+1)} - \eta^{-}\{p < p_{-1}\} - \eta^{+}\{p > p_{-1}\}$.

   (b) $\frac{v^{(n)}(S,p)}{\beta} = \frac{\pi(S,p)}{\beta} + \delta_f \mathbb{1}_{I'(n,k,l+1)>0}$
   $$\times \sum_{p' \in P}[\frac{v^{(n)}(S',p')}{\beta} + \lambda - \log(P^{(n,k,l)}(p'|S'))]P^{(n,k,l)}(p'|S').$$

   (c) Iterate on 2-8 until $v^{(n)}(S,p)$ converges within κ.

9. Compute optimal pricing policy $P^*(p|S) = \frac{\exp(v^{(n)}(S,p)/\beta)}{\sum_{j\in P}\exp(v^{(n)}(S,j)/\beta)}$

10. Use $P^*, W^*, E[R]^*$ to simulate the equilibrium market path for initial market size and inventory M_0, I_0 in the data.

Similar to the supply side estimation, we discretize the state space for inventory, market size, and prices respectively into 12,4,8 uniform grid points based on the minimum and maximum values observed in the data within each product category. The available price decisions are eight to align with the number of grid points for lagged price. We now add an additional state variable for sum of speculation actions, which we discretize into 4 uniform grid points based on the minimum and maximum values observed in the resale quantity. This makes $|\mathcal{G}| = 24,577$. As in demand estimation, we use functional approximation for values between the grid points through multilinear interpolation. We use inverse transform sampling to simulate randomness in demand and pricing decisions. For a multinomial random variable, inverse transform involves ordering the alternatives by cumulative probability, sampling a uniform random variable between 0 and 1, and then assigning the action within the bin of mass covered by the alternative. For example, if flipping a fair coin ordered alternatives heads then tails, a uniform draw of .7 would be assigned an action of tails.

Note that our resale functions can be particularly unstable away from the fixed point. When the resale price is much higher than equilibrium, many resellers enter the market on a given iteration reducing the resale price dramatically; on the next iteration few resellers enter the market, again making the resale price much higher than equilibrium. Judd (1998) suggests a dampening parameter to reduce the size of the update in each iteration. We use a dampening parameter of $\rho = .1$, which gives us convergence in all applications. The dampening parameter is similar to a learning parameter or step size in other contexts (e.g. Hastie et al., 2009).

While we do not prove uniqueness of our solved equilibrium, our intuition supports its uniqueness due to each product having a terminal state from limited inventory. Further, demand is monotone in each of the equilibrium functions, suggesting a unique fixed point in any state leading to a terminal state; from backward induction each prior state reaches an already-solved state. We test multiple starting points and find the same equilibrium solution to verify this intuition.

A.11 Predicted Equilibrium

In Table A.2, we present the equilibrium results summarizing all three product categories, compared to the data. We generate 1000 replications of the equilibrium using the estimated demand and supply parameters, the initial states of market size and inventory for each SKU in the data, and the estimated equilibrium functions. We compute our predicted metrics by averaging across the results of each replication. Across all metrics the equilibrium values are within 10% of what we observe in the data. Some of this deviation could be explained by the limitations of a relatively simple model in capturing nuanced aspects of a complicated system. Some of the deviation could also be captured by the data we observe representing only one sample.

Table A.2: Comparison of Data and 1000 Replications of Predicted Equilibrium

	Observed	Predicted
Firm Revenue	\$1,033,493.00	\$929,448.70
Firm Avg Price	\$28.59	\$27.44
Firm Avg Time to Stockout	5.09	4.75
Percent Prices Remain Same	88%	81%
Resale Revenue	\$35,166.08	\$32,673.03
Resale Avg Price	\$35.06	\$34.94
Avg Resale Quantity	2.44	2.29
Resale Profit		\$10154.04
Number Replications	1	1000

In comparing our model to the observed data, it is worth pointing out that the model grants us visibility into reseller profit, whereas this is not observable in the data. This is because we do not observe when resellers purchase the product, so the firm is unable to diagnose when speculation actions occur. Examining the table, on average reseller profit margin is about 30% of resale revenue. The \$10,154.04 in reseller profit represents the additional gains the resellers are extracting from customers. This is an important point because the firm has already collected revenue from the remaining portion of resale revenue in the primary market – the revenue collected by the firm is represented from \$32,673.03 minus \$10,154.04.

A.12 Details on Resale Market Impacts

Table A.3 provides additional details related to Figure 2.5 on when the firm benefits from the resale market. The first two columns give the inventory and market size quartiles as displayed in the figure. The third column gives the percentage of SKUs in each quartile range. The fourth column gives the average profit impact as displayed in Figure 2.5. The fifth column shows that the firm must lower its initial price with resellers. The sixth column shows that those SKUs that are impacted most negatively from resellers are SKUs with relatively longer stockout times (using the case without resale for comparison). The seventh column shows that the resale market is relatively small compared to the firm's initial inventory when the resale market benefits the firm most (see for example row 9 and row 13). In these cases, the additional value from speculators adding purchases to stockout earlier dominates the reduction in sales from customers waiting for the resale market. The remaining columns detail how profit breaks down according to payoffs in the model. We can see that how holding costs change directionally maps onto how profit changes due to resellers. When holding costs decrease with resellers, the firm benefits from the resale market; when holding costs increase with resellers, the firm prefers to not have resellers.

Table A.3: Market Outcomes from Introducing Resellers by Quartile of Initial States

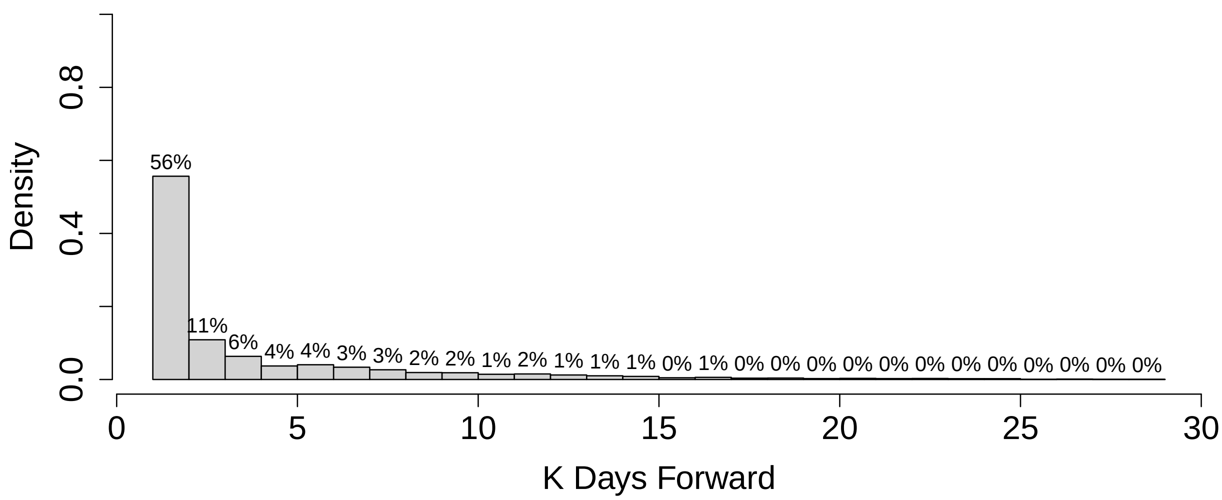
	Inventory Quartile	Market Size Quartile	% SKU	% Profit Impact	Initial Price Change	Stockout Time w/out Resale	Resale Qty	Profit Change	Revenue Change	Holding Cost Change	Adjustment Cost Change
1	[0,0.25]	[0,0.25]	6.1	3.2	-0.03	3.59	1.91	112.19	-23.27	-55.87	-79.60
2	[0,0.25]	(0.25,0.5]	5.8	0.3	0.00	1.33	1.39	41.32	-0.18	-34.94	-6.56
3	[0,0.25]	(0.5,0.75]	5.8	0.3	-0.02	1.21	1.32	38.23	-14.80	-33.11	-19.91
4	[0,0.25]	(0.75,1]	8.0	-0.0	-0.02	1.15	2.12	-4.71	-29.18	10.83	-35.31
5	(0.25,0.5]	[0,0.25]	5.8	3.2	-0.06	6.39	2.79	288.72	-95.00	-125.08	-258.64
6	(0.25,0.5]	(0.25,0.5]	5.2	-4.9	-0.16	3.66	2.91	-610.72	-201.20	356.72	52.80
7	(0.25,0.5]	(0.5,0.75]	8.6	-7.2	-0.22	3.75	3.31	-1905.40	-500.83	1153.86	250.71
8	(0.25,0.5]	(0.75,1]	6.8	-2.8	-0.30	3.18	2.46	-846.85	-534.56	221.65	90.64
9	(0.5,0.75]	[0,0.25]	8.6	13.9	-0.03	6.61	2.69	800.24	-78.35	-469.45	-409.14
10	(0.5,0.75]	(0.25,0.5]	6.4	2.1	-0.08	5.43	3.29	337.79	-182.26	-269.35	-250.71
11	(0.5,0.75]	(0.5,0.75]	4.3	3.3	-0.19	6.08	4.36	394.71	-291.02	-338.45	-347.28
12	(0.5,0.75]	(0.75,1]	4.3	-3.8	-0.40	5.18	4.21	-750.99	-613.18	292.12	-154.31
13	(0.75,1]	[0,0.25]	5.2	10.2	-0.02	6.87	2.60	634.65	-58.22	-372.64	-320.23
14	(0.75,1]	(0.25,0.5]	6.8	1.5	-0.12	6.60	4.25	401.23	-395.44	-407.52	-389.14
15	(0.75,1]	(0.5,0.75]	6.1	2.8	-0.23	6.56	4.71	865.93	-682.16	-812.23	-735.86
16	(0.75,1]	(0.75,1]	6.1	-4.5	-0.41	6.45	5.44	-1712.87	-1278.83	630.25	-196.21

APPENDIX B: LOCAL FULFILLMENT IN E-COMMERCE: STRUCTURAL ESTIMATION OF FULFILLING DEMAND SENSITIVE TO DELIVERY SPEED

B.1 Evidence for Next-Day Replenishment

E-commerce companies make a number of inventory decisions daily (Chen and Graves, 2021). One key decision for local fulfillment is how often to replenish front DCs with inventory given limited storage space in the front DCs. Figure B.1 provides empirical evidence that JD.com replenishes inventory daily. For days where a given SKU is stocked out of inventory at the end of the day, Figure B.1 plots the frequency of K number of days before the SKU again has end-of-day inventory. We can see that 56% of the time that a SKU stocks out, it is restocked the next day with $K = 1$. For replenishment times longer than one day, so that $K > 1$, it is possible the central planner chose to not replenish inventory instead of facing a set lead time greater than one day. This is supported by the fact that the chart is downward sloping from $K = 1$ such that there is not a set lead time of $K > 1$.

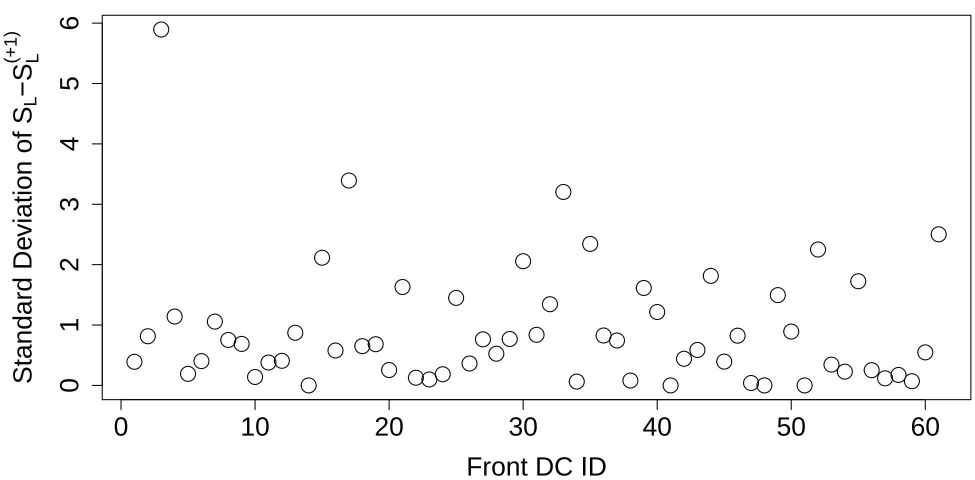
Figure B.1: Distribution of Relenishment K Days Forward



B.2 Evidence for a Nonstationary (s_t, S_t) Base Stock Policy

As discussed in Bray et al. (2019), an (s_t, S_t) policy is appropriate when order-up-to levels vary dramatically. Figure B.2 plots the standard deviation of local sales across front DCs period-to-period. Given the average difference in local sales period-to-period is zero, Figure B.2 demonstrates that an (s_t, S_t) policy is appropriate for JD.com's Pre-Ship decision.

Figure B.2: Observed Standard Deviation of Interperiod Local Sales Quantity by Front DC



B.3 Customers Presented One Promised Delivery Speed

Figure B.3 provides an example product listing on the JD.com website, accessed on February 10, 2022. As highlighted in red, the customer is presented a single delivery speed when considering to make the purchase.

B.4 Global Maximizer for $\mathbf{Q}^e$

In this section, we show when Q^e returned from the first-order condition is a global maximizer for the manager's decision problem. Our approach is to show that the manager's objective is strictly quasiconcave, allowing for sufficient conditions for the Karush-Kuhn-Tucker (KKT) conditions where a global maximizer is found when the gradient is zero (Mas-Colell et al., 1995).

First, we rewrite the expected profit function to isolate how the parameters impact expected

Figure B.3: Example Product Listing On JD.com's Website

profit when Q changes. Leveraging the identities $\min(a, b) = a - [a-b]^+$ and $a = b - [b-a]^+ + [a-b]^+$ (Dong and Rudi, 2004) as well as $\max(a, b) = -\min(-a, -b)$ and leveraging that expectation is a linear operator, we re-write as follows:

$$
\begin{aligned}
E\pi(Q) &= pE(Q - [Q - D^L]^+) - hE[Q - D^L]^+ - rE[Q - Q^{(+1)} - D^L]^+ \\
&\quad + (p-b)E(D^B - Q + [Q - D^B]^+) - cQ \\
&= E\Big[(b-c)Q + (p-b)D^B - p([Q - D^L]^+ - [Q - D^B]^+) - r[Q - Q^{(+1)} - D^L]^+ \\
&\quad - h[Q - D^L]^+ - b[Q - D^B]^+\Big] \\
&= E\Big[(b-c)Q + (p-b)D^B + p(\min(Q, D^L) - \min(Q, D^B)) \\
&\quad + r\min(Q^{(+1)} + D^L - Q, 0) + h\min(D^L - Q, 0) + b\min(D^B - Q, 0)\Big]
\end{aligned}
$$

where $p(\min(Q, D^L) - \min(Q, D^B)) \geq 0$ as $D^L \geq D^B$.

Now, suppose $E\pi(Q) \geq E\pi(Q')$ for $Q \neq Q'$. Let $\alpha \in (0, 1)$ and define Q^* as the linear combination $Q^* = \alpha Q + (1-\alpha)Q'$. We need to show that $E\pi(Q^*) > \min(E\pi(Q), E\pi(Q'))$ to show stict quasiconvexity (Mas-Colell et al., 1995). Leveraging the linearity of the expectation operator and that it preserves ordering in Q, as well the fact that $Q^* > \min(Q, Q')$ and $Q^* < \max(Q, Q')$,

$$
\begin{aligned}
E\pi(Q^*) = E\Big[&(b-c)Q^* + (p-b)D^B + p(\min(Q^*, D^L) - \min(Q^*, D^B)) \\
&+ r\min(Q^{(+1)} + D^L - Q^*, 0) + h\min(D^L - Q^*, 0) + b\min(D^B - Q^*, 0)\Big] \\
> E\Big[&(b-c)\min(Q, Q') + (p-b)D^B + p(\min(Q^*, D^L) - \min(Q^*, D^B)) \\
&+ r\min(Q^{(+1)} + D^L - Q^*, 0) + h\min(D^L - Q^*, 0) + b\min(D^B - Q^*, 0)\Big] \\
\geq E\Big[&(b-c)\min(Q, Q') + (p-b)D^B + p(\min(\min(Q, Q'), D^L) - \min(\min(Q, Q'), D^B)) \\
&+ r\min(Q^{(+1)} + D^L - Q^*, 0) + h\min(D^L - Q^*, 0) + b\min(D^B - Q^*, 0)\Big] \\
\geq E\Big[&(b-c)\min(Q, Q') + (p-b)D^B + p(\min(\min(Q, Q'), D^L) - \min(\min(Q, Q'), D^B)) \\
&+ r\min(Q^{(+1)} + D^L - \max(Q, Q'), 0) + h\min(D^L - \max(Q, Q'), 0) + \\
&b\min(D^B - \max(Q, Q'), 0)\Big] \\
\geq \min&\Big(E\pi(Q), E\pi(Q')\Big)
\end{aligned}
$$

B.5 Equilibrium Estimation

In this section we describe how we estimate our equilibrium for a given set of parameters $\theta = \{\theta_b, \theta_c\}$. Recall that the manager considers a forecast of next period demand when making the Pre-Ship decision. Further, the manager considers future inventory decisions strategically. We seek a rational expectations equilibrium where the manager's optimal decision is consistent with expectations on future outcomes. To solve the rational expectations equilibrium, we leverage backward induction, as in other structural works (Ishihara and Ching, 2019). To account for uncertainty in the manager's forecast, we simulate demand with R Halton draws to compute demand shocks ϵ_r for $r = 1 \ldots R$. We then compute expected operational outcomes by averaging across the outcomes for a given simulated outcome. Our procedure to estimate the equilibrium Pre-Ship quantity and profit is described as follows:

1. Inputs: A DC locality i, SKU j, parameters θ, and simulated demand shocks ϵ_r

2. Initialize $t = T$, $Q_{ijT+1} \to \infty$

- Compute optimal expected Pre-Ship quantities $Q_{ijt}(\theta, Q_{ijt+1})$
- Compute expected profit $\pi_{ijt} = 1/R \sum_{r=1}^{R} \pi_{ijtr}(Q_{ijt}, \theta, \epsilon_r)$

3. Repeat 2 for $t = t - 1$ until $t = 0$

B.6 Predicted Equilibrium

In Table B.1, we compare the results of the predicted equilibrium to the equilibrium observed in the data. We generate 100 replications of the equilibrium and compute the predicted metrics by averaging across the results of each replication. Across all metrics, the values we observe in the data are within 15% of the values of our predicted equlibrium. Thus, our model provides good fit in capturing multiple outcomes across sales, revenue, promise time, and service level.

Table B.1: Comparison of Predicted and Observed Equilibrium

	Observed	Predicted
Average Sales Per Observation	0.93	1.08
Average Revenue Per Observation	93.73	101.19
Average Promise Time Per Observation	1.77	1.75
Average Sales Local Per Observation	0.58	0.69

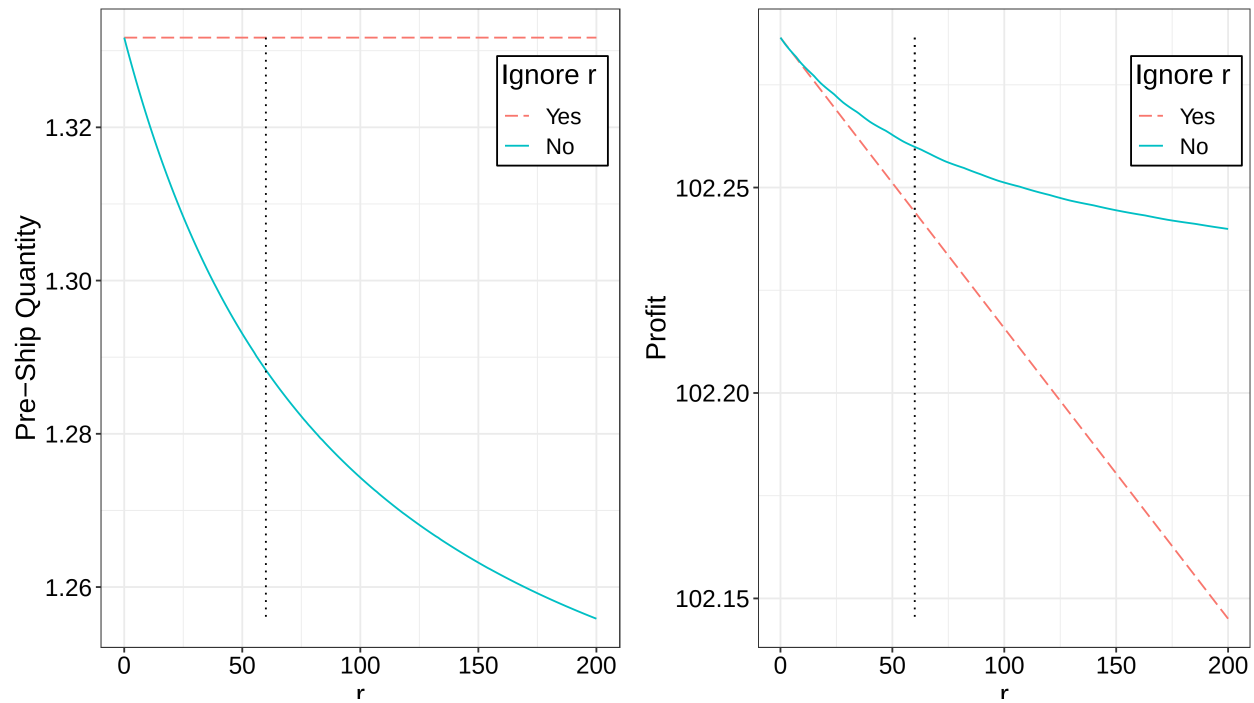
B.7 Importance of Incorporating Rebalancing Costs

In this section we examine the importance of incorporating rebalancing costs into the model. As demand is stochastic, solving one-shot Pre-Ship decisions that do not include rebalancing costs would incorrectly overstate profit in scenarios with low realized current period demand and low expected next-period demand. The extent of the impact is an empirical question.

First, we run a counterfactual analysis similar to those in the counterfactual analyses section. We consider a scenario where the central planner incorrectly chooses a Pre-Ship policy that ignores rebalancing costs, i.e., a policy $Q_{r=0}$. We find that on average the profit and sales impacts are less than 0.1% despite an average Pre-Ship quantity change of 2.6%, but the impacts differ across observations. Thus, in aggregate ignoring balancing costs does not have a large impact to profit in our specific context, but in other contexts with a different distribution of data it might.

Second, to explore this in more detail we run a set of simulations. We set the demand parameters according to the base case, set the cost parameters at the median estimated parameters, use the average price and delivery time differences in the data, and use the average predicted Pre-Ship quantity in the data of 1.22. We then vary r from 0 to 200 to see how profit is impacted. Figure B.4 presents the results of our simulations. In Panel (a) of Figure B.4, we see that the Pre-Ship

Figure B.4: Simulated Pre-Ship Quantity and Profit Differences From Ignoring r



(a) Pre-Ship quantity does not reduce as r increases when ignoring rebalancing costs

(b) Profit losses from ignoring rebalancing costs increase as r increases

quantity becomes smaller when incorporating rebalancing costs, as r increases. At the median value of r, denoted by the dashed vertical line, the optimal Pre-Ship quantity of 1.29 is 3% smaller than the Pre-Ship quantity when ignoring rebalancing costs of 1.33. In Panel (b) of Figure B.4 we see that the difference in profit is much less dramatic. At the median value of r, the optimal profit of 102.26 is less than 0.1% larger than the suboptimal profit of 102.24. At the extreme when $r = 200$, the impacts to Pre-Ship quantity and profit increase to 5.6% and 0.1%, respectively.

We then conduct an additional simulation to demonstrate a scenario where rebalancing costs should be important in the data. To account for scenarios with dramatic changes in demand under the (s_t, S_t) policy, we set the next-period Pre-Ship quantity to zero. Now we notice a 41% Pre-Ship quantity difference and 2.7% profit difference at the median value of r; the impacts increase to

70% and 16.1% respectively when $r = 200$. We thus conclude that while the average impacts are minimal for our data set, rebalancing costs should be included in the model in general.

APPENDIX C: INCENTIVIZING RECYCLING TO IMPROVE SUSTAINABILITY: EVIDENCE FROM FIELD EXPERIMENTS

C.1 Pre-survey to Create Sample of Participants

In this section we present the survey used to determine which customers would be eligible for the experiment. Figure C.1 presents the questions in the pre-survey.

Figure C.1: Pre-survey to Collect Sample for Experiment

Do you have any headsets in your home that you would like to recycle? (any brand)

- ○ Yes
- ○ No

If we had an easy process to recycle your headset, would you be interested in learning more?

- ○ Yes
- ○ No

Are you based in the US?

- ○ Yes
- ○ No

What is your email address?

Please opt-in to receive emails from us. We will only contact you if you expressed an interest in learning more about recycling or are the lucky winner of a free headset for completing this survey and you can opt out at any time.

- ○ Opt in
- ○ Opt out

C.2 Initial Email with Incentive

In addition to Figure 4.3 in Section 4.4.4 which outlines the initial email sent to the customer when randomly offered an environmental incentive, in this section we present Figure C.2 and Figure C.3 which outline the initial emails offered to the customer for no incentive (control group) or a convenience-based incentive, respectively.

Figure C.2: Initial Email Without Incentive (Control)

Figure C.3: Initial Email Offering Convenience of Pickup

RECYCLE YOUR OLD HEADSETS

Do you have any old or broken headsets that you're not sure what to do with? We recently started an awesome new headset recycling program, and now we can pick up your old, used, or broken headsets (any brand) right from your house and responsibly recycle them for you.

Follow the steps below to recycle old headsets — free of charge.

1. STEP ONE

Gather the headsets you'd like to recycle (any brand) — within the next 2 weeks.

2. STEP TWO

Click here to arrange a pre-paid label to drop off your package at your nearest FedEx location; OR
Click here to arrange a free pick-up of your package from your location.

3. STEP THREE

We responsibly recycle your headset for you.

C.3 Returns Portal

We leverage Qualtrics to host a return portal through an online survey. Once the customer fills out the appropriate information, this triggers Logitech to generate and email the customer a shipping label based on the details provided.

For the sake of brevity, we omit a graphic of the survey and outline the items requested of the customer. For both drop-off and pickup options, the customer provides the following details related to generating the shipping label and authenticating their return: name, email address, zip code, and number of headsets mailed back. Additionally, the customer provides details useful for analysis: brand of headset returned, frequency of general recycling habits, whether or not the customer has recycled electronics before, whether the customer is aware of recycling facilities around them, what motivated them to recycle, and the approximate value of the items returned. Last, in the pickup option specifically, pickup-specific details are collected including pickup date, location, phone number, and other special instructions (see Figure C.5 for a visual of these additional details).

C.4 Instructions for Return

In this section we display the instructions the customer receives via email with an attached shipping label, after filling out the online questionnaire to recycle their product. Figure C.4 shows the details provided to the customer for the drop-off option. The customer is told to print the

Figure C.4: Email Instructions for Dropoff

THANK YOU FOR CHOOSING TO RECYCLE

ATTACHED IS YOUR PRE-PAID FEDEX SHIPPING LABEL

If you have a printer, please box up your old headsets, print the attached shipping label and tape the label to the outside of your box.

You can find your nearest Fedex dropoff location here and drop it off for recycling. We'll take care of the rest!

If you don't have a printer, you can bring your box to your closest Fedex store and they will print your shipping label for free and add it to the box and take it from there.

Thanks again for choosing to recycle!

shipping label, which is an attachment in the email, and attach the shipping label to a package containing the headset. The details also provide a link for finding a nearest FedEx location, and offer the option to have FedEx print the label if the customer does not have a shipping label.

Figure C.5 shows the details provided to the customer for the pick-up option. Like the drop-off

Figure C.5: Email Instructions for Pickup

THANK YOU FOR CHOOSING TO RECYCLE

ATTACHED IS YOUR PRE-PAID FEDEX SHIPPING LABEL

Please box up your old headsets, print the attached shipping label and tape the label to the outside of your box.

We have scheduled a Fedex pick-up of your devices as you requested. The details of the pickup are below.

Tracking Code	
Pickup Date	
Pickup ZIP/Postal code	
Pickup location	
Special instructions	
Number of Packages	
Phone number	

Thanks again for choosing to recycle!

option, the customer is told to print the shipping label, which is an attachment in the email, and attach the shipping label to a package containing the headset. Now, however, the customer does not need to research a FedEx location or drop-off at a FedEx location. The table provides the customer the details on when the pickup will occur, along with additional details if the customer needs to follow-up with FedEx.

C.5 Preliminary Power Analysis

In this section we perform preliminary power analysis for the return rate from the incentive. We focus on this dependent variable because there are available studies for comparison on how recycling behavior differs in different contexts.

List et al. (2010) (equation 8, page 12) and Dell et al. (2002) (equation 1, page 9) provide formulas to calculate the necessary sample size for dichotomous experimental designs using population proportion. We choose the equation presented in Dell et al. (2002). Dichotomous experimental designs occur when the subject can make a "yes-no" decision as a result of the treatment. In our case, that yes-no decision is whether to recycle the product. Necessary sample size has four components: power, significance, effect size, variation across groups. When comparing the effect size from population proportions, variation across groups is derived from the effect size. List et al. (2010) states 80% power and 5% significance are standard so we choose those. We present a preliminary power analysis in Table C.1 across various control group recycling proportions and effect sizes that we feel may make sense. Note that the N required is symmetric about .5 in the first two columns.

Table C.1: Preliminary Power Analysis

Control group recycling proportion	Effect size	Number required (per condition)
0	0.05	152
0	0.10	73
0	0.20	34
0	0.30	21
0.10	0.05	686
0.10	0.10	199
0.10	0.20	62
0.10	0.30	31
0.20	0.05	1094
0.20	0.10	293
0.20	0.20	81
0.20	0.30	38
0.50	0.05	1563
0.50	0.10	387
0.50	0.20	93
0.50	0.30	38

Before conducting an experiment there is no way to know for sure what effect size to expect. Smaller effect sizes are harder to detect due to variation in the data. Furthermore, the effect at the control impacts the formula for computing sample size, as the closer the control's effect size is to zero, the smaller a sample size is required.

Across a variety of studies the baseline recycling rate can vary dramatically from .4% to 80% (Litchfield et al., 2018; Ongondo and Williams, 2011; Viscusi et al., 2011; Shevchenko et al., 2019;

Delcea et al., 2020). Further, the impact of recycling incentives is not well-understood, but one study, Allen et al. (1993), examines the impact of incentivizing recycling of aluminum cans. In Allen et al. (1993), the treatment effect is estimated to be about 20% for customers that consider recycling, which is detectable for the sample sizes in each experiment when the control has an effect size less than 20%.

C.6 Randomization Checks

If randomization were correctly implemented, the probability of getting allocated to a treatment group would not be correlated with individual characteristics and past transactions (Sahni et al., 2017). We present observable characteristics of individuals across each treatment group in Table C.2, which shows that the groups are similar based on observable data. In the first experiment, customers are selected based on an email distribution list, and we use all observable information from this list including average number of emails opened that were sent, the average number of clicks within the emails opened, and the average days since an email was received and opened. In the second experiment, we leverage information collected from Qualtrics survey metrics for the pre-survey on social media including time to complete the survey, time to start survey from when it is received, and the distributions of locations according to US regions.

We statistically test a difference in means across all treatment groups to ensure that each group is similar based on observable data. The p-values show the test of equality of each characteristic across the groups, where numeric variables use an ANOVA difference in means test and categorical variables use a Pearson chi-squared test.

Table C.2: Average Observable Characteristics of Individuals in Treatment Groups

Experiment 1				
	Number of Emails	Avg Open Email	Avg Clicks in Email	Avg Days Since Opened
No incentive	500	10.77	0.82	79.52
Environmental	500	10.33	0.89	83.09
p-values		0.903	0.617	0.359

Experiment 2				
	Number of Emails	Avg Time to Complete	Avg Time to Start Survey	US Regions (4 total)
No incentive	57	48.00	0.61	4
Environmental	57	43.46	0.65	4
Convenience	58	52.57	0.53	4
p-values		0.73	0.82	0.57

Notes. Each column displays balance of observable characteristics across each treatment group in the different experiments, prior to randomization. The p-values show the test of equality of each characteristic across the groups, where numeric variables use an ANOVA difference in means test and categorical variables use a Pearson chi-squared test.

REFERENCES

Accenture (2017). Waste to wealth: Creating advantage in a circular economy. Accessed July 1, 2018, https://www.accenture.com/_acnmedia/Accenture/Conversion-Assets/DotCom/Documents/Global/PDF/Strategy_7/Accenture-Waste-Wealth-Infographic.pdf.

Acimovic, J. and Graves, S. C. (2015). Making better fulfillment decisions on the fly in an online retail environment. *Manufacturing & Service Operations Management*, 17(1):34–51.

Agrawal, V., Atasu, A., and Van Wassenhove, L. (2017). 4 obstacles on the way to a circular economy. Accessed March 1, 2022, https://www.huffpost.com/entry/4-obstacles-on-the-way-to_b_11019722.

Agrawal, V., Atasu, A., and Ülkü, S. (2021). Leasing, modularity, and the circular economy. *Management Science*.

Agrawal, V. V., Atasu, A., and Van Wassenhove, L. N. (2019). Om forum—new opportunities for operations management research in sustainability. *Manufacturing & Service Operations Management*, 21(1):1–12.

Agrawal, V. V. and Bellos, I. (2017). The potential of servicizing as a green business model. *Management Science*, 63(5):1545–1562.

Aguirregabiria, V. (1999). The dynamics of markups and inventories in retailing firms. *The Review of Economic Studies*, 66(2):275–308.

Aguirregabiria, V. and Alonso-Borrego, C. (2014). Labor contracts and flexibility: Evidence from a labor market reform in spain. *Economic Inquiry*, 52(2):930–957.

Aguirregabiria, V. and Mira, P. (2010). Dynamic discrete choice structural models: A survey. *Journal of Econometrics*, 156(1):38 – 67.

Aksin, Z., Ata, B., Emadi, S. M., and Su, C.-L. (2013). Structural estimation of callers' delay sensitivity in call centers. *Management Science*, 59(12):2727–2746.

Alfredsson, P. and Verrijdt, J. (1999). Modeling emergency supply flexibility in a two-echelon inventory system. *Management science*, 45(10):1416–1431.

Allen, J., Davis, D., and Soskin, M. (1993). Using coupon incentives in recycling aluminum: A market approach to energy conservation policy. *Journal of Consumer Affairs*, 27(2):300–318.

Allon, G., Federgruen, A., and Pierson, M. (2011). How much is a reduction of your customers' wait worth? an empirical study of the fast-food drive-thru industry based on structural estimation methods. *Manufacturing & Service Operations Management*, 13(4):489–507.

Alvarez, E. (2016). Adidas tries to make buying yeezys fair but misses the mark. *Engadget*.

Ariely, D., Bracha, A., and Meier, S. (2009). Doing good or doing well? image motivation and monetary incentives in behaving prosocially. *The American Economic Review*, 99(1):544–555.

Arrow, K. J., Harris, T., and Marschak, J. (1951). Optimal inventory policy. *Econometrica: Journal of the Econometric Society*, pages 250–272.

Atasu, A., Sarvary, M., and Van Wassenhove, L. N. (2008). Remanufacturing as a marketing strategy. *Management Science*, 54(10):1731–1746.

Atasu, A. and Subramanian, R. (2012). Extended producer responsibility for e-waste: Individual or collective producer responsibility? *Production and Operations Management*, 21(6):1042–1059.

Athey, S. and Imbens, G. (2017). The econometrics of randomized experiments. *Handbook of Economic Field Experiments*, 1:73–140.

Azadeh, K., De Koster, R., and Roy, D. (2019). Robotized and automated warehouse systems: Review and recent developments. *Transportation Science*, 53(4):917–945.

Bajari, P., Benkard, C. L., and Levin, J. (2007). Estimating dynamic models of imperfect competition. *Econometrica*, 75(5):1331–1370.

Barile, L., Cullis, J., and Jones, P. (2015). Will one size fit all?: Incentives designed to nurture prosocial behaviour. *Journal of Behavioral and Experimental Economics*, 57:9–16.

Beatty, T. K., Berck, P., and Shimshack, J. P. (2007). Curbside recycling in the presence of alternatives. *Economic Inquiry*, 45(4):739–755.

Benkard, C. L. (2004). A dynamic analysis of the market for wide-bodied commercial aircraft. *The Review of Economic Studies*, 71(3):581–611.

Berry, S., Levinsohn, J., and Pakes, A. (1995). Automobile prices in market equilibrium. *Econometrica*, 63(4):841–890.

Bertsimas, D. and Thiele, A. (2005). A data-driven approach to newsvendor problems. *Working Papere, Massachusetts Institute of Technology*, 51.

Best, H. and Kneip, T. (2011). The impact of attitudes and behavioral costs on environmental behavior: A natural experiment on household waste recycling. *Social Science Research*, 40(3):917–930.

Bourne, D., Snyder, C., Rooks, J., Meegan, A., and Werner, M. (2021). Electronics hibernation: Understanding barriers to consumer participation in electronics recycling services. *Google white paper*.

Bray, R. L. (2020). Operational transparency: Showing when work gets done. *Manufacturing & Service Operations Management*.

Bray, R. L. and Stamatopoulos, I. (2021). Menu costs and the bullwhip effect: Supply chain implications of dynamic pricing. *Operations Research*.

Bray, R. L., Yao, Y., Duan, Y., and Huo, J. (2019). Ration gaming and the bullwhip effect. *Operations Research*, 67(2):453–467.

Brown, S. (2001). Torment your customers (they'll love it). *Harvard Business Review*.

Butler, K. and Stephens, M. A. (2017). The distribution of a sum of independent binomial random variables. *Methodology and Computing in Applied Probability*, 19(2):557–571.

Cachon, G. P. and Feldman, P. (2020). Pricing capacity and recourse strategies: Facilitate reselling, offer refunds, or overbook. *Working Paper*.

Cachon, G. P. and Swinney, R. (2009). Purchasing, pricing, and quick response in the presence of strategic consumers. *Management Science*, 55(3):497–511.

Caro, F. and Gallien, J. (2012). Clearance pricing optimization for a fast-fashion retailer. *Operations research*, 60(6):1404–1422.

Caro, F., Kök, A. G., and Martínez-de Albéniz, V. (2020). The future of retail operations. *Manufacturing & Service Operations Management*, 22(1):47–58.

Chen, A. I. and Graves, S. C. (2021). Item aggregation and column generation for online-retail inventory placement. *Manufacturing & Service Operations Management*, 23(5):1062–1076.

Chen, J., Esteban, S., and Shum, M. (2013). When Do Secondary Markets Harm Firms? *American Economic Review*, 103(7):2911–2934.

Chen, X., Zhou, S. X., and Chen, Y. F. (2011). Integration of inventory and pricing decisions with costly price adjustments. *Operations Research*, 59(5):1144–1158.

Chevalier, J. and Goolsbee, A. (2009). Are durable goods consumers forward-looking? evidence from college textbooks. *The Quarterly Journal of Economics*, 124(4):1853–1884.

Choi, T.-M. (2012). *Handbook of Newsvendor problems: Models, extensions and applications*, volume 176. Springer.

Clark, A. J. and Scarf, H. (1960). Optimal policies for a multi-echelon inventory problem. *Management science*, 6(4):475–490.

Clemen, R. T. and Reilly, T. (1999). Correlations and copulas for decision and risk analysis. *Management Science*, 45(2):208–224.

Courty, P. (2003). Ticket pricing under demand uncertainty. *The Journal of Law & Economics*, 46(2):627–652.

Courty, P. and Davey, L. (2020). The impact of variable pricing, dynamic pricing, and sponsored secondary markets in major league baseball. *Journal of Sports Economics*, 21(2):115–138.

Craig, N., DeHoratius, N., and Raman, A. (2016). The impact of supplier inventory service level on retailer demand. *Manufacturing & Service Operations Management*, 18(4):461–474.

Cui, R., Li, M., and Li, Q. (2019). Value of high-quality logistics: Evidence from a clash between sf express and alibaba. *Management Science*, 66(9):3879–3902.

Cui, Y., Duenyas, I., and Şahin, (2014). Should event organizers prevent resale of tickets? *Management Science*, 60(9):2160–2179.

Daniels, H. E. (1954). Saddlepoint approximations in statistics. *Ann. Math. Statist.*, 25(4):631–650.

de Kok, A. d. and Graves, S. C. (2003). *Supply chain management: Design, coordination and operation*. Elsevier.

Debo, L. G., Toktay, L. B., and Van Wassenhove, L. N. (2005). Market segmentation and product technology selection for remanufacturable products. *Management science*, 51(8):1193–1205.

DeGraba, P. (1995). Buying frenzies and seller-induced excess demand. *The RAND Journal of Economics*, 26(2):331–342.

DeHoratius, N., Mersereau, A. J., and Schrage, L. (2008). Retail inventory management when records are inaccurate. *Manufacturing & Service Operations Management*, 10(2):257–277.

Delcea, C., Crăciun, L., Ioanăș, C., Ferruzzi, G., and Cotfas, L.-A. (2020). Determinants of individuals' e-waste recycling decision: A case study from romania. *Sustainability*, 12(7).

Dell, R. B., Holleran, S., and Ramakrishnan, R. (2002). Sample Size Determination. *ILAR Journal*, 43(4):207–213.

Deng, V. (2018). Jordan brand doesn't want you to resell these air jordan 1 sneakers. *Footwear News*.

Deshpande, V. and Pendem, P. K. (2022). Logistics performance, ratings, and its impact on customer purchasing behavior and sales in e-commerce platforms. *Manufacturing & Service Operations Management*.

Dhaene, J., Denuit, M., Goovaerts, M. J., Kaas, R., and Vyncke, D. (2002). The concept of comonotonicity in actuarial science and finance: theory. *Insurance: Mathematics and Economics*, 31(1):3–33.

Dhanorkar, S. and Muthulingam, S. (2020). Do e-waste laws create behavioral spillovers? quasi-experimental evidence from california. *Production and Operations Management*, 29(7):1738–1766.

Dixit, S. and Vaish, A. (2015). Perceived barriers, collection models, incentives and consumer preferences: An exploratory study for effective implementation of reverse logistics. *International Journal of Logistics Systems and Management*, 21:304–318.

Dong, L., Kouvelis, P., and Tian, Z. (2009). Dynamic pricing and inventory control of substitute products. *Manufacturing & Service Operations Management*, 11(2):317–339.

Dong, L. and Rudi, N. (2004). Who benefits from transshipment? exogenous vs. endogenous wholesale prices. *Management Science*, 50(5):645–657.

Dye, R. (2000). The buzz on buzz. *Harvard Business Review*.

Eisinga, R., Te Grotenhuis, M., and Pelzer, B. (2013). Saddlepoint approximations for the sum of independent non-identically distributed binomial random variables. *Statistica Neerlandica*, 67(2):190–201.

Elmaghraby, W., Gülcü, A., and Keskinocak, P. (2008). Designing optimal preannounced markdowns in the presence of rational customers with multiunit demands. *Manufacturing & Service Operations Management*, 10(1):126–148.

Elmaghraby, W. and Keskinocak, P. (2003). Dynamic pricing in the presence of inventory considerations: Research overview, current practices, and future directions. *Management Science*, 49(10):1287–1309.

Eppen, G. D. and Iyer, A. V. (1997). Improved fashion buying with bayesian updates. *Operations Research*, 45(6):805–819.

Erdem, T., Imai, S., and Keane, M. P. (2003). Brand and quantity choice dynamics under price uncertainty. *Quantitative Marketing and economics*, 1(1):5–64.

Erdem, T. and Keane, M. P. (1996). Decision-making under uncertainty: Capturing dynamic brand choice processes in turbulent consumer goods markets. *Marketing Science*, 15(1):1–20.

Esenduran, G., Atasu, A., and Van Wassenhove, L. N. (2019). Valuable e-waste: Implications for extended producer responsibility. *IISE Transactions*, 51(4):382–396.

European Parliament (2015). Circular economy: definition, importance and benefits. Accessed March 27, 2022, `https://www.europarl.europa.eu/news/en/headlines/economy/20151201STO05603/circular-economy-definition-importance-and-benefits`.

Faris, R. (2014). How to build brand religion. *Harvard Business Review*.

FedEx (2022). Fedex website. Accessed February 1, 2022, `http://www.fedex.com/`.

Ferreira, K. J., Lee, B. H. A., and Simchi-Levi, D. (2016). Analytics for an online retailer: Demand forecasting and price optimization. *Manufacturing & Service Operations Management*, 18(1):69–88.

Ferrer, G. and Swaminathan, J. M. (2006). Managing new and remanufactured products. *Management science*, 52(1):15–26.

Fiegerman, S. (2018). Amazon made prime indispensable - here's how. *CNN Business*.

Fisher, M., Olivares, M., and Staats, B. R. (2020). Why empirical research is good for operations management, and what is good empirical operations management? *Manufacturing & Service Operations Management*, 22(1):170–178.

Fisher, M. and Raman, A. (1996). Reducing the cost of demand uncertainty through accurate response to early sales. *Operations Research*, 44(1):87–99.

Flammer, C. (2015). Does corporate social responsibility lead to superior financial performance? a regression discontinuity approach. *Management Science*, 61(11):2549–2568.

Fleischmann, M., Bloemhof-Ruwaard, J. M., Dekker, R., Van der Laan, E., Van Nunen, J. A., and Van Wassenhove, L. N. (1997). Quantitative models for reverse logistics: A review. *European journal of operational research*, 103(1):1–17.

Frey, B. S. (1994). How intrinsic motivation is crowded out and in. *Rationality and Society*, 6(3):334–352.

Frey, B. S. and Oberholzer-Gee, F. (1997). The cost of price incentives: An empirical analysis of motivation crowding- out. *The American Economic Review*, 87(4):746–755.

Fullerton, D. and Kinnaman, T. C. (1996). Household responses to pricing garbage by the bag. *The American Economic Review*, 86(4):971–984.

Gallino, S. and Moreno, A. (2014). Integration of online and offline channels in retail: The impact of sharing reliable inventory availability information. *Management Science*, 60(6):1434–1451.

Gallino, S., Moreno, A., and Stamatopoulos, I. (2017). Channel integration, sales dispersion, and inventory management. *Management Science*, 63(9):2813–2831.

Gao, F. and Su, X. (2017). Omnichannel retail operations with buy-online-and-pick-up-in-store. *Management Science*, 63(8):2478–2492.

Geng, X., Wu, R., and Whinston, A. B. (2007). Profiting from partial allowance of ticket resale. *Journal of Marketing*, 71(2):184–195.

Girotra, K. and Netessine, S. (2013). Om forum—business model innovation for sustainability. *Manufacturing & Service Operations Management*, 15(4):537–544.

Gneezy, A., Imas, A., Brown, A., Nelson, L. D., and Norton, M. I. (2012). Paying to be nice: Consistency and costly prosocial behavior. *Management Science*, 58(1):179–187.

Godes, D. and Mayzlin, D. (2004). Using online conversations to study word-of-mouth communication. *Marketing Science*, 23(4):545–560.

Gowrisankaran, G. and Rysman, M. (2012). Dynamics of consumer demand for new durable goods. *Journal of Political Economy*, 120(6):1173–1219.

Griffith, E. (2019). Buy low-tops, sell high-tops: Stockx sneaker exchange is worth $1 billion. *The New York Times*.

Guide Jr, V. D. R. and Van Wassenhove, L. N. (2009). Or forum—the evolution of closed-loop supply chain research. *Operations research*, 57(1):10–18.

Hastie, T., Tibshirani, R., and Friedman, J. (2009). *The elements of statistical learning: data mining, inference and prediction*. Springer, 2 edition.

Hendel, I. and Lizzeri, A. (1999). Adverse selection in durable goods markets. *American Economic Review*, 89(5):1097–1115.

Hendel, I. and Nevo, A. (2006). Measuring the implications of sales and consumer inventory behavior. *Econometrica*, 74(6):1637–1673.

Hendel, I. and Nevo, A. (2013). Intertemporal price discrimination in storable goods markets. *The American Economic Review*, 103(7):2722–2751.

Holmes, T. J. (2011). The diffusion of walmart and economies of density. *Econometrica*, 79(1):253–302.

Hotz, V. J. and Miller, R. A. (1993). Conditional choice probabilities and the estimation of dynamic models. *The Review of Economic Studies*, 60(3):497–529.

Houston, M., Kupfer, A.-K., Hennig-Thurau, T., and Spann, M. (2018). Pre-release consumer buzz. *Journal of the Academy of Marketing Science*, (46):338–360.

Ishihara, M. and Ching, A. T. (2019). Dynamic demand for new and used durable goods without physical depreciation: The case of japanese video games. *Marketing Science*, 38(3):392–416.

Iyer, A. V. and Bergen, M. E. (1997). Quick response in manufacturer-retailer channels. *Management science*, 43(4):559–570.

Janiszewski, C. (1993). Preattentive mere exposure effects. *Journal of Consumer Research*, 20:379–392.

Jenkins, R. R., Martinez, S. A., Palmer, K., and Podolsky, M. J. (2003). The determinants of household recycling: a material-specific analysis of recycling program features and unit pricing. *Journal of environmental economics and management*, 45(2):294–318.

Jouini, M. N. and Clemen, R. T. (1996). Copula models for aggregating expert opinions. *Operations Research*, 44(3):444–457.

Judd, K. L. (1998). *Numerical Methods in Economics*, volume 1 of *MIT Press Books*. The MIT Press.

Kaplan, D. A. (2017). The real cost of e-commerce logistics. *Supply Chain Dive*.

Kinnaman, T. C. and Fullerton, D. (2000). Garbage and recycling with endogenous local policy. *Journal of Urban Economics*, 48(3):419–442.

Kodali, S., Hult, P., and Johnson, C. (2008). The future of online secondary ticketing. *Forrester Research, Inc.*

Krishnan, H., Kapuscinski, R., and Butz, D. A. (2010). Quick response and retailer effort. *Management Science*, 56(6):962–977.

Lee, H. L., Padmanabhan, V., and Whang, S. (1997). Information distortion in a supply chain: The bullwhip effect. *Management science*, 43(4):546–558.

Lee, R. S. (2013). Vertical integration and exclusivity in platform and two-sided markets. *American Economic Review*, 103:2960–3000.

Leighton, M. (2020). 10 companies that reward you for recycling old products you don't want or use anymore. *Business Insider*.

Leslie, P. and Sorensen, A. (2014). Resale and Rent-Seeking: An Application to Ticket Markets. *The Review of Economic Studies*, 81(1):266–300.

Lewis, M., Wang, Y., and Wu, C. (2019). Season ticket buyer value and secondary market options. *Marketing Science*, 38(6):973–993.

Li, J., Granados, N., and Netessine, S. (2014). Are consumers strategic? structural estimation from the air-travel industry. *Management Science*, 60(9):2114–2137.

Li, X., Zheng, Y., Zhou, Z., and Zheng, Z. (2019). Demand prediction, predictive shipping, and product allocation for large-scale e-commerce. *Working Paper*.

List, J. A. (2011). Why economists should conduct field experiments and 14 tips for pulling one off. *Journal of Economic Perspectives*, 25(3):3–16.

List, J. A., Sadoff, S., and Wagner, M. (2010). So you want to run an experiment, now what? some simple rules of thumb for optimal experimental design. Working Paper 15701, National Bureau of Economic Research.

Litchfield, C. A., Lowry, R., and Dorrian, J. (2018). Recycling 115,369 mobile phones for gorilla conservation over a six-year period (2009-2014) at zoos victoria: A case study of 'points of influence' and mobile phone donations. *PLOS ONE*, 13:1–18.

Liu, Q. and van Ryzin, G. J. (2008). Strategic capacity rationing to induce early purchases. *Management Science*, 54(6):1115–1131.

Liu, Y. (2006). Word of mouth for movies: Its dynamics and impact on box office revenue. *Journal of Marketing*, 70(3):74–89.

Logitech (2021). Logitech sustainability report FY 2021. Accessed on January 1, 2022, `https://www.logitech.com/en-us/sustainability.html`.

Logitech (2022). Logitech products page. Accessed on March 27, 2022, `https://www.logitech.com/en-us/products.html`.

Lu, F. (2018). A beginner's guide to your first supreme drop. *Paper Magazine*.

Lyon, T. P. and Maxwell, J. W. (2011). Greenwash: Corporate environmental disclosure under threat of audit. *Journal of Economics & Management Strategy*, 20(1):3–41.

Ma, C., Lu, J., and Yuan, R. (2018). The secret behind JD.com's super fast delivery. *JD Technology Blog*.

Maheshwari, S. (2019). The realreal i.p.o.: Secondhand fashion goes mainstream. *The New York Times*.

Martin, E. (2019). 14 companies that recycle their own products. Accessed February 1, 2022, `https://www.goodhousekeeping.com/uk/consumer-advice/consumer-rights/a25915660/brands-that-recycle-products/`.

Mas-Colell, A., Whinston, M. D., Green, J. R., et al. (1995). *Microeconomic theory*, volume 1. Oxford university press New York.

McFadden, D. (1979). Quantitative methods for analyzing travel behavior of individuals: Some recent developments in hensher d., & stopher p.(eds.), behavioral travel modeling (pp. 279–318). *London: Croom Helm.[Google Scholar]*.

McKinsey (2016). The circular economy: Moving from theory to practice. *McKinsey Center for Business and Environment*.

McKinsey (2021). NEF spotlight: The path forward for retail's sustainable future. Accessed February 1, 2022, `https://www.mckinsey.com/business-functions/strategy-and-corporate-finance/our-insights/nef-spotlight-the-path-forward-for-retails-sustainable-future`.

McKinsey Quarterly (2017). Mapping the benefits of a circular economy. Accessed February 1, 2022, `https://www.mckinsey.com/business-functions/sustainability/our-insights/mapping-the-benefits-of-a-circular-economy`.

Montgomery, D. B., Silk, A. J., and Zaragoza, C. E. (1971). A multiple-product sales force allocation model. *Management Science*, 18(4-part-ii):P–3–P–24.

Moon, K., Bimpikis, K., and Mendelson, H. (2018). Randomized markdowns and online monitoring. *Management Science*, 64(3):1271–1290.

Mullin, S. (2020). The complete guide to a/b testing: Expert tips from google, hubspot, and more. *Shopify Blog*.

Musalem, A., Olivares, M., Bradlow, E. T., Terwiesch, C., and Corsten, D. (2010). Structural estimation of the effect of out-of-stocks. *Management Science*, 56(7):1180–1197.

Nair, H. (2007). Intertemporal price discrimination with forward-looking consumers: Application to the US market for console video-games. *Quantitative Marketing and Economics*, 5(3):239–292.

National Forest Foundation (2022). Tree planting programs. Accessed February 1, 2022, `https://www.nationalforests.org/tree-planting-programs`.

Netessine, S. and Rudi, N. (2006). Supply chain choice on the internet. *Management Science*, 52(6):844–864.

Olivares, M., Terwiesch, C., and Cassorla, L. (2008). Structural estimation of the newsvendor model: An application to reserving operating room time. *Management Science*, 54(1):41–55.

Ongondo, F. and Williams, I. (2011). Greening academia: Use and disposal of mobile phones among university students. *Waste Management*, 31(7):1617–1634.

Ouorou, A., Mahey, P., and Vial, J.-P. (2000). A survey of algorithms for convex multicommodity flow problems. *Management science*, 46(1):126–147.

Ozer, O. and Phillips, R. (2012). *The Oxford Handbook of Pricing Management*. Oxford University Press.

Patel, S. (2020). Sneaker platform goat group raises $100 million to fund expansion plans. *The Wall Street Journal*.

Paton, E. (2016). Kylie Jenner and the year of the drop. *The New York Times*.

Peacock, L. (2020). The price is right: 13 strategies for finding the ideal price for your products. *Shopify Blog*.

Perakis, G., Singhvi, D., and Spanditakis, Y. (2020). Leveraging the newsvendor for inventory distribution at a large fashion e-Retailer with depth and capacity constraints. *Working paper*.

Randall, T., Netessine, S., and Rudi, N. (2006). An empirical examination of the decision to invest in fulfillment capabilities: A study of internet retailers. *Management Science*, 52(4):567–580.

Reiss, P. and Wolak, F. (2007). Chapter 64 structural econometric modeling: Rationales and examples from industrial organization. *Handbook of Econometrics*.

Rigby, D. (2014). How retailers are transforming the shopping experience. *Harvard Business Review*.

Rudi, N., Kapur, S., and Pyke, D. F. (2001). A two-location inventory model with transshipment and local decision making. *Management science*, 47(12):1668–1680.

Russell, R. and Taylor, B. (2006). *Operations management : quality and competitiveness in a global environment*. John Wiley and Sons, 5th edition.

Rust, J. (1987). Optimal replacement of gmc bus engines: An empirical model of harold zurcher. *Econometrica*, 55(5):999–1033.

Sahni, N. S., Zou, D., and Chintagunta, P. K. (2017). Do targeted discount offers serve as advertising? evidence from 70 field experiments. *Management Science*, 63(8):2688–2705.

Savaskan, R. C., Bhattacharya, S., and Van Wassenhove, L. N. (2004). Closed-loop supply chain models with product remanufacturing. *Management Science*, 50(2):239–252.

Shen, M., Tang, C. S., Wu, D., Yuan, R., and Zhou, W. (2020). Jd. com: Transaction-level data for the 2020 msom data driven research challenge. *Manufacturing & Service Operations Management*.

Shevchenko, T., Laitala, K., and Danko, Y. (2019). Understanding consumer e-waste recycling behavior: Introducing a new economic incentive to increase the collection rates. *Sustainability*, 11(9).

Shiller, B. R. (2013). Digital distribution and the prohibition of resale markets for information goods. *Quantitative Marketing and Economics*, 11:403–435.

Simester, D., Hu, Y. J., Brynjolfsson, E., and Anderson, E. T. (2009). Dynamics Of Retail Advertising: Evidence From A Field Experiment. *Economic Inquiry*, 47(3):482–499.

Singh, J., Teng, N., and Netessine, S. (2019). Philanthropic campaigns and customer behavior: Field experiments on an online taxi booking platform. *Management Science*, 65(2):913–932.

Slade, M. E. and G.R.E.Q.A.M. (1998). Optimal pricing with costly adjustment: Evidence from retail-grocery prices. *The Review of Economic Studies*, 65(1):87–107.

Soper, S. (2020). Amazon plans to put 1000 warehouses in suburban neighborhoods. *Bloomberg*.

Stamatopoulos, I., Bassamboo, A., and Moreno, A. (2020). The effects of menu costs on retail performance: Evidence from adoption of the electronic shelf label technology. *Management Science*.

Stern, P. C. (1999). Information, incentives, and proenvironmental consumer behavior. *Journal of Consumer Policy*, 22:461–478.

Stock, A. and Balachander, S. (2005). The making of a “hot product”: A signaling explanation of marketers’ scarcity strategy. *Management Science*, 51(8):1181–1192.

Su, X. (2007). Intertemporal pricing with strategic customer behavior. *Management Science*, 53(5):726–741.

Su, X. (2010). Optimal pricing with speculators and strategic consumers. *Management Science*, 56(1):25–40.

Swaminathan, J. M. and Tayur, S. R. (2003). Models for supply chains in e-business. *Management Science*, 49(10):1387–1406.

Talluri, K. and van Ryzin, G. (2005). *The Theory and Practice of Revenue Management*. Oxford University Press.

Tanaka, M. (2013). Deflation in durable goods markets: An empirical model of the tokyo condominium market. *Structural Econometric Models (Advances in Econometrics)*, 31:337–386.

Terwiesch, C., Olivares, M., Staats, B. R., and Gaur, V. (2020). OM forum - review of empirical operations management over the last two decades. *Manufacturing & Service Operations Management*, 22(4):656–668.

The Recycling Partnership (2020). 2020 state of curbside recycling report. Accessed March 1, 2022, `https://recyclingpartnership.org/wp-content/uploads/dlm_uploads/2020/02/2020-State-of-Curbside-Recycling.pdf`.

Thi Thu Nguyen, H., Hung, R.-J., Lee, C.-H., and Thi Thu Nguyen, H. (2019). Determinants of residents' e-waste recycling behavioral intention: A case study from vietnam. *Sustainability*, 11(1).

Thogerson, J. (2003). Monetary incentives and recycling: Behavioural and psychological reactions to a performance-dependent garbage fee. *Journal of Consumer Policy*, 26:197–228.

Train, K. (2000). Halton sequences for mixed logit. *Unpublished technical report*.

Train, K. (2009). *Discrete Choice Methods With Simulation*, volume 2009.

Ufford, L. (2018). The art of the drop: How retailers flash sales use hype to move product (and fast). *Shopify Retail Marketing Blog*.

Van Elven, M. (2018). The business of hype: why so many fashion brands are now doing "product drops". *Fashion United*.

Van Mieghem, J. A. and Rudi, N. (2002). Newsvendor networks: Inventory management and capacity investment with discretionary activities. *Manufacturing & Service Operations Management*, 4(4):313–335.

Van Roy, B., Bertsekas, D., Lee, Y., and Tsitsiklis, J. (1997). A neuro-dynamic programming approach to retailer inventory management. In *Proceedings of the 36th IEEE Conference on Decision and Control*, volume 4, pages 4052–4057 vol.4.

Varin, C. and Vidoni, P. (2005). A note on composite likelihood inference and model selection. *Biometrika*, 92(3):519–528.

Veinott, A. F. (1965). Optimal policy for a multi-product, dynamic, nonstationary inventory problem. *Management science*, 12(3):206–222.

Viscusi, W. K., Huber, J., and Bell, J. (2011). Promoting recycling: Private values, social norms, and economic incentives. *American Economic Review*, 101(3):65–70.

Viscusi, W. K., Huber, J., Bell, J., and Cecot, C. (2013). Discontinuous behavioral responses to recycling laws and plastic water bottle deposits. *American law and economics review*, 15(1):110–155.

Von Wilpert, C. (2019). Supreme streetwear's insane success. *Sumo Blog*.

Wagner, T. P. (2013). Examining the concept of convenient collection: An application to extended producer responsibility and product stewardship frameworks. *Waste Management*, 33(3):499–507. Special Thematic Issue: Urban Mining.

Waldman, M. (2003). Durable goods theory for real world markets. *Journal of Economic Perspectives*, 17(1):131–154.

Walmart (2017). Toward a zero waste future. Accessed February 1, 2022, `https://cdn.corporate.walmart.com/a4/32/d7eb7ffa416c951694eb95099953/grr-12-zero-waste-future.pdf`.

Wang, R. and Sahin, O. (2018). The impact of consumer search cost on assortment planning and pricing. *Management Science*, 64(8):3649–3666.

Wilson, G. T., Smalley, G., Suckling, J. R., Lilley, D., Lee, J., and Mawle, R. (2017). The hibernating mobile phone: Dead storage as a barrier to efficient electronic waste recovery. *Waste Management*, 60:521–533. Special Thematic Issue: Urban Mining and Circular Economy.

Winkler, N. (2021). Ecommerce fulfillment, free shipping two-day delivery: How to compete with amazon while increasing profit margins. *Shopify Plus blog*.

Wolverson, R. (2012). High and low: Online flash sales go beyond fashion to survive. *Time Magazine*.

Wooldridge, J. M. (2002). *Econometric analysis of cross section and panel data*. MIT Press, Cambridge and London.

Wright, M. (2005). The interior-point revolution in optimization: history, recent developments, and lasting consequences. *Bulletin of the American mathematical society*, 42(1):39–56.

Wu, C. J. and Hamada, M. S. (2011). *Experiments: planning, analysis, and optimization*, volume 552. John Wiley & Sons.

Xiong, G. and Bharadwaj, S. (2014). Prerelease buzz evolution patterns and new product performance. *Marketing Science*, 33(3):401–421.

Xu, P. J., Allgor, R., and Graves, S. C. (2009). Benefits of reevaluating real-time order fulfillment decisions. *Manufacturing & Service Operations Management*, 11(2):340–355.

Yin, J., Gao, Y., and Xu, H. (2014). Survey and analysis of consumers' behaviour of waste mobile phone recycling in china. *Journal of Cleaner Production*, 65:517–525.

Yohn, D. L. (2020). The pandemic is rewriting the rules of retail. *Harvard Business Review*.

Zbaracki, M. J., Ritson, M., Levy, D., Dutta, S., and Bergen, M. (2004). Managerial and customer costs of price adjustment: Direct evidence from industrial markets. *The Review of Economics and Statistics*, 86(2):514–533.

Zhao, H., Deshpande, V., and Ryan, J. K. (2005). Inventory sharing and rationing in decentralized dealer networks. *Management Science*, 51(4):531–547.

Zhao, H., Ryan, J. K., and Deshpande, V. (2008). Optimal dynamic production and inventory transshipment policies for a two-location make-to-stock system. *Operations Research*, 56(2):400–410.

Zhu, F. and Sun, S. (2019). JD: Envisioning the future of retail. *Harvard Business School Case 618-051*.

Zhu, J.-D. (2014). Effect of resale on optimal ticket pricing: Evidence from major league baseball tickets. *Working Paper*.