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Essays on Retail Operations

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Essays on Retail Operations

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Abstract

This dissertation consists of three individual essays that look at different dimensions of retail operations. The first essay investigates the strategic implementation of free in-store pickup services in the retail industry. Motivated by the increasing prevalence of omni-channel strategies, we analytically model the decision-making process of a profit-maximizing retailer considering the adoption of free ship-to-store services for online-exclusive products. Our analysis highlights how such services impact pricing, shipping fee decisions, and customer behavior by attracting foot traffic to local stores, thereby boosting in-store sales. We provide prescriptive models that facilitate retailers in evaluating the potential value and customer response to adopting ship-to-store services.

The second essay shifts focus to consumers' purchase behavior by investigating the impact of negative environmental, social, and governance (ESG) news coverage on brand sales at a major U.S. retailer. Utilizing retail transaction data and firm-level ESG information, this empirical study uncovers that negative ESG incidents significantly affect brand sales, though the direction of impact varies by the type of violation. Surprisingly, while social and governance incidents hurt sales, news coverage related to environmental and cross-cutting issues may inadvertently enhance them. This nuanced impact is further moderated by brand and market-specific factors, offering actionable insights for brands and retailers in mitigating risks associated with ESG violations.

In the third essay, we examine whether Nike's bold and controversial campaign, spurred by its partnership with Colin Kaepernick in 2018, undermines sales of other sportswear brands within the same retailer in comparison to the brands that should not be impacted by Nike's campaign. Employing a unique transactional dataset from a major U.S. department store, we show that Nike's political advocacy leads to a significant sales decline in the sportswear department, compared to the control department that includes furniture and home decor items. These findings demonstrate the significant influence of major brands' public political positions on the sales dynamics of related brands and departments within brick-and-mortar stores. Collectively, these essays contribute to a deeper understanding of retail operations, ESG-related consumer behavior, and the implications of corporate political advocacy, offering valuable guidance for retailers navigating these complex dimensions.

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Chapter 1

The Value of Offering Free Ship-to-store Service for Online-exclusive Products

Abstract

Implementing free in-store pickup services has become increasingly widespread in the retail industry as part of an omni-channel strategy. Retailers considering to launch a new service need to evaluate the value gained and resulting changes to customer behavior to understand if implementation should move forward. The operations literature on omni-channel retailing is growing, has generally been empirically focused, and has recently attracted more attention since the COVID-19 pandemic has made services such as ship-to-store or curbside pickup vital for retailers to stay competitive. We add to this body of work by analytically modeling the setting of free ship-to-store services for online-exclusive products, providing prescriptive optimal decisions and comparative statics across a wide range of market parameters. We analytically model a profit-maximizing retailer faced with a heterogeneous customer base and derive optimal pricing and shipping fee decisions. We further analyze how demand segments and the resulting profit change under different market conditions to understand the impact of free ship-to-store service on customer shopping behavior. By its nature, adopting free ship-to-store service attracts customers to local stores for the pickup process, which in turn increases store foot traffic. We show that the retailer's price and shipping fee decisions depend on the additional sales arising from the increased store foot traffic. Furthermore, we show that the impact of additional profit arising from the increased in-store traffic on the optimal price depends on the hassle cost difference between the home-delivery and ship-to-store services. We develop prescriptive models that enable a retailer to evaluate the value of adopting such omni-channel service along with expected customer purchase behavior after implementation.

Keywords: Omni-channel retailing, Buy-online and ship-to-store service, Channel integration.

1.1 Introduction

With the advent of new technologies and smartphones, the current shopping journey for customers includes switching between mobile, online, catalog, and brick-and-mortar channels. This blended shopping journey has put pressure on retailers to harmonize their existing channels and has led to innovative fulfillment services such as buy-online and ship-to-store (STS), buy-online and pick-up-in-store, buy-online and return-to-store, ship-from-store, and reserve-online and pick-up-in-store in order to match seamless shopping expectations of customers (Bell et al., 2014).

In recent years, the retail industry has quickly adapted to support consumers' new expectations for online shopping (Gallino et al., 2017). Such new expectations have been further consolidated due to the outbreak of COVID-19 pandemic. When people were prohibited from going into stores, online shopping became essential. Consumers expected more choices of products, together with more flexible pickup options for these online orders (Ketzenberg and Akturk, 2021). Thus, buy-online and curbside pickup service has been adopted during lockdown periods by most major retailers including Walmart and CVS, among others. These new service processes are known as omni-channel retailing practices and require aligning promotion campaigns, assortment planning, inventory systems, and warehouses across both online and offline channels (Gallino and Moreno, 2014). Consider a leading department store such as Macy's. The company has made leaps and bounds in optimizing and synchronizing its supply chain to support an omni-channel strategy, with the COVID-19 pandemic expediting the process (Ali, 2021). With these omni-channel services, Macy's online customers can order a wide range of products and enjoy the flexibility to use either home-delivery or free in-store pickup options. Such omni-channel practice is critical for the retailer to meet customers' different requirements, and in turn we have witnessed Macy's e-commerce boom in 2020, where 25% of its digital sales were fulfilled from stores (Macy's, 2021).

Essentially, the main idea behind omni-channel retailing is to create a consistent shopping experience for consumers regardless of the channel they prefer (Rigby, 2011; Carroll and Guzman, 2013). From the retailer's perspective, launching omni-channel services not only benefits the online channel but also serves as a way to attract customers to visit the store and potentially stimulate further in-store sales.

In this paper, our focus will be on the value of launching STS service. With STS, retailers ship online orders to customers' preferred store locations for free. Furthermore, customers have the flexibility to pick up their online orders at their earliest convenience once their orders are available at the store. For example, Best Buy offers free STS service in addition to the traditional fee-based home-delivery (HD) shipping option and there is no additional charge for orders that are picked up at the store. Similar free STS service options are also available at all Walgreen's and Kohl's store locations. To motivate more customers to visit and pick up orders in store, Nordstrom holds STS items in-store for 10 days without any fees and customers are also eligible for free gift wrapping.

Although store pickup services such as STS and buy-online and pick-up-in-store services are different from one another such that they require different processes and fulfillment tradeoffs, sometimes they are used interchangeably. Note that while both services require customers to visit local stores, STS service involves an actual shipment from a retailer's warehouse or other stores to the customers' preferred store locations. In the buy-online and pick-up-in-store case, however, the order is actually fulfilled by a store's existing inventory, mostly in couple hours. As such, the launch of STS services provides consumers with an augmented product assortment. To capture these features and evaluate the unique value of STS services, we focus on online-exclusive products.

From the customers' standpoint, the benefit of the STS service is the perceived increase in the product assortment not immediately available in the physical store (Radial, 2016). Consider the largest home improvement retailer in the United States, The Home Depot, which recently implemented free STS service. The retailer promotes the new service as "Free in-store pickup over one million online items eligible" on its website. For example, if one searches for "framed cord board" via Home Depot's website, the page returns over 90 results. However, none of those items are available for pickup in a nearby store based on the first author's location. For similar cases, customers need to have the cord boards shipped to their address with an additional shipping fee. Alternatively, Home Depot offers free STS service such that customers may pick up their online orders in a local store without any extra charge. Clearly, STS eliminates the traditional shipping fee, which is a hindrance for online shopping and remote purchases (Teo et al., 2004). Recent studies indicate that shipping and handling surcharges in online shopping may undermine purchase intentions of customers (Lewis et al., 2006; Leng and Arreola, 2010). Likewise, findings in customer surveys show that the primary reason for cart abandonment in e-commerce shopping is high shipping fees (Forrester, 2011; Barilliance.com, 2019). As a response to high shipping fees, 36% of customers choose store pickup options to qualify for free shipping according to another recent study by the United Parcel Service (UPS, 2015). Evidently, customers value free shipping opportunities for online shopping.

Most omni-channel service processes are created by retail professionals to attract customers to offline stores (Shopify.com, 2018; O'Carroll, 2019) and thereby boost foot traffic at the brick and mortar channel (Yantra, 2005; Gannon, 2019). Note that store traffic plays a crucial role to generate in-store sales (Chapados et al., 2014; Chuang et al., 2015; Ketzenberg and Akturk, 2021), which can come through either impulse purchases (Stahlberg and Maila, 2010) or the ability of store employees to convert store traffic into sales (Perdikaki et al., 2012; Mani et al., 2015). For example, Bae et al. (2011) indicate that at department stores, impulse purchases account for 27% to 62% of in-store sales. Thus, retailers need to increase and maintain their store traffic in order to stay competitive. Due to its nature, STS delivery requires customers to visit their local stores to pick up their online orders, which in turn increases store foot traffic. Furthermore, a recent survey shows that among customers that use in-store pickup option, 45% spend more on additional items during the pickup process (UPS, 2015). As such, there exist opportunities for retailers to increase store foot traffic and thereby increase in-store sales by offering STS to customers.

When evaluating the pros and cons of adopting an STS service, retail executives may be concerned about the investment required in process changes, information technologies, and operating challenges (Davis, 2008; Zhang et al., 2010). To address these concerns, we first investigate under what circumstances offering a free STS service is more profitable than offering only HD service. Next, we explore how the optimal price and shipping fee decisions under an omni-channel scenario change compared to the HD only case? Finally, we want to address how STS service and the corresponding optimal price and shipping fee decisions impact customer behavior as well as the retailer's customer demand segments.

To answer our research questions, we start with a benchmark model, in which customers can only choose fee-based HD service. Building upon the benchmark model, we next develop an omni-channel model, in which customers can choose either fee-based HD or free STS service. We evaluate the retailer's optimal decisions on price and shipping fee, and further identify the value of launching additional STS service. Assuming STS is costless to implement, we find that introducing ship-to-store service is always at least as profitable as offering traditional fee-based home-delivery service only when the retailer charges a shipping fee for HD service. The additional profit arising from the STS pickup process provide important managerial insights for the retailers that plan to implement such omni-channel services. Furthermore, we show that customer hassle cost and the retailer's ability to convert foot traffic into additional sales interact with the optimal pricing decision in different ways based on market conditions.

The rest of this paper is organized as follows. In Section 1.2, we review literature. In Section 1.3, we build analytical models and present optimality results under different market conditions. Finally, we discuss our major findings and conclude in Section 1.4.

1.2 Literature Review

We study the integration of online and offline channels via an omni-channel service offering called STS and investigate the value of adopting it from a retailer's perspective. Our work is primarily related to two streams of literature: the operations of channel-integration; customer behavior after omni-channel implementation.

The first stream of literature covers a wide range of channel-integration settings and investigates the operational impact on firms. To better facilitate customers' changing requirements, traditional physical stores are now functioning as a fulfillment center for the online orders (Gallino et al., 2017). Thus, the underlying channel integration enhances the perceived level of service quality while it mitigates the inherent risk associated with online shopping (Herhausen et al., 2015). Studying the cross-channel competition dimension, Brynjolfsson et al. (2009) observe that e-tailers deal with greater competition from traditional offline retailers for common items compared to uncommon items. Exploring the impact of launching omni-channel services (i.e., STS) on a retailer's inventory decisions, Gallino et al. (2017) find that STS service offering enhances the sales dispersion by increasing the contribution of the lowest-selling items. Investigating the store-level fulfillment strategy, Jin et al. (2018) develop a theoretical model to find the recommended service area for STS fulfillment.

Focusing on a focal firm's performance after channel integration, Cao and Li (2015) find that integrating existing channels leads to higher sales conditional on the firm's physical store presence as well as prior online experience. In an empirical setting, Huang and Van Mieghem (2014) investigate a case in which a retailer runs a showroom for information provision purposes while accepting orders only at the physical (offline) channel. The authors assess the efficacy of employing online click-stream data to make better decisions at the offline channel and find that such information may be utilized to make predictions regarding the timing of offline channel orders, order size, and the probability of placing an order. Focusing on the relationship between a firm's ability to retain its customer base and product availability information, Bendoly et al. (2005) find that for stock-out incidents, channel integration can stop customers from switching to competitor retailers by motivating them to use the secondary channel. Most studies under this stream of literature empirically examine the outcome of the practical implementation of an omni-channel strategy. In contrast, this paper develops an analytical model to prescribe optimal decisions and assess the value of implementing an omni-channel strategy, adding to the literature.

The second stream of related literature explores customer behavior after a retailer implements an omni-channel strategy, and the resulting impact on the online channel and offline store. For example, Ansari et al. (2008) find that marketing efforts can encourage customers to move to the online channel. Using an empirical setting and focusing on the channel choice for grocery shopping, Chintagunta et al. (2012) find that transaction costs at different channels influence customer decisions regarding the choice between online versus offline channels for shopping. Exploring customer behavior in a multi-channel setting, Hu et al. (2021) investigate the demand-pooling phenomenon and the retailer's inventory re-optimization problem after the adoption of an omni-channel strategy. In addition, Jerath et al. (2015) show that customers have different objectives when they prefer different channels.

Focusing on the competitor relationship between online and offline channels, Forman et al. (2009) show that customers switch channels (i.e., from online to offline) after the firm opens a physical store in a nearby location. Likewise, Avery et al. (2012) focus on physical store openings and show that in the short run, opening a physical store may lead to a decrease in catalog sales while it does not influence online sales. In the long run, however, sale of both online and catalog channels increase. Investigating the competitive dimension of omni-channel retailing, Akturk and Ketzenberg (2022) show that both online and store sales at a focal retailer are adversely affected after the competitor's launch of buy-online and pick-up-in-store service. Similarly, Ertekin et al. (2021), show that in-store pickup visits entail the risk of losing some customers by exposing them to alternative products at nearby competitors.

In this paper, we study an innovative service offering to attract online customers into stores under an omni-channel setting, in which customers are able to buy products that are not immediately available at their local stores, have them shipped to their local stores for free, and then pick up online orders at their preferred store location and at their earliest convenience. We contribute to the existing literature with a novel analytical approach such to model a setting where customers strategically choose between the available fulfillment options. For this setting, we identify the retailer's optimal price and shipping fee decisions. Consistent with the practice, we differentiate between hassle costs arising from HD and STS services and take customers' sensitivity to such costs into account in our analyses. This approach enables our model to capture customer heterogeneity in the choice between HD and STS fulfillment options. Finally, from a technical perspective, we investigate the retailer's decisions on *both* price and HD shipping fee, which better reflects real-world complexity compared to much of the previous analytical work in this domain that considers a single pricing decision variable.

To investigate the value of adopting free STS service, we also incorporate a key literature finding that in-store traffic generates additional sales in the local store over online shopping alone. Gao and Su (2016) study the consequences of offering free buy-online and pick-up-in-store service on a retailer's operations and show that it boosts the overall customer demand. However, it also leads to channel switching incidents such that a fraction of customers move from the online channel to the physical store channel (Gao and Su, 2016). In addition, Akturk et al. (2018) use transaction data to evaluate the impact of launching STS service offering on sales and consumer returns both at the online and offline channels. For sales, the authors find that some customers move from the online to the offline channel despite the fact that information with respect to product availability does not exist for online customers.

1.3 Model

Consider a profit-maximizing retailer with both online and offline channels. The retailer offers a large variety of products through its online channel with limited product selection at the offline locations. We model the retailer's pricing decision and customers' purchase decisions for a product available in the online channel but not at the closest store location.

We first build a benchmark (BM) model, where the retailer only offers HD service. In this setting, the retailer sets the purchase price, p and we assume that p is the same for all customers. We then extend our model to include both HD and STS services and call this the omni-channel (OM)

model. In practice, it is common for the retailer to adjust the shipping charge for the traditional HD services, especially when there is a new shipping option available. For instance, after the launch of STS services (also known as "Drive Up") in 2018 , Target started to charge \$5.99 for HD services for orders under \$35, while the threshold was \$25 before 2018. Thus, it becomes a strategic decision for the retailer to adjust HD-related shipping cost so as to motivate customers to use the new free STS services.

Therefore, in the OM model, the retailer sets p and the shipping fee for HD, f, where we again assume that p and f are the same for all customers. Subsequently, customers can choose either HD service and pay a shipping fee f or free STS service and pick up their items at a preferred store location. Typically, HD is faster since the retailer will use third-party shipping services, but the customer bears an additional shipping cost to acquire the product. Retailers offer free STS options since they can use their existing distribution network to ship items from centralized distribution centers or between store locations at little marginal cost. In addition, consistent with Akturk et al. (2018), we assume that STS increases foot traffic, which in turn increases sales at the offline channel. Given the price of the product, the shipping fee for HD, and the inconvenience of the STS option, customers choose whether or not to purchase a product, and, if purchasing, which fulfillment option to use.

For both models, we derive the optimal decisions for the retailer as well as the corresponding profits. Subsequently, we analyze how decisions and demand segments change with respect to underlying model parameters. We present the detailed proofs of all lemmas and corollaries in the Appendix. We use subscripts i ($i = BM$ represents the benchmark model, $i = OM$ represents the omni-channel model) to differentiate between models and superscripts j ($j = HD$ represents home-delivery, $j = STS$ represents ship-to-store, $j = NP$ represents no-purchase) to differentiate between fulfillment specific parameters. Note, however, that we omit subscripts and superscripts when it is clear which model, or fulfillment type, we refer to.

1.3.1 Benchmark (BM) Model

We start with the BM model, in which the retailer offers only a fee-based HD service for online orders. In this setting, customers observe the product's price, p, the shipping fee, f, and the hassle cost of acquiring the product through home-delivery, t^{HD}, which mainly captures the delay time between placing an order and receiving the product. Let γ denote the sensitivity of customers to hassle cost, t^{HD}, where γ is uniformly distributed between zero and one on the standard Hotelling line and known only to the customers. All customers have a valuation v for the product, where $v \in (0, 1)$, and we assume this is known to both the retailer and customers. Let s denote a proportionality constant to scale hassle cost, which is similar to the one used by Mehra et al. (2018), where $s \in (0, 1)$. Let u^{HD} be the net utility a customer gets by receiving the product through home delivery and therefore the expected net utility of a HD customer is given by,

$$\mathbb{E}[u^{HD}] = v - s\gamma t^{HD} - f - p. \tag{1.1}$$

When $\mathbb{E}[u^{HD}] > 0$, the customer purchases the product through the HD fulfillment option, otherwise, the customer does not make a purchase and receives zero utility. To identify the two segments of customers, purchase through HD and NP, we will focus on the boundary customer who is indifferent between making a purchase or not making a purchase. Let γ^{HD} denote the sensitivity of this boundary customer to delay time, which implies that all customers with the sensitivity that is higher than γ^{HD} will not purchase the product. Setting $\mathbb{E}[u^{HD}] = 0$ and solving for γ, we get,

$$\gamma^{HD} = \frac{v - f - p}{st^{HD}}. \tag{1.2}$$

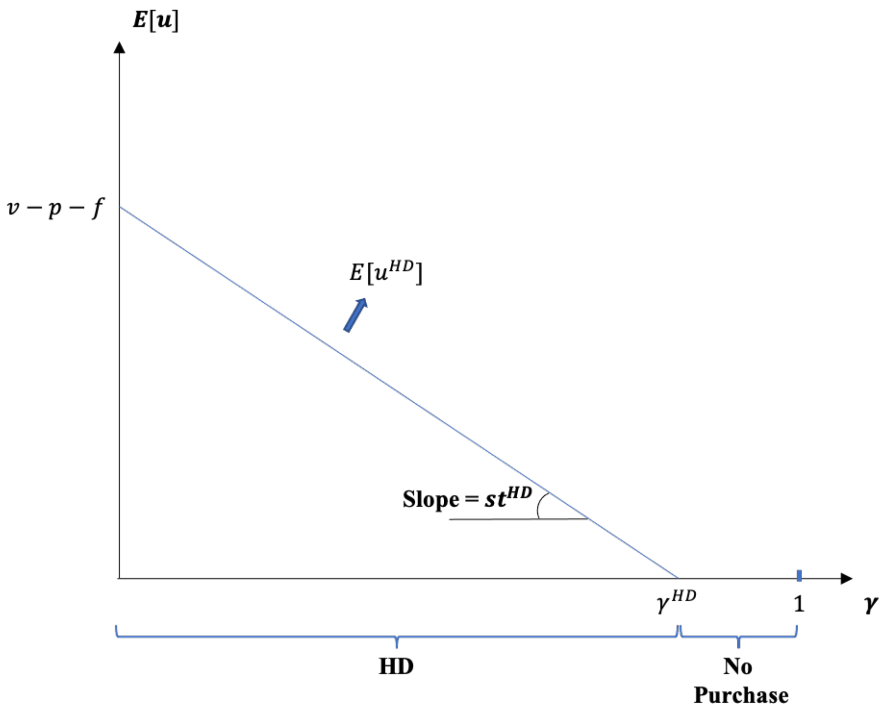


Figure 1.1: Expected Utility of a HD Customer with Respect to γ.

Figure 1.1 illustrates the market segments of HD customers and NP customers. Note that the segment on the horizontal axis to the left of γ^{HD} identifies the customers who purchase the product. As γ^{HD} shifts to the right (left), the customer demand increases (decreases). Furthermore, the HD segment is given by γ^{HD} and the NP segment is given by $(1 - \gamma^{HD})$.

1.3.1.1 BM Retailer

The retailer wishes to maximize its profit by setting the product price, p. In the BM model, we treat the shipping fee, f, as a parameter (not as a decision), which is mainly a pass-through cost to the customer (i.e., the shipping fee is not a meaningful source of profit). We later expand our OM model to incorporate the shipping fee f as a decision made by the retailer. The procurement cost per unit of the product is given by c, and we assume $0 < c \leq p$. Once the price and shipping fee are set by the retailer, the corresponding demand (i.e. market segments) can be determined from Equation (1.2). Notice if $v - f - p > st^{HD}$, all customers purchase the product using HD and if $v - f - p < 0$, no customer purchases the product. We therefore impose constraints on the model to study the case where both HD and NP customers exist. For completeness, we provide analyses for the two less interesting scenarios in the Appendix. In the BM model, the retailer earns a profit of $(p - c)$ for each unit of the product sold through the HD channel. We denote the retailer's profit as π_{BM} and see that $\pi_{BM} = (p - c)(\gamma^{HD})$. The profit-maximizing retailer solves the following optimization problem,

$$\begin{aligned} \max_{p} \ & \pi_{BM} \\ \text{s.t.:} \ & v - f - p < st^{HD} \\ & v - f - p > 0 \\ & p > 0 \end{aligned}$$

We solve the retailer's optimization problem for the BM model and present the optimal solution in Lemma 1.

Lemma 1. *The retailer's optimal price and corresponding optimal profit in the BM model are given by:*

$$p^*_{BM} = \frac{1}{2}(c - f + v), \tag{1.3}$$

$$\pi^*_{BM} = \frac{(c + f - v)^2}{4st^{HD}}. \tag{1.4}$$

The closed-form solution in Lemma 1 gives the retailer the ability to optimally set a price and compute the optimal profit for that pricing decision when it offers only HD service. While this result is not novel on its own, we will use this benchmark model to compare results in our OM model. In addition, we use this result for comparative statics to understand how model parameters affect optimal decisions and market outcomes.

1.3.1.2 BM Sensitivity Analysis

We perform sensitivity analysis and present how the optimal price and optimal profit in the BM model change with respect to changes in underlying model parameters. We summarize the results in Table 1.1.

Table 1.1: Sensitivity Analysis for the BM model

Parameter	Impact on p^*	Impact on π^*
f	$-$	$-$
c	$+$	$-$
v	$+$	$+$
s		$-$
t^{HD}		$-$

$+$ represents positive relationship.
$-$ represents negative relationship.

First, we find that both the optimal price and profit decrease as the shipping fee, f, increases. This arises because customers pay the shipping fee in the BM model and when f increases, customers are less willing to complete a purchase. As a result, the retailer reduces the price in order to attract more customers, which in turn reduces its profit. Second, we find that the optimal price increases with respect to procurement cost, because a higher procurement cost will lead to a higher price. In addition, such increase in procurement cost leads to lower profit as the retailer incurs a higher cost for each order. Third, the optimal price and profit increase as the customer's valuation of the product increases. Note that a higher valuation represents the customer's higher willingness to buy the product, which then enables the retailer to charge a higher price. This also leads to a higher overall profit. Fourth, we find that the proportionality constant and hassle cost do not influence the optimal price, but have a negative impact on the optimal profit. This arises because customers incur higher hassle cost as s or t increases, and therefore both the demand and the overall profit decrease.

1.3.1.3 Market Segments

In the BM model, customers are divided into two segments: the HD segment, denoted as D_{BM}^{HD}; NP segment, denoted as D_{BM}^{NP}. Given the retailer's optimal price decision, we derive the corresponding market segments by substituting p^* into Equation (1.2) and get,

$$D_{BM}^{HD} = \frac{-c-f+v}{2st^{HD}},$$
$$D_{BM}^{NP} = \frac{c+f+2st^{HD}-v}{2st^{HD}}.$$

Figure 1.2 provides a two-dimensional visualization to illustrate how the market segments change

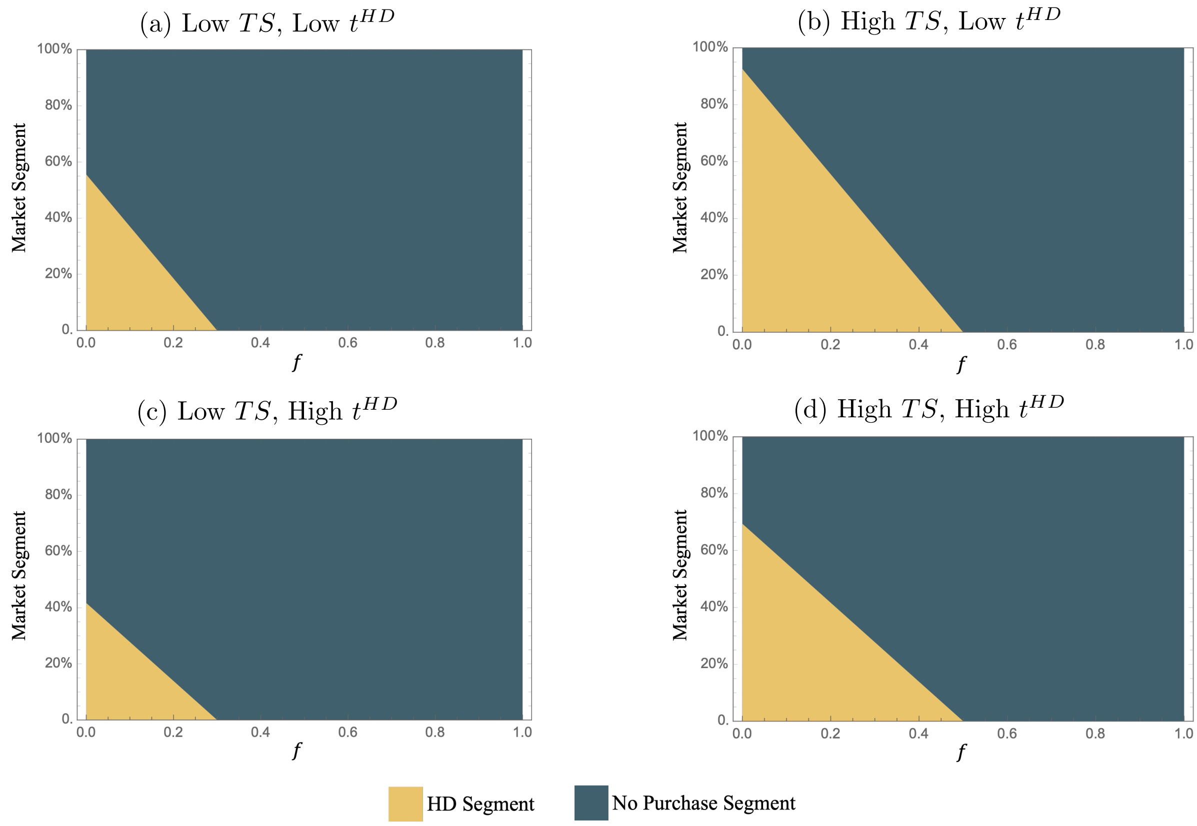


Figure 1.2: (Color Online) Impact of Total Surplus and t^{HD} on BM Segments

with respect to shipping fee, f, under different market settings. Note that the rows in Figure 1.2 represent different level of hassle cost t^{HD} for HD customer, while the columns represent different levels of total surplus (TS), $v-c$. Consistent with the basic ideas from microeconomics field, we define the total surplus as the difference between the customer's valuation for the product, v, and the retailer's acquisition cost, c, which delineates the measure of the market efficiency or net benefits accruing to all participants in the market (McConnell et al., 2005). In Figure 1.2, as expected, we first notice a drop in demand as the retailer increases HD shipping fee. In addition, looking at Figure 1.2 vertically, we observe a negative impact of hassle cost on the HD demand. Holding total surplus constant, we find that higher t^{HD} leads to lower demand when the shipping fee is zero. This arises because customers face higher hassle cost and need to wait longer for the delivery. Furthermore, Figure 1.2 also indicates the positive impact of total surplus on the HD segments. When the total surplus increases, the net benefits accruing to both customers and the retailer increase (McConnell et al., 2005), which then leads to the higher overall demand.

1.3.2 Omni-channel (OM) Model

We now extend our BM model to capture a retailer that offers both fee-based home-delivery (HD) and free ship-to-store (STS) fulfillment services. We first look at the customer's choice, then investigate the retailer's optimal decisions.

1.3.2.1 OM Customers

Customers shopping in the online channel for a product observe the price, HD shipping fee f, the hassle cost t^{HD} for home delivery, and the hassle cost associated with the STS option, t^{STS}. The STS hassle cost, t^{STS}, captures the delay time between purchasing a product and its availability for pickup *and* the hassle of having to pickup the product. We assume that $t^{STS} > t^{HD}$, meaning STS fulfillment is more of a hassle for customers due to longer delay times and the need to pick up the product in store. Furthermore, we assume that t^{HD} is proportional to t^{STS}, $t^{HD} := \alpha t^{STS}$, where $\alpha \in (0, 1)$. Our definitions of the sensitivity parameter γ, the customer valuation v, and the proportionality scaling constant s remain unchanged. Therefore, customers who purchase through the HD option have the same net expected utility as Equation (1.1), but it can be rewritten as,

$$\mathbb{E}[u^{HD}] = v - s\gamma\alpha t^{STS} - f - p. \tag{1.5}$$

Let u^{STS} be the net utility a customer obtains from the product through the STS option and therefore the net expected utility of a STS customer is,

$$\mathbb{E}[u^{STS}] = v - s\gamma t^{STS} - p. \tag{1.6}$$

For both fulfillment options, when the net utilities are negative (i.e., $\mathbb{E}[u^{STS}] < 0$ and $\mathbb{E}[u^{HD}] < 0$), customers do not make any purchase through either the HD or STS service. A customer with either $\mathbb{E}[u^{STS}] > 0$ or $\mathbb{E}[u^{HD}] > 0$ will purchase the product and will use the HD service if $\mathbb{E}[u^{HD}] > \mathbb{E}[u^{STS}]$, while use the STS option if $\mathbb{E}[u^{HD}] < \mathbb{E}[u^{STS}]$. To understand the market segments, we use a similar analysis to the BM model by setting $\mathbb{E}[u^{HD}] = 0$, $\mathbb{E}[u^{STS}] = 0$, and $\mathbb{E}[u^{HD}] = \mathbb{E}[u^{STS}]$, then solving for γ in each case. The results give the sensitivity parameter, γ, where customers are indifferent between

NP or HD, NP or STS, and HD or STS respectively. We get the following results:

$$\begin{aligned}
\mathbb{E}[u^{HD}] = 0 \quad &\Rightarrow \quad \gamma^{HD} = \frac{v-f-p}{s\alpha t^{STS}}, \\
\mathbb{E}[u^{STS}] = 0 \quad &\Rightarrow \quad \gamma^{STS} = \frac{v-p}{st^{STS}}, \\
\mathbb{E}[u^{HD}] = \mathbb{E}[u^{STS}] \quad &\Rightarrow \quad \gamma^{*} = \frac{f}{st^{STS}(1-\alpha)}.
\end{aligned}$$

Figure 1.3 illustrates these indifference boundaries where all three customer segments (HD, STS, and NP) exist, such that $0 < \gamma^* < \gamma^{STS} < \gamma^{HD} < 1$. We observe that the NP segment is given by $(1-\gamma^{HD})$, the HD segment is given by $(\gamma^{HD} - \gamma^*)$, and the STS segment is given by γ^*.

Note there are six other possible market scenarios where either one or two market segments exist: HD and STS; HD and NP; STS and NP; HD only; STS only; NP only. We focus our analysis on the most interesting case, where all three market segments exist, however, for completeness we provide the analyses for the other six scenarios, where some subset of market segments exist, in the Appendix.

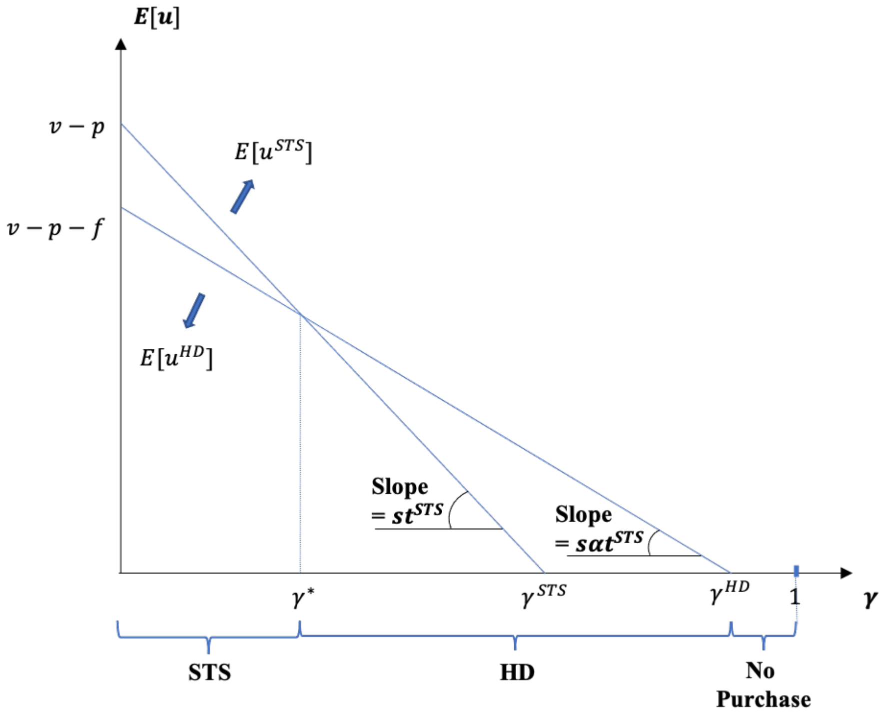


Figure 1.3: Expected Utility of a Customer in the OM model with Respect to γ.

1.3.2.2 OM Retailer

The retailer seeks to maximize its profit by setting the price, p, and the shipping fee, f. The retailer offers free STS fulfillment option and we assume there is no marginal cost for the retailer to offer this service. Essentially we assume that the retailer has the product in stock at either its warehouse or another store location so that it can relocate the product to the customer's preferred location using its existing distribution network. One benefit of offering this service is that driving customers to the store can generate additional profit arising from the increased foot traffic as shown by Akturk et al. (2018). We capture this added profit by multiplying the profit made by the sale of the STS product by a profit factor β, where $\beta \in [1, M]$, $M < \infty$. Note that some retailers distinguish themselves from their competitors by offering high-quality in-store shopping experience via personal assistance and premium services, which in turn gives them the ability to convert the increased foot traffic arising from STS into additional sales. Hence, the value of β is high for these retailers.

The direct profit made from HD customers is the same as in the BM model $(p - c)$, but since the retailer now decides the shipping fee, f, to influence customers' fulfilment choice, we assume that the retailer is able to make a small profit via the HD shipping fee, f. In our model, we capture it by assuming a proportional profit from the charged shipping fee, δf. For each unit sold through the HD channel, the retailer makes $p - c + \delta f$ and for each unit sold through the STS channel the retailer makes $\beta(p - c)$. Therefore, the retailer's overall profit in the OM model is given by $\pi_{OM} = \beta(p - c)\gamma^* + (p - c + \delta f)(\gamma^{HD} - \gamma^*)$. The retailer's optimization problem is,

$$
\begin{aligned}
\max_{p,f} \quad & \pi_{OM} \\
\text{s.t.:} \quad & f < (1 - \alpha)(v - p) \\
& v - f - p < s\alpha t^{STS} \\
& v - f - p > 0 \\
& f > 0 \\
& p > 0
\end{aligned}
$$

where the first two constraints ensure the existence of all three market segments. For the STS service, we assume it is operationally costless in the profit function. Note that, in practice, the retailer's operations regarding STS items and relevant costs may vary. To provide a straightforward understanding on the additional profit from STS service, we assume it is costless for the retailer in this manuscript. However, our results enable a retailer to directly evaluate the implementation of STS given their unique operational costs. We solve the retailer's optimization problem in the OM model and get Lemma 2.

Lemma 2. *The retailer's optimal price and shipping fee in the OM model are given by:*

$$p^*_{OM} = \frac{c(\alpha\beta - 1)^2 + (\alpha - 1)\delta(\alpha\beta + 1)(c + v) + (\alpha - 1)^2\delta^2 v}{\alpha^2(\beta + \delta)^2 - 2\alpha\left((\beta - 1)\delta + \beta + \delta^2\right) + (\delta - 1)^2},$$
$$f^*_{OM} = \frac{(1 - \alpha)(c - v)(\alpha(\beta - \delta) + \delta - 1)}{\alpha^2(\beta + \delta)^2 - 2\alpha\left((\beta - 1)\delta + \beta + \delta^2\right) + (\delta - 1)^2}.$$

The corresponding optimal profit is given by

$$\pi^*_{OM} = \frac{(\alpha - 1)\beta\delta(c - v)^2}{st^{STS}\left(\alpha^2(\beta + \delta)^2 - 2\alpha\left((\beta - 1)\delta + \beta + \delta^2\right) + (\delta - 1)^2\right)}.$$

1.3.2.3 Sensitivity Analysis

In this section, we perform a sensitivity analysis to observe how the optimal price, optimal shipping fee, and optimal profit in the OM setting change with respect to different model parameters and summarize the results at the end of this section in Table 1.2. Note that we provide the detailed expressions of the thresholds in the Appendix.

First, we find that the optimal price decreases with respect to δ. This arises because as δ increases, the retailer is able to gain more profit from the shipping fee, which in turn gives the retailer the flexibility to charge a lower price p. However, the impact of δ on the optimal shipping fee is more complicated. There exists a threshold for α such that when α is below a certain threshold ($\alpha < \overline{\alpha}$), meaning the hassle cost for HD is significantly less than that for STS, the retailer's optimal shipping fee increases as δ increases. In essence, if HD shipping time is much faster than STS service, then as the profit from shipping increases, the retailer will charge a higher shipping fee to and capture more of the shipping profit since customers will pay more for HD when it is much faster than STS. Otherwise, when the difference between hassle costs is low ($\alpha > \overline{\alpha}$), STS option is more attractive. As for the impact on the optimal profit, we find that the optimal profit increases as δ increases since the retailer is able to capture more profit from the shipping fee.

Second, we investigate how the additional profit from increased store foot traffic, β, impacts optimal price and shipping fee decisions. Naturally, higher β motivates the retailer to encourage some of the existing HD customers to use the STS fulfillment option by raising the HD shipping fee. We, however, find the impact of β on the optimal price depends on the value of α. When the difference between the HD and STS hassle cost is low (α is greater than a certain threshold), price increases as β increases. This arises because easy access to the store allows customers to shop with STS service without paying for extra shipping cost, but experience a delivery that is as fast as the fee-based HD service. Then, both the proportion and amount of STS customer increase. Hence, if β increases, the retailer will increase the price to encourage customers that are nearly indifferent to STS and HD to shift to STS

service. While some customers on the boundary between HD and NP will now not make a purchase, the additional sales and profit from the new STS customers outweigh the loss in overall demand.

In contrast, if α is less than a certain threshold, the hassle cost difference between HD and STS is high and therefore it is costly for customers to switch between channels. In other words, customers will pay an additional shipping fee for HD but enjoy much faster delivery. When β increases, the retailer's desire to increase the size of the STS customer segment can only be achieved by decreasing optimal price, which in turn increases the overall demand. Thus, there exists a threshold for α such that when α is above such threshold, the retailer's optimal price increases as β increases, otherwise, the retailer's optimal price decreases as β increases when α is below such threshold. We summarize the impact of β on optimal price in Lemma 3.

Lemma 3. *When* $\alpha > 2\sqrt{-\frac{\beta^2\delta-\beta^2+\beta\delta^2-\beta\delta-\delta^2}{(\beta+\delta)^4}} + \frac{\beta\delta-\beta+\delta^2+\delta}{(\beta+\delta)^2}$*, the optimal OM price increases as* β *increases. Otherwise, when* $\alpha < 2\sqrt{-\frac{\beta^2\delta-\beta^2+\beta\delta^2-\beta\delta-\delta^2}{(\beta+\delta)^4}} + \frac{\beta\delta-\beta+\delta^2+\delta}{(\beta+\delta)^2}$*, the optimal OM price decreases as* β *increases.*

Furthermore, we find that β has a positive impact on the optimal shipping fee. The increased profit from store traffic enables the retailer to set a higher shipping fee for the HD option so as to encourage customers to purchase the product using the free STS option instead. Ultimately, the optimal profit increases as β increases since the retailer is able to earn more from the increasing in-store traffic.

Third, we find that the impact of α on the optimal price depends on the value of δ. When δ is greater a certain threshold, the retailer tends to encourage more HD orders as the profit margin from HD shipping fee is high. As the HD option is more expensive but offers a faster delivery compared to STS, when such difference between waiting costs decrease (α increases), the customer is more willing to use the STS option so as to avoid paying the shipping fee for the HD option. Then the retailer needs to increase the price to leverage more HD segments. While this result comes from our mathematical model, in practice it is unlikely that a retailer earns a large portion of profit from shipping fees. In contrast, when the profit margin from shipping fee is below a threshold, the profitability of HD and STS services are similar such that the retailer's focus becomes the overall market coverage instead of any single segment. Such phenomenon is more significant when the hassle cost difference between HD and STS decreases (α increases). In such case, the retailer decreases the optimal price to attract more customers. Thus, there exists a threshold for δ such that when δ is above such threshold, the retailer's optimal price increases as α increases, otherwise, the retailer's optimal price decreases as α increases when δ is less than a certain threshold.

In addition, we see a positive relationship between α and the optimal shipping fee. To illustrate, consider how the increase (decrease) of α leads to a higher (lower) optimal shipping fee. Recall that as α increases, the difference between HD and STS hassle costs become less meaningful. Customers will prefer STS option to avoid shipping fee. In such a case, the retailer will further increase the HD shipping fee so as to increase the percentage of STS orders to generate addition in-store traffic and sales. When it comes to a decrease in α, the the difference between HD and STS options becomes larger more meaningful to customers. Therefore customers need to make their own comparison and judgement between the monetary cost (shipping fee) and hassle costs between the two options. When the difference between the two purchase options is subtle, motivating HD customers to choose STS service by increasing the shipping fee may decrease the overall customer demand. Instead, the retailer tends to decrease the optimal shipping fee so as to increase the overall market, which at the same time increase the STS segment. Therefore, we see a positive relationship between α and optimal shipping fee. As for the impact on optimal profit, it decreases with respect to α. High α means the difference between HD and STS hassle costs is low and customers are more willing to use STS service to avoid paying the HD shipping fee, but still enjoy similar delivery speed. Simultaneously, the NP segment increases as α increases since the overall cost for the boundary customer that is willing to make a purchase increases as α increases. Thus, the optimal profit decreases with respect to α.

The impacts and interpretations of c, v, and s on the OM optimal price and profit are the same as the results presented in the BM section, thus, we do not repeat them here. As for the STS hassle cost, t^{STS}, similar to the t^{HD} in the BM model, we find that the total profit decreases as t^{STS} increases. Now, we summarize the above results in Table 1.2.

Table 1.2: Sensitivity Analysis for the OM model

Parameter	Impact on $\mathbf{p}^*$	Impact on $\mathbf{f}^*$	Impact on π^*
δ	$-$	$+$ if $\alpha < \overline{\alpha}$ $-$ if $\alpha > \overline{\alpha}$	$+$
β	$+$if $\alpha > \dot{\alpha}$ $-$ if $\alpha < \dot{\alpha}$	$+$	$+$
α	$+$ if $\delta > \dot{\delta}$ $-$ if $\delta < \dot{\delta}$	$+$	$-$
c	$+$	$-$	$-$
v	$+$	$+$	$+$
s			$-$
t^{STS}			$-$

$+$ represents positive relationship.
$-$ represents negative relationship.
The expressions of $\bar{\alpha}$, $\dot{\alpha}$, and $\dot{\delta}$ are presented in the Appendix.

1.3.2.4 Market Segments

As we presented in Figure 1.3, the whole market can be divided into STS segment (D_{OM}^{STS}), HD segment (D_{OM}^{HD}) and NP segment (D_{OM}^{NP}). Given the retailer's optimal price and shipping fee, we

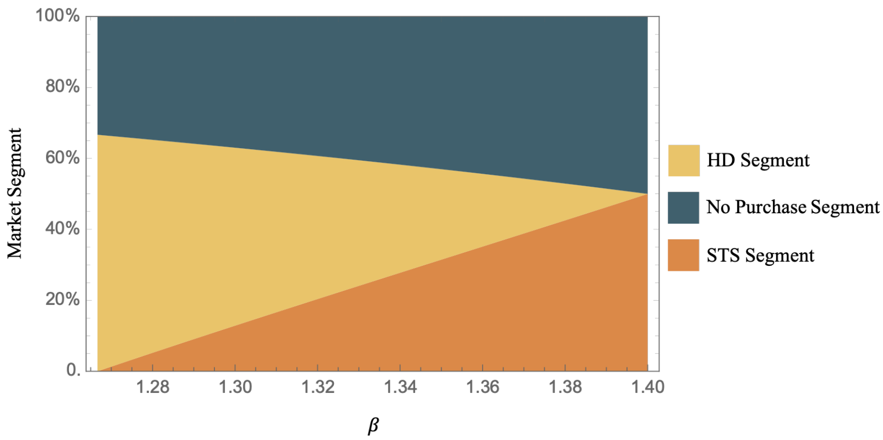
Table 1.3: Sensitivity Analysis for Market Segments in the OM model

Parameter	Impact on D_{OM}^{STS}	Impact on D_{OM}^{HD}	Impact on D_{OM}^{NP}
β	$+$	$-$	$+$
α	$+$	$-$	$+$
c	$-$	$-$	$+$
v	$+$	$+$	$-$
s	$-$	$-$	$+$
t^{STS}	$-$	$-$	$+$
δ	$+$ if $\alpha < \overline{\alpha}$ $-$ if $\alpha > \overline{\alpha}$	$+$ if $\alpha > \dot{\alpha}$ $-$ if $\alpha < \dot{\alpha}$	$+$ if $\alpha < \hat{\alpha}$ $-$ if $\alpha > \hat{\alpha}$

$+$ represents positive relationship.
$-$ represents negative relationship.
The expressions of $\overline{\alpha}$, $\dot{\alpha}$, and $\hat{\alpha}$ are presented in the Appendix.

can then derive the corresponding market segments. We provide the detailed expressions for the market segments in the Appendix.

We present how the model parameters influence different segments in Table 1.3. In addition, Figure 1.4 provides a numerical example of how different segments will change with respect to β when we hold all other parameters constant. Note that in this example, we focused on the scenario where STS, HD, and NP segments exist. This leads to a specific range of β in Figure 1.4, given the fixed parameters used in our numerical study. It shows that as β increases, the portion of STS segment increases while the HD segment decreases. We also find that the overall market shrinks as β increases.

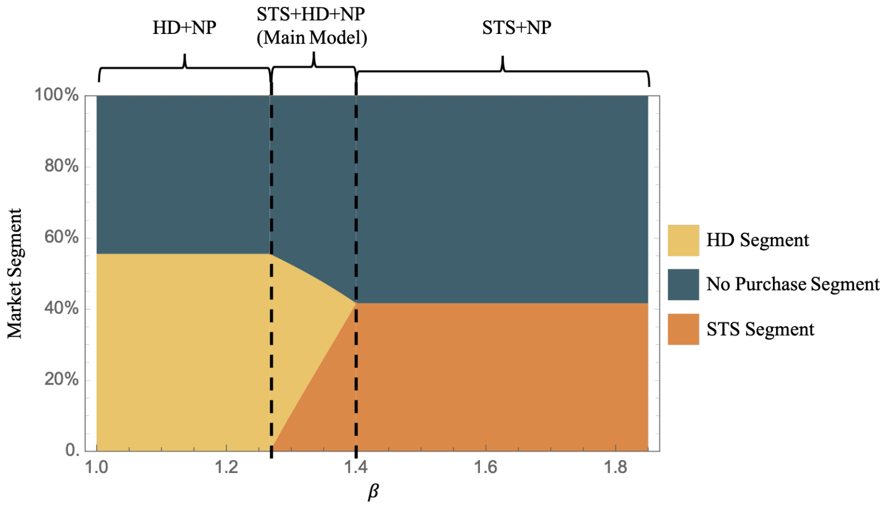


Note: The following parameter values are used: $v = 0.8$, $c = 0.5$, $s = 0.6$, $t^{STS} = 0.6$, $\alpha = 0.75$, $\delta = 0.2$.

Figure 1.4: (Color Online) Change of Segments with respect to β in the OM model (the Main Scenario)

Next, we add other scenarios and discuss the corresponding results. Instead of setting a fixed interval for the value of β, we now expand the range of β to see how different scenarios and the corresponding segments will change. We again use the same set of parameter values and present the numerical example in Figure 1.5. We find that when the additional traffic from STS customers is moderate, both

HD and STS customers exist in addition to the NP segment. As β increases, the HD segment decreases and eventually disappears when β becomes large, where we see only STS and NP segments.



Note: The same parameter values are used as in Figure 1.4.

Figure 1.5: (Color Online) Change of Segments with respect to β in the OM model (An Extension of Figure 1.4)

1.3.3 Optimal Strategy Under Different Market Conditions

In this section, we compare the BM and OM models to find the optimal strategy under different market conditions. Recall that we did not incorporate the profit margin from shipping fee in Section 1.3.1. To make the BM model comparable to OM model and to derive the managerial insights in a cleaner way, we now modify the objective function for the BM model by adding a δf term so that the two models capture the same sources of potential profit. Thus, the retailer's profit in the BM model can be rewritten as,

$$\pi_{BM} = (p - c + \delta f)(\gamma^{HD}). \tag{1.7}$$

In addition, it is convenient to replace t^{HD} by t^{STS} based on the relationship of $t^{HD} = \alpha t^{STS}$. Thus, we restate Lemma 1 in Corollary 1 with these modifications to the BM model,

Corollary 1. *The retailer's optimal price and corresponding optimal profit in the BM model are given by:*

$$p^*_{BM} = \frac{1}{2}(c - \delta f - f + v), \tag{1.8}$$

$$\pi^*_{BM} = \frac{(c - \delta f + f - v)^2}{4\alpha s t^{STS}}. \tag{1.9}$$

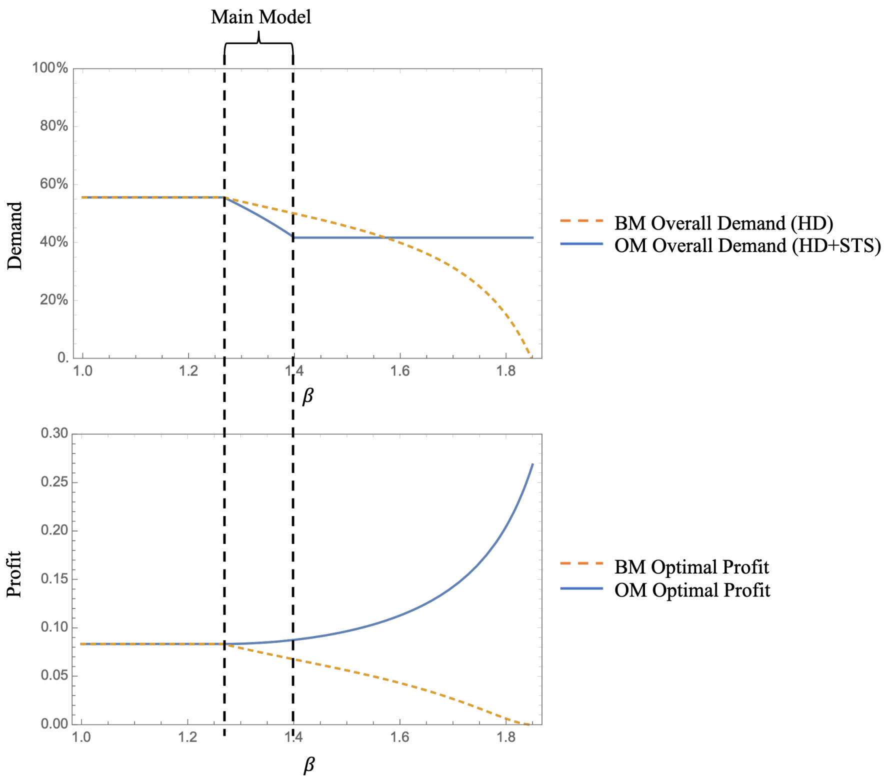
Corollary 1 shows the optimal profit in the BM model as a function of shipping fee, f_{BM}, which is a parameter in the BM model. To compare the two models, we use the same value for shipping fee in both models. We first solve for the optimal value, f^*_{OM}, then set $f_{BM} = f^*_{OM}$. We then compare corresponding optimal profits. We find that the retailers profit is always higher when introducing the free STS service, assuming costless implementation, which we address below. In addition, instead of assuming equal shipping fee, we also vary the shipping fee parameter in the BM model to see how the change of f_{BM} will influence the choice of optimal strategy. We show that adopting both HD and free STS services is better than offering only HD service if the HD shipping fee is being charged. We summarize the above results.

Proposition 1. *If we set $f_{BM} = f^*_{OM}$, then $\pi^*_{BM} \leq \pi^*_{OM}$. Further, for any $f_{BM} \geq 0$, $\pi^*_{BM} \leq \pi^*_{OM}$.*

Note that we derive the previous analytical results assuming that STS service is costless to implement for the retailer. However, offering omni-channel practices such as free STS service can require significant investment in terms of information technology infrastructure and workforce training, among others. Since different retailers vary in their existing facilities and networks, our results are an upper bound on the profit gained from STS implementation. The question for the retailers becomes: what is the affordable implementation cost if they want to be better off after the adoption of STS service? Since our OM model captures the potential monetary benefit from STS customers, by directly comparing the results from BM and OM models, we are able to derive insights on how much retailers should be willing to pay to launch the free STS service. In other words, when $\Delta_\pi = \pi^*_{OM} - \pi^*_{BM} > 0$, Δ_π gives the retailers information on the marginal profit so as to help them decide if the implementation cost is worthwhile. Next, we explore the comparison of these two models from the perspective of market segments and price.

1.3.3.1 Segment Comparison

To compare the market segments in different models, we again use f^*_{OM} as the shipping fee in the BM model, where $f_{BM} = f_{OM} = f^*_{OM}$. As an extension of Figure 1.5, Figure 1.6 shows the OM and BM segments in the same plot, together with the plot of optimal profit in different models. Compared to the traditional HD service in the BM model, we find that the adoption of free STS service leads to demand shift as well as demand cannibalization. Intuitively, eliminating shipping fee increases the overall demand, however, given the same level of shipping fee in these two models, the free STS service is not generating new demand. The additional profit in the OM model comes from the new STS customers who switch from the HD option. These new STS customers increase foot traffic at stores and thereby additional sales, which in turn makes the free STS service attractive to the retailer.



Note: The same parameter values are used as in Figure 1.4. Additionally, we use

$$f_{BM} = f_{OM} = \begin{cases} f^*_{OM}|_{\beta=1.267} = 0 & , \text{if } \beta \leq 1.267 \\ f^*_{OM} & , \text{if } \beta > 1.267 \end{cases}.$$

Figure 1.6: (Color online) Demand and Profit Comparison

1.3.3.2 Price Comparison

To compare the optimal prices across the two models, we again use f^*_{OM} as the shipping fee in the BM model, where $f_{BM} = f_{OM} = f^*_{OM}$. When the shipping fee is set to be the same, the expected utility for the boundary HD customer in different models depends on the price. Notice that there exists only HD customers in the BM model, while both HD and STS customers exist in the OM model. Even though higher price leads to lower expected utility for the HD boundary customer, which ultimately decreases the HD demand, the OM retailer is able to increase overall profit with the higher proportion of STS customers. Furthermore, we assume that the shipping fee in the BM model is the same as the OM shipping fee, which is one of the decision variables in the OM model. Thus, the retailer tends to set a higher price when offering both HD and STS services simultaneously. We summarize this result in Lemma 4.

Lemma 4. *If the shipping fee $f_{BM} = f_{OM} = f^*_{OM}$, then $p^*_{OM} > p^*_{BM}$.*

From the customers' perspective, paying more for the product is understandable because they are able to save money by not paying for the HD shipping fee.

1.4 Conclusion

Customers strategically switch between shopping channels and compare alternative fulfillment options when they make a purchase. Such behavior has become a trend and unavoidable during the COVID-19 pandemic. To stay competitive in the market, retailers adopt new services to match customers' seamless shopping expectations. In this paper, we focus on an omni-channel firm that operates both online and offline channels, and investigate the firm's decisions when it offers free buy-online and ship-to-store service. Since an increasing number of retailers has recently implemented this innovative service, we provide analytical models to understand the key trade-offs of adopting ship-to-store service including pricing decisions and customer purchase behavior.

To address our research questions, we build two models to capture and discuss the essential elements of free ship-to-store service. We capture customer heterogeneity via sensitivity to hassle cost and preference in choosing fulfillment options. We provide closed form solutions for the optimal pricing decisions of a retailer facing heterogeneous customers and the resulting market demand segments by fulfillment option. Our comparative static analysis further gives retailers insights into how outcomes and optimal decisions change due to shifts in underlying market parameters. We find that offering additional free ship-to-store service is more profitable than the traditional home delivery-only service as long as the retailer charges a shipping fee in the home delivery-only setting. One of the key drivers of this result is that ship-to-store customers need to visit stores to pick up their items, which enables the retailer to convert the increased foot traffic into additional in-store sales. While we assume that the operating costs of implementing ship-to-store service is zero in our models, we directly measure the difference in profit between offering ship-to-store and home delivery services together over home delivery service only. This enables a retailer to evaluate whether implementing ship-to-store would be a profitable decision based on their unique implementation costs and evaluate a break-even analysis before making costly capital investments in new logistics capabilities.

Another interesting question that we investigate is how the customer demand structure would evolve after the adoption of ship-to-store service. We find that implementing free ship-to-store service cannibalizes the overall demand, while shifting some of the home-delivery customers to the ship-to-store option. The former effect arises because the launch of new omni-channel strategy leads to a higher product price such that fewer customers are willing to complete a purchase. Even though free ship-to-store service eliminates the traditional shipping fee, customers face a higher overall cost to buy the product, which in turn shrinks the retailer's total demand. The latter effect arises because the free ship-to-store service offers customers a new and possibly more convenient option of delivery. For customers who live nearby a retail store, using ship-to-store service eliminates the shipping fee, and it is reasonable to assume that cost of visiting a local store is less than the traditional shipping fee. The fact that some customers switch from home delivery service to ship-to-store service also reflects how launching a free ship-to-store service improves customers' shopping experience through offering alternative shipping options that better match their shipping preferences. Such improvement is able to strengthen customer loyalty and have positive effect for the retailer in the long run, which can also be a future research topic.

1.4.1 Limitations and Future Research

We believe our model captures a rich class of problems in omni-channel retail settings that has both academic relevance and direct practical implications. However, there are several limitations and extensions that can be considered in future work. We assume that ship-to-store is costless to implement and operate, and use the overall profit gap between our benchmark and omni-channel models to evaluate the benefit of adding ship-to-store service. While it is possible that retailers can minimize the additional shipping cost via synchronizing ship-to-store deliveries with store replenishment, a natural extension would be to directly incorporate the operating cost of ship-to-store service into the pricing decisions. Furthermore, our setting considers a single retailer which does not face direct competition from other retailers. While in many cases this holds true, considering competition could expand our setting to a competitive market and can help derive additional insights.

Next, our analysis reveals that free ship-to-store service may attract new in-store customers via eliminating traditional shipping fee or motivating some existing customers to switch from fee-based home-delivery service to free ship-to-store service. This poses another potential question regarding the in-store inventory. Knowing that ship-to-store service increases store foot traffic and thereby additional in-store sales, future study can investigate how retailers can effectively and efficiently adjust inventory levels to cope with the demand dispersion that is brought by ship-to-store service. Finally, there is a growing body of literature on how product returns impact omni-channel retailers (Hwang et al., 2021). As such, exploring the pricing and shipping fee decisions in the face of product returns would be another interesting extension of this work.

Appendices

Appendix A Expressions

1. $\dot{\alpha} = 2\sqrt{-\frac{\beta^2\delta-\beta^2+\beta\delta^2-\beta\delta-\delta^2}{(\beta+\delta)^4}} + \frac{\beta\delta-\beta+\delta^2+\delta}{(\beta+\delta)^2}$.

2. $\dot{\delta} = 2\sqrt{\frac{\alpha^2\beta^2-\alpha\beta^3-\alpha\beta+\beta^2}{(\alpha-1)^2(\beta+1)^2}} + \frac{-\alpha\beta^2+\alpha\beta+\beta-1}{(\alpha-1)(\beta+1)}$.

3. $\overline{\alpha} = \frac{\beta\delta+\beta-\delta^2+\delta}{3\beta^2+2\beta\delta-\delta^2} + 2\sqrt{\frac{\beta^2\delta^2-\beta^2\delta+\beta^2-\beta\delta^2+\beta\delta}{(3\beta^2+2\beta\delta-\delta^2)^2}}$.

4.

$$\hat{\alpha} = \begin{cases} \frac{\beta\delta-\beta+\delta-1}{\beta^2+\beta\delta-3\beta+\delta} - 2\sqrt{-\frac{\beta^3\delta-\beta^3-2\beta^2\delta+2\beta^2+\beta\delta-\beta}{(\beta+\delta)(\beta^2+\beta\delta-3\beta+\delta)^2}} & \text{if } 1<\beta<3 \text{ and } 0<\delta<\frac{3\beta-\beta^2}{\beta+1}, \\ \frac{\beta\delta+3\beta+\delta-1}{2\beta^2+2\beta\delta+2\beta+2\delta} & \text{if } 1<\beta<3 \text{ and } \delta=\frac{3\beta-\beta^2}{\beta+1}, \\ \frac{\beta\delta-\beta+\delta-1}{\beta^2+\beta\delta-3\beta+\delta} + 2\sqrt{-\frac{\beta^3\delta-\beta^3-2\beta^2\delta+2\beta^2+\beta\delta-\beta}{(\beta+\delta)(\beta^2+\beta\delta-3\beta+\delta)^2}} & \text{if } (1<\beta<3 \text{ and } \frac{3\beta-\beta^2}{\beta+1}<\delta<1) \text{ or } \beta\geq 3. \end{cases}$$

Appendix B Proof of Lemmas and Corollaries

Proof of Lemma 1. To solve for the optimal price in this constrained optimization problem, we use the Lagrange multiplier method by deriving the Karush–Kuhn–Tucker (i.e., KKT) conditions (Karush, 1939; Kuhn and Tucker, 2014). First, based on the objective function and constraints, we formulate the Lagrangean as follows,

$$L(p,\lambda_1,\lambda_2,\lambda_3) = (p-c)(\frac{-f-p+v}{st^{HD}}) - \lambda_1(-f-p-st^{HD}+v) - \lambda_2(f+p-v) - \lambda_3(-p). \quad (10)$$

The corresponding KKT conditions are stated as follows,

$$\frac{\partial L}{\partial p}(p,\lambda_1,\lambda_2,\lambda_3) = 0, \quad (11)$$

$$\lambda_1(-f-p-st^{HD}+v) = 0, \quad (12)$$

$$\lambda_2(f+p-v) = 0, \quad (13)$$

$$\lambda_3(-p) = 0, \quad (14)$$

$$p \geq 0, \quad (15)$$

$$\lambda_1,\lambda_2,\lambda_3 \geq 0. \quad (16)$$

To solve for the problem, we start from the Equation 12, 13, and 14. As each of them is set to equal zero, we know either the multiplier λ or the equation within the parenthesis or both of them should be zero. We now consider 8 cases with different combination of the zero-valued multipliers: (0, λ_2, λ_3), (λ_1, 0, λ_3), (λ_1, λ_2, 0), (0,0, λ_3),(0, λ_2, 0), (λ_1, 0,0), (0,0,0), (λ_1, λ_2, λ_3). For each individual case, our aim is to use these values to solve for a set of solution (p, λ_1, λ_2, λ_3) that can satisfy all conditions.

Finally, we find that the case of (0,0,0) is able to derive a solution that satisfies all conditions, which gives us the optimal solution for this maximization problem. The detailed proof is shown as follows.

Case 1 (0, λ_2, λ_3). In this case, Equation 12, 13, and 14 are equivalent as $\lambda_1 = 0$, $f + p - v = 0$, and $-p = 0$. Together with Equation 11, we are not able to derive a full set of solution of (p, λ_1, λ_2, λ_3). Thus, this case does not hold.

Case 2 (λ_1,0, λ_3). In this case, Equation 12, 13, and 14 are equivalent as $-f - p - st^{HD} + v = 0$, $\lambda_2 = 0$, and $-p = 0$. Together with Equation 11, we are not able to derive a full set of solution of (p, λ_1, λ_2, λ_3). Thus, this case does not hold.

Case 3 (λ_1, λ_2, 0). In this case, Equation 12, 13, and 14 are equivalent as $-f - p - st^{HD} + v = 0$, $f + p - v = 0$, and $\lambda_3 = 0$. Together with Equation 11, we are not able to derive a full set of solution of (p, λ_1, λ_2, λ_3). Thus, this case does not hold.

Case 4 (0,0, λ_3). In this case, Equation 12, 13, and 14 are equivalent as $\lambda_1 = 0$, $\lambda_2 = 0$, and $-p = 0$. Together with Equation 11, we can derive $p = 0$, $\lambda_1 = 0$, $\lambda_2 = 0$, and $\lambda_3 = -\frac{c-\delta f-f+v}{\alpha st}$. Then, we substitute these values into the original conditions, which are stated in Equation 1.3. We find that this set of condition violates the original conditions. Thus, this case does not hold.

Case 5 (0, λ_2, 0). In this case, Equation 12, 13, and 14 are equivalent as $\lambda_1 = 0$, $f + p - v = 0$, and $\lambda_3 = 0$. Together with Equation 11, we can derive $p = -f + v$, $\lambda_1 = 0$, $\lambda_2 = -\frac{-c+\delta f-f+v}{\alpha st}$, and $\lambda_3 = 0$. Then, we substitute these values into the original conditions, which are stated in Equation 1.3. We find that this set of condition violates the original conditions. Thus, this case does not hold.

Case 6 (λ_1, 0,0). In this case, Equation 12, 13, and 14 are equivalent as $-f-p-st^{HD}+v = 0$, $\lambda_2 = 0$, and $\lambda_3 = 0$. Together with Equation 11, we can derive $p = -f - \alpha st + v$, $\lambda_1 = -\frac{c-\delta f+f+2\alpha st-v}{\alpha st}$, $\lambda_2 = 0$, and $\lambda_3 = 0$. Then, we substitute these values into the original conditions, which are stated in Equation 1.3. We find that this set of condition violates the original conditions. Thus, this case does not hold.

Case 7 (0,0,0). In this case, Equation 12, 13, and 14 are equivalent as $\lambda_1 = 0$, $\lambda_2 = 0$, and $\lambda_3 = 0$. Together with Equation 11, we can derive $p = \frac{1}{2}(c - \delta f - f + v)$, $\lambda_1 = 0$, $\lambda_2 = 0$, and $\lambda_3 = 0$. Then, we substitute these values into the original conditions, which are stated in Equation 1.3. We find that this set of condition satisfies the original conditions. Thus, $p = \frac{1}{2}(c - \delta f - f + v)$ is the optimal solution of the maximization problem.

Case 8 (λ_1, λ_2, λ_3). In this case, Equation 12, 13, and 14 are equivalent as $-f-p-st^{HD}+v=0$, $f+p-v=0$, and $-p=0$. Together with Equation 11, we are not able to derive a full set of solution of $(p, \lambda_1, \lambda_2, \lambda_3)$. Thus, this case does not hold.

Ultimately, there exists one unique solution that satisfies all the constrains, which is given by

$$p^*_{BM} = \frac{1}{2}(c - f + v).$$

Now, we substitute the optimal price in the profit function to obtain the corresponding optimal profit for the BM model,

$$\pi^*_{BM} = \frac{(c + f - v)^2}{4st^{HD}}.$$

Note that this is a constrained optimization problem. We can rewrite the original constraints as follows,

$$f < v - c \text{ and } s > \frac{-c - f + v}{2t^{HD}}.$$

□

Proof of Lemma 2. Based on the relationship between t^{HD} and t^{STS} ($t^{HD} = \alpha t^{STS}$), we are able to eliminate the use of t^{HD} by the expression of t^{STS}. For the purpose of simplification, we use t to denote t^{STS} in the following context.

To solve for the optimal price and shipping fee in this constrained optimization problem, we follow in a way similar to that for Lemma 1. First, based on the objective function and constraints, we formulate the Lagrangean as follows,

$$\begin{aligned} L =& \frac{\beta(p-c)f}{(1-\alpha)st} + (-c + \delta f + p)\left(\frac{-f-p+v}{\alpha st} - \frac{f}{(1-\alpha)st}\right) - \lambda_1(f+p-v) - \lambda_2(f-(1-\alpha)(v-p)) \\ &- \lambda_3(v - f - p - s\alpha t) - \lambda_4(-f) - \lambda_5(-p). \end{aligned}$$

Similarly the proof of Lemma 1, we analyze all possible cases of the multipliers and find one unique solution that satisfies all conditions, which is given by

$$p^*_{OM} = \frac{c(\alpha\beta-1)^2+(\alpha-1)\delta(\alpha\beta+1)(c+v)+(\alpha-1)^2\delta^2 v}{\alpha^2(\beta+\delta)^2-2\alpha\left((\beta-1)\delta+\beta+\delta^2\right)+(\delta-1)^2},$$
$$f^*_{OM} = \frac{(1-\alpha)(c-v)(\alpha(\beta-\delta)+\delta-1)}{\alpha^2(\beta+\delta)^2-2\alpha\left((\beta-1)\delta+\beta+\delta^2\right)+(\delta-1)^2}.$$

Now, we substitute the optimal price and shipping fee in the profit function to obtain the corresponding optimal profit for the OM model,

$$\pi^*_{OM} = \frac{(\alpha-1)\beta\delta(c-v)^2}{st\left(\alpha^2(\beta+\delta)^2-2\alpha\left((\beta-1)\delta+\beta+\delta^2\right)+(\delta-1)^2\right)}.$$

Note that this is a constrained optimization problem. We can rewrite the original constraints as follows,

$$\frac{\delta-1}{\delta-\beta} < \alpha < \frac{\delta+1}{\beta+\delta} \text{ and } 0 < c < v \text{ and } s > \frac{(c-v)(-(\alpha-1)(\beta+1)\delta-(\beta-1)(\alpha\beta-1))}{t\left(\alpha^2(\beta+\delta)^2-2\alpha\left((\beta-1)\delta+\beta+\delta^2\right)+(\delta-1)^2\right)}.$$

□

Proof of Lemma 3. The impact of β on the optimal price can be verified by checking the sign of $\frac{\partial p^*_{OM}}{\partial\beta}$.

We take the first derivative of p^*_{OM} with respective to β, which is given by

$$\frac{\partial p^*_{OM}}{\partial\beta} = \frac{(\alpha-1)\alpha\delta(c-v)\left(\alpha^2(\beta+\delta)^2-2\alpha\left(\beta(\delta-1)+\delta^2+\delta\right)+(\delta-1)(\delta+3)\right)}{\left(\alpha^2(\beta+\delta)^2-2\alpha\left((\beta-1)\delta+\beta+\delta^2\right)+(\delta-1)^2\right)^2}.$$

Next, we find that the sign of $\frac{\partial p^*_{OM}}{\partial\beta}$ depends on the value of other parameters. To find out the specific condition under which $\frac{\partial p^*_{OM}}{\partial\beta} > 0$, we solve for $\frac{\partial p^*_{OM}}{\partial\beta} = 0$, which gives us two solutions as follows

$$\alpha_1 = 2\sqrt{-\frac{\beta^2\delta-\beta^2+\beta\delta^2-\beta\delta-\delta^2}{(\beta+\delta)^4}}+\frac{\beta\delta-\beta+\delta^2+\delta}{(\beta+\delta)^2},$$
$$\alpha_2 = -2\sqrt{-\frac{\beta^2\delta-\beta^2+\beta\delta^2-\beta\delta-\delta^2}{(\beta+\delta)^4}}+\frac{\beta\delta-\beta+\delta^2+\delta}{(\beta+\delta)^2}.$$

Recall that this is a constrained optimization problem, we have a set of conditions to make sure the existence of all three segments (HD, STS, and NP). Once we take into consideration of these constraints, it is easy to verify that $\alpha_2 < 0$. Thus, we eliminate this solution and focus on α_1. We further derive that $\frac{\partial p^*_{OM}}{\partial\beta} > 0$ when $\alpha > \alpha_1$, while $\frac{\partial p^*_{OM}}{\partial\beta} < 0$ when $\alpha < \alpha_1$. We use $\dot{\alpha}$ to denote such threshold (α_1) in the manuscript.

Note that this is a constrained optimization problem, and we focus on the case with the existence of HD, STS, and NP segments. Thus, in addition to $\dot{\alpha}$, we should notice that the range of α is also determined by the constraints in the optimization model. According to the condition that we derived in previous section, we know the lower bound for α is $\frac{\delta-1}{\delta-\beta}$ while the upper bound for α is $\frac{\delta+1}{\beta+\delta}$. In other words, $\frac{\partial p^*_{OM}}{\partial \beta} > 0$ when $\frac{\delta+1}{\beta+\delta} > \alpha > \dot{\alpha}$, while $\frac{\partial p^*_{OM}}{\partial \beta} < 0$ when $\frac{\delta-1}{\delta-\beta} < \alpha < \dot{\alpha}$.

□

Proof of Lemma 4. According to Lemma 1 and Lemma 2, we can now compare the optimal price under different strategies by checking the difference between p^*_{BM} and p^*_{OM} when $f_{BM} = f_{OM} = f^*_{OM}$, which is defined as

$$\begin{aligned}\Delta_p &= p^*_{OM} - p^*_{BM} \\ &= \frac{\alpha(\beta-1)(c-v)(\alpha(\beta-\delta)+\delta-1)}{2\left(\alpha^2(\beta+\delta)^2 - 2\alpha\left((\beta-1)\delta+\beta+\delta^2\right)+(\delta-1)^2\right)}.\end{aligned}$$

We find that Δ_p is always positive. Thus, BM optimal price is always less than OM optimal price. □

Proof of Corollary 1. We first derive the optimal price in BM model in Lemma 1, where we ignore the retailer's additional profit via shipping fee . Now, we incorporate the profit margin from shipping fee, which is given by the term δf. In addition, we replace t^{HD} by t^{STS} based on the relationship of $t^{HD} = \alpha t^{STS}$. Thus, we revise expression of p^*_{BM} and π^*_{BM} as follows,

$$\begin{aligned}p^*_{BM} &= \frac{1}{2}(c-\delta f - f + v), \\ \pi^*_{BM} &= \frac{(c-\delta f + f - v)^2}{4\alpha s t^{STS}}.\end{aligned}$$

□

Proof of Proposition 1. We define $\Delta_\pi = \pi^*_{OM} - \pi^*_{BM}$. Recall that π^*_{BM} is a function of BM shipping parameter f_{BM}. Thus, Δ_π is also a function of f_{BM}. First, it is easy to show that, under the condition that both BM and OM models exist, $\Delta_\pi \geq 0$ always holds if the BM shipping parameter is set to be equal as the OM optimal shipping fee, $f_{BM} = f^*_{OM}$.

Next, we relax the assumption of $f_{BM} = f^*_{OM}$ to show how the change of BM shipping parameter will impact Δ_π. We find that Δ_π is always non-negative if $f_{BM} \geq 0$. We will prove this by contradiction.

The goal is to show: if $f_{BM} \geq 0$, then $\Delta_\pi = \pi^*_{OM} - \pi^*_{BM} \geq 0$. We now assume that if $f_{BM} \geq 0$, then $\Delta_\pi = \pi^*_{OM} - \pi^*_{BM} < 0$. Solving for $\frac{\partial \Delta_\pi}{\partial f_{BM}} = 0$ gives us two solutions,

$$f_{BM1} = \frac{c-v}{\delta-1} - \frac{2\alpha\sqrt{\frac{(\alpha-1)\beta(\delta-1)^2\delta(c-v)^2}{\alpha(2(\alpha-1)\delta(\alpha\beta+1)+(\alpha\beta-1)^2+(\alpha-1)^2\delta^2)}}}{(\delta-1)^2} \text{ and,}$$
$$f_{BM2} = \frac{c-v}{\delta-1} + \frac{2\alpha\sqrt{\frac{(\alpha-1)\beta(\delta-1)^2\delta(c-v)^2}{\alpha(2(\alpha-1)\delta(\alpha\beta+1)+(\alpha\beta-1)^2+(\alpha-1)^2\delta^2)}}}{(\delta-1)^2}.$$

The second-order condition $\frac{\partial^2 \Delta_\pi}{\partial^2 f_{BM}} = -\frac{(\delta-1)^2}{2\alpha st}$ is negative, which implies that Δ_π is negative if $f_{BM} < f_{BM1}$ or $f_{BM} > f_{BM2}$. We discuss these two scenarios separately and find the contradiction respectively:

1. When $f_{BM} < f_{BM1}$. Remember that we have to first satisfy the condition under which both OM and BM models exist. Under such condition, $f_{BM1} < 0$. In other words, Δ_π is negative if $f_{BM} < f_{BM1} < 0$, which contradicts our assumption that $f_{BM} > 0$.

2. When $f_{BM} > f_{BM2}$. If we set $f_{BM} > f_{BM2}$, the condition under which both OM and BM model exist does not hold any more. In other words, $f_{BM} > f_{BM2}$ violates our basic assumption and makes the original problem unfeasible.

Therefore, if $f_{BM} \geq 0$, then $\Delta_\pi = \pi^*_{OM} - \pi^*_{BM} \geq 0$.

□

Appendix C OMarket Segments

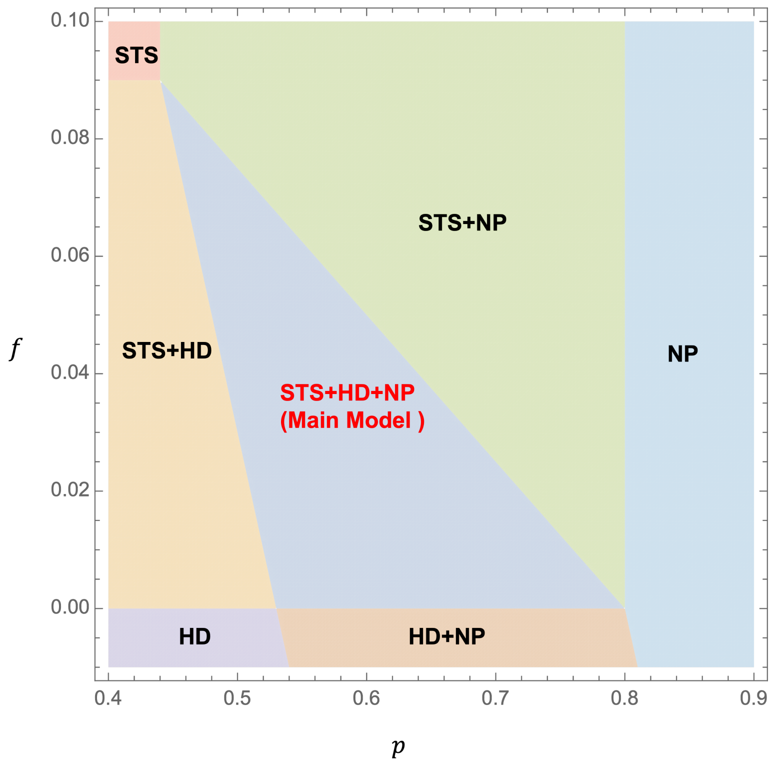
Given the retailer's optimal price and shipping fee in the OM model, we derive the corresponding market segments as follows,

$$D^{STS}_{OM} = \frac{(c-v)(\alpha(\beta-\delta)+\delta-1)}{st\left(\alpha^2(\beta+\delta)^2 - 2\alpha\left((\beta-1)\delta+\beta+\delta^2\right)+(\delta-1)^2\right)},$$
$$D^{HD}_{OM} = -\frac{\beta(c-v)(\alpha(\beta+\delta)-\delta-1)}{st\left(\alpha^2(\beta+\delta)^2 - 2\alpha\left((\beta-1)\delta+\beta+\delta^2\right)+(\delta-1)^2\right)},$$
$$D^{NP}_{OM} = \frac{(\alpha-1)\delta((\beta+1)c+2s(\alpha\beta t+t)-(\beta+1)v)+(\alpha\beta-1)((\beta-1)c+st(\alpha\beta-1)-\beta v+v)+(\alpha-1)^2\delta^2 st}{st\left(\alpha^2(\beta+\delta)^2 - 2\alpha\left((\beta-1)\delta+\beta+\delta^2\right)+(\delta-1)^2\right)}.$$

Appendix D Other Scenarios in the OModel

In the main model, we focused on the most interesting case where we can find the existence of STS, HD, and no purchase segments. In this section, we will analyze all other possible scenarios and the corresponding results.

There are seven possible scenarios in the OM model depending on the values of parameters and the retailer's decision: HD, STS, and NP; HD and STS; HD and NP; STS and NP; HD only; STS



Note: The following parameter values are used: $v = 0.8$, $c = 0.5$, $s = 0.6$, $t^{STS} = 0.6$, $\alpha = 0.75$, $\delta = 0.2$, $\beta = 1.2$.

Figure 7: (Color online) Feasible Regions (with Respect to p and f) of All Possible Scenarios in the OM Model

only; no purchase at all. Given the values of all the parameters, Figure 7 provides an example of how different scenarios change with respect to price p and shipping fee f. For mathematical completeness we analyze the optimal shipping fee and price for all of these scenarios. Note that we follow the same logic as the proof of Lemma 1. We report the optimal solution but do not expand the detailed proof for each case here.

D.1 $STS + HD + NP$

See Figure 1.3 and the proof of Lemma 2.

D.2 $STS + HD$

See Figure 8. The optimization problem and the constraints are given as follows,

$$
\begin{aligned}
&\max \pi = (p-c)\beta\gamma^* + (p-c+\delta f)(1-\gamma^*)\\
&\text{s.t.: } \gamma^{HD} \geq 1\\
&\qquad \gamma^* < 1\\
&\qquad \gamma^* < \gamma^{STS}\\
&\qquad \gamma^{STS} < \gamma^{HD}\\
&\qquad f > 0\\
&\qquad p > 0
\end{aligned}
$$

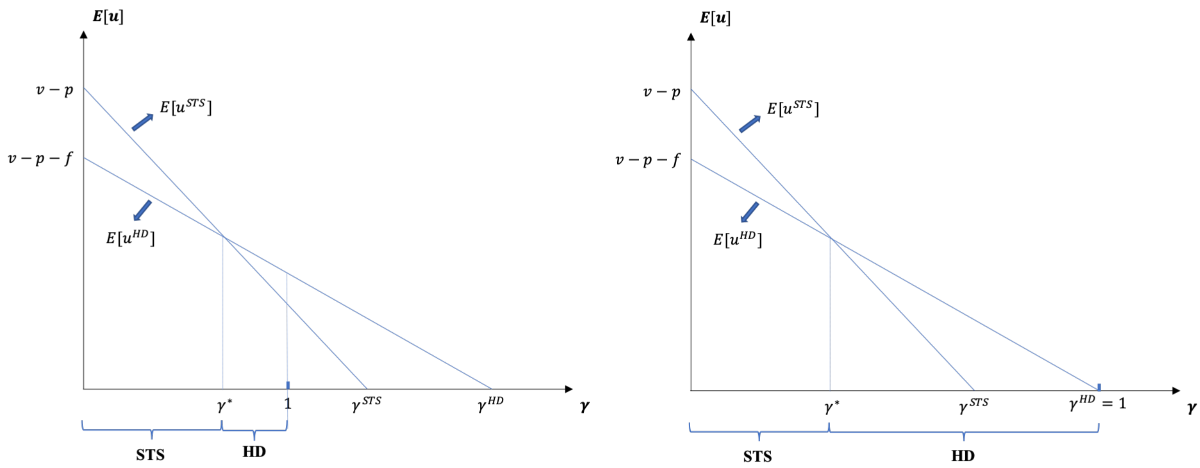


Figure 8: Expected Utility of a Customer in OM model (STS + HD case) with Respect to γ

The optimal solution is given by

$$
\begin{aligned}
p^*_{StsHd} &= -\frac{-\beta c + c + \alpha\beta st + \alpha\delta st + \delta st - st - \beta v - 2\delta v + v}{2(\beta+\delta-1)},\\
f^*_{StsHd} &= -\frac{\beta c - c + \alpha\beta st + \alpha\delta st - 2\alpha st - \delta st + st - \beta v + v}{2(\beta+\delta-1)},
\end{aligned}
$$

where we assume $c + \frac{st(\alpha(\beta+\delta-2)-\delta+1)}{\beta-1} < v$ and $[(\alpha st < v \leq st$ and $\frac{st(\alpha(\beta+\delta)+\delta-1)-v(\beta+2\delta-1)}{\beta-1} < c)$ or $(v > st$ and $\frac{st((\alpha-2)\beta+(\alpha-1)\delta+1)}{\beta-1} + v < c)]$.

The corresponding optimal profit is given by

$$\pi^*_{StsHd} = -\frac{2(\alpha-1)\delta st((\beta+1)c+s(\alpha\beta t+t)-(\beta+1)v)+((\beta-1)c+st(\alpha\beta-1)-\beta v+v)^2+(\alpha-1)^2\delta^2 s^2 t^2}{4(\alpha-1)st(\beta+\delta-1)}.$$

D.3 $STS + NP$

See Figure 9. The optimization problem and the constraints are given as follows,

$$\begin{aligned} \max\ \pi &= (p-c)\beta\gamma^* \\ \text{s.t.: } &\gamma^{STS} > 0 \\ &\gamma^{STS} < 1 \\ &\gamma^{HD} \leq \gamma^{STS} \\ &f > 0 \\ &p > 0 \end{aligned}$$

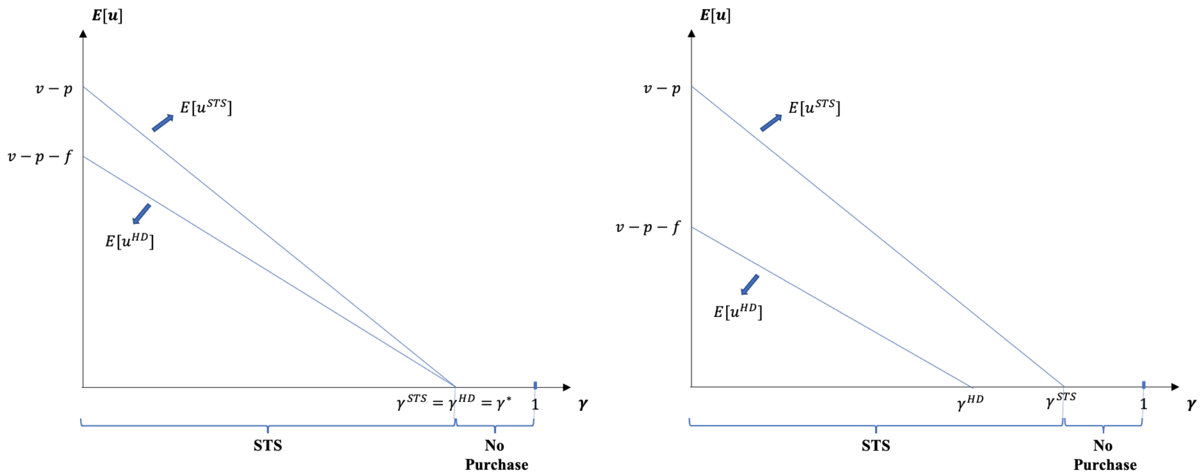


Figure 9: Expected Utility of a Customer in OM model ($STS + NP$ case) with Respect to γ

The optimal solution is given by

$$p^*_{StsNp} = \frac{c+v}{2},$$

where we assume $f \geq \frac{1}{2}(\alpha c - c - \alpha v + v)$ and $s > \frac{v-c}{2t}$.

The corresponding optimal profit is given by

$$\pi^*_{StsNp} = \frac{\beta(c-v)^2}{4st}.$$

D.4 STS *only*

See Figure 10. For the first case in Figure 10, the optimization problem can be formulated as follows,

$$\begin{aligned} &\max\ \pi = (p-c)\beta \\ &\text{s.t.: } \gamma^{STS} \geq 1 \\ &\qquad \gamma^{HD} \leq \gamma^{STS} \\ &\qquad f > 0 \\ &\qquad p > 0 \end{aligned}$$

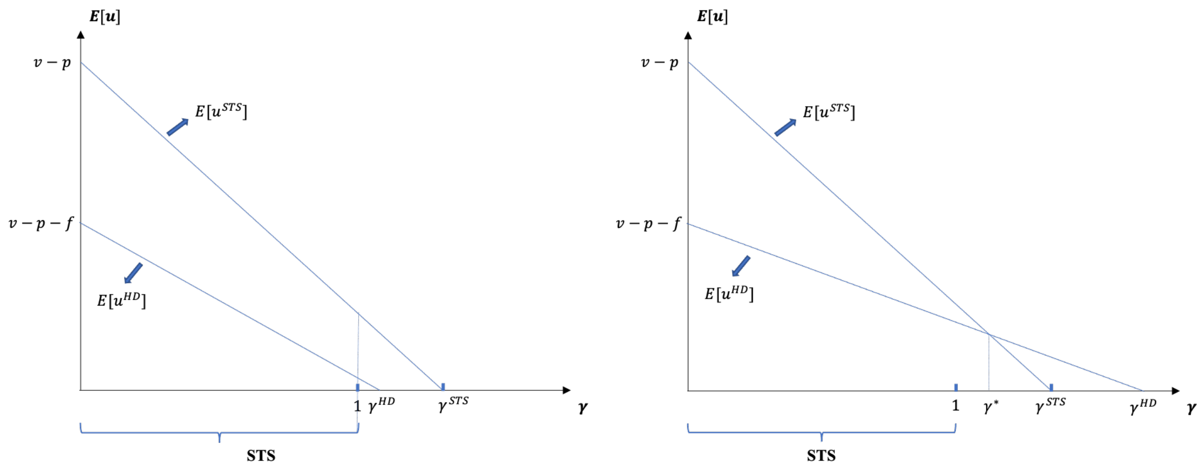


Figure 10: Expected Utility of a Customer in OM model (STS only case) with Respect to γ

For the second case in Figure 10, the optimization problem can be formulated as follows,

$$
\begin{aligned}
&\max\ \pi = (p-c)\beta \\
&\text{s.t.: } \gamma^{HD} \geq 1 \\
&\qquad \gamma^* > 1 \\
&\qquad \gamma^{STS} \leq \gamma^{HD} \\
&\qquad f > 0 \\
&\qquad p > 0
\end{aligned}
$$

Note that the optimal solution for the scenario of STS only comes from the first case, and there is no optimal solution in the second case.

The optimal solutions is given by

$$p^*_{Sts} = -st + v,$$

where we assume $0 < s < \frac{v}{t}$ and $f \geq st - \alpha st$.
The corresponding optimal profit is is given by

$$\pi^*_{Sts} = \beta(-(c + st - v)\beta).$$

D.5 HD *only*

See Figure 11. The optimization problem and the constraints are given as follows,

$$
\begin{aligned}
&\max\ \pi = p - c + \delta f \\
&\text{s.t.: } \gamma^{HD} \geq 1 \\
&\qquad f \leq 0 \\
&\qquad p > 0
\end{aligned}
$$

The optimal solution is given by

$$
\begin{aligned}
&p^*_{Hd} = v - \alpha st, \\
&f^*_{Hd} = 0,
\end{aligned}
$$

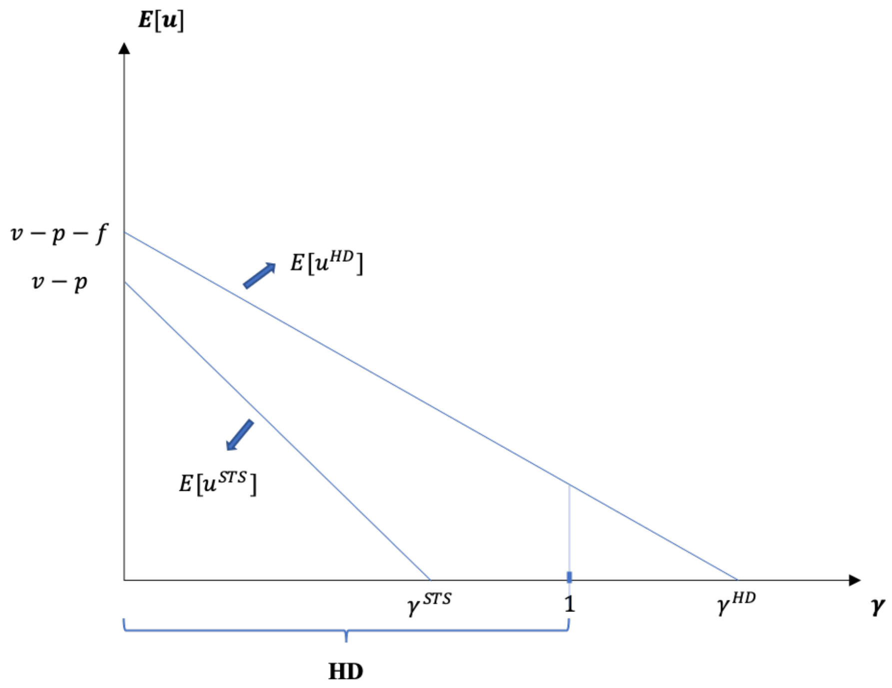


Figure 11: Expected Utility of a Customer in OM model (HD only case) with Respect to γ

where we assume $0 < s < \frac{v}{\alpha t}$.

The corresponding optimal profit is given by

$$\pi^*_{Hd} = -c - \alpha st + v.$$

D.6 HD + NP

See Figure 12. The optimization problem and the constraints are given as follows,

$$\begin{aligned}
&\max\ \pi = (p - c + \delta f)\gamma^{HD} \\
&\text{s.t.: } \gamma^{STS} < \gamma^{HD} \\
&\qquad \gamma^{HD} > 0 \\
&\qquad \gamma^{HD} < 1 \\
&\qquad f \leq 0 \\
&\qquad p > 0
\end{aligned}$$

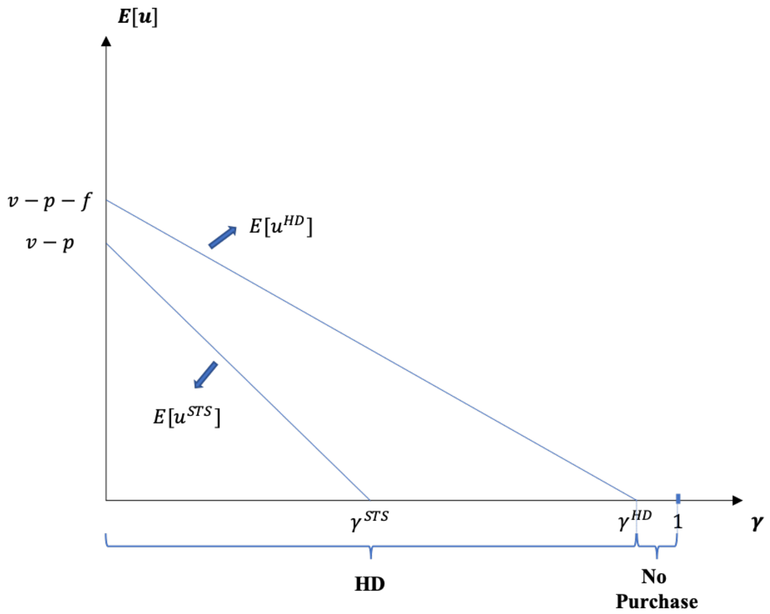


Figure 12: Expected Utility of a Customer in OM model (HD + NP case) with Respect to γ

The optimal solution is given by

$$p^*_{HdNp} = \frac{c+v}{2},$$
$$f^*_{HdNp} = 0,$$

where we assume ($0 < c < v$ and $s > \frac{v-c}{2\alpha t}$) or ($c > v$ and $s < \frac{v-c}{2\alpha t}$).

The corresponding optimal profit is given by

$$\pi^*_{HdNp} = \frac{(c-v)^2}{4\alpha st}.$$

Chapter 2

Does News Coverage of ESG Violations Affect Brand Sales? An Empirical Analysis

Abstract

This study examines the effects of negative environmental, social, and governance (ESG) news coverage on brand sales at a large U.S. retailer. While previous research has studied the impacts of ESG engagement on firms' financial performance, limited guidance exists on how ESG violations affect consumer purchase behaviors. Using retail transaction data and firm-level ESG information, we empirically show that news coverage of ESG violations has a significant and negative impact on brand sales at the retail level. However, the relationship between negative ESG news and sales is more nuanced, contingent upon the type of violation, i.e., environmental, social, governance, and cross-cutting. While we find that the social- and governance-related incidents lead to a decrease in brand sales, we surprisingly uncover a counterintuitive phenomenon wherein news coverage related to environmental and cross-cutting issues actually exerts a positive influence on brand sales. Additionally, our study reveals the important role played by brand- and market-specific factors, including brand value, consumer demographics and political leanings based on store locations, in moderating the extent to which negative ESG news affects brand sales. These findings provide crucial insights for retail brands, offering a holistic understanding of the nuanced effects of ESG violations on sales. Hence, brands may proactively mitigate the adverse consequences stemming from ESG news coverage, while retailers can tailor their sourcing strategies to minimize their risks. We validate our main findings via a series of robustness analyses that account for potential endogeneity issues, alternative model specifications, and estimation strategies, including difference-in-differences with propensity score weighting.

Keywords: Environmental, Social, and Governance (ESG), Retail Operations, Brand Sales

2.1 Introduction

The significance of environmental, social, and governance (ESG) considerations is rapidly increasing as customers hold organizations accountable for their impact on society and the planet. Rooted deeply within the realm of the United Nations' Sustainable Development Goals, ESG initiatives by organizations are key to addressing the pressing environmental and social imperatives that confront the world

(Rashed and Shah, 2021). Previous studies consistently show that the adoption of ESG practices not only improves an organization's reputation and financial performance (Eccles et al., 2014; Albuquerque et al., 2019) but also has a positive impact on stakeholders' perception (Fombrun and Shanley, 1990; Lins et al., 2017). In addition, customers are increasingly seeking out sustainable and socially responsible products and services, thus making positive ESG performance a key factor in brand loyalty and purchasing decisions (Young, 2022).

Although the existing literature extensively examined the effects of firm participation in ESG activities (Albuquerque et al., 2019), there still remains a significant gap in the literature on the effects of disclosed ESG violations. These violations cover a range of issues, such as environmental scandals, unethical labor practices, and corruption, among others. Concerning these negative ESG practices, previous studies have primarily focused on a particular incident or the consequences of a specific type of violation. For example, Lo et al. (2018) study the impact of environmental-related violations on shareholder value, while Jacobs and Singhal (2020) analyze the Volkswagen emission scandal and its spillover effects on the performance of Volkswagen's suppliers. However, limited attention has been given to understanding the heterogeneous effects of various types of violations on firms' performance. Furthermore, the focus of previous research has been on examining the impacts of ESG violations on financial performance, with relatively little attention given to sales performance, which is often crucial for operational decision-making. In this study, we seek to address this gap in the literature by systematically examining the heterogeneous effects of various types of ESG violations on the sales performance of retail brands. The reason for evaluating the sales performance of retail brands comes from their customer-facing nature. As customers are exposed to firms' ESG violations through news coverage, they can react by refraining from purchasing the products, directly impacting sales performance. Therefore, understanding the effects of ESG violations on sales performance will provide valuable information for firms on strategically responding to news coverage regarding ESG violations.

2.1.1 Research Questions

As customers become more aware of the need for sustainable practices highlighted by the Sustainable Development Goals of the United Nations, they are increasingly looking for brands that demonstrate a commitment to environmental and social responsibility. A study by UBS Group AG found that more than half of consumers surveyed have changed their shopping behaviors due to awareness related to sustainability (Kalb, 2021). While the negative impacts of certain types of ESG violations on the financial value of firms are documented in the literature (Li and Wu, 2020), the results of these prior studies do not necessarily inform us of the effects of violations on brand sales. This is because financial performance is mainly based on firm profitability and shareholder perceptions. In contrast, sales performance is influenced by how customers prioritize socially responsible considerations when making purchasing decisions (Guajardo et al., 2016; Hsu and Bui, 2022; Puriwat and Tripopsakul, 2022). Thus, our study aims to provide empirical evidence regarding the impact of firms' ESG violations on their sales performance.

Firms often self-publicize their ESG efforts, yet customers are more likely to become aware of a brand's ESG violations through news coverage (Kölbel et al., 2017). This mechanism can escalate brand crises and substantially influence purchase decisions. Anecdotal evidence highlights various effects stemming from news about brands' ESG violations. For instance, in the wake of a major corruption scandal, the engineering giant Siemens sustained its sales growth in certain sectors in 2008 (Agencies, 2008). In contrast, fashion brand Balenciaga experienced public backlash after it was reported to deliberately ignore child exploitation in its ad campaign in 2022 (Elizabeth Paton, 2023). Given these divergent effects of ESG news coverage, the first question we seek to answer is: (1) *How does the news coverage of ESG-related violations of a brand affect sales at a retail store?* This research question is vital in the highly competitive retail industry, as understanding the consequences of negative news related to ESG violations can enable brands to respond strategically and improve their operations.

To further understand the impacts of ESG violations, we delve deeper into studying the differential effects of news coverage of violations related to environmental, social, and governance issues on the sales performance of retail brands. Formally, the second question we ask is: (2) *How do different types of ESG violations, as depicted in the news coverage, impact the sales of retail brands?* Addressing this question provides two key insights. First, we document a deeper understanding of how customers react to different types of ESG violations. Second, answering this question reveals a more nuanced understanding of the impact regarding ESG violations on sales, thereby identifying specific areas that warrant attention. Thus, targeted strategies can be formulated to mitigate the adverse effects of negative news coverage.

To identify the underlying mechanisms behind the effects of ESG violations on sales, we explore the existence of any brand- and market-specific heterogeneities. More specifically, to shed light on the existence of a crucial brand-specific heterogeneity, namely the perceived value of brands from customers' perspective, on the relationship between ESG news coverage and brand sales. Previous research suggests that customers have higher expectations of sustainability standards and quality from high-value or luxury brands (Torelli et al., 2012). Customers who purchase luxury products expect those brands to align their operations with their own values (Chang et al., 2019), including responsible sourcing, ethical labor practices, and environmental consciousness. Consequently, when news coverage highlights ESG violations by luxury brands, it can lead to a heightened sense of disappointment and betrayal among consumers, potentially resulting in more severe consequences for sales. Therefore, we ask the following question: (3) *Are the effects of ESG news coverage on sales more severe for high-value brands compared to low-value* *brands?*

Our next research question explores the presence of market-specific heterogeneity based on the political affiliation of the geographical region. ESG issues are often intertwined with political discussions, with different groups advocating for various approaches. One side of the political spectrum advocates for stricter regulations and higher ESG standards, while the opposing side assigns less significance to ESG matters (Zahn, 2023). Consequently, the political leanings of the geographical regions could influence the impact of ESG news coverage on brand sales. Therefore, we pose the question: (4) *Do the effects of ESG news coverage on sales vary based on the political leanings of different geographical regions?* Recognizing the existence of market-specific heterogeneity is pivotal in developing effective strategies to mitigate the negative consequences of ESG violations in different geographical regions.

Next, we explore the effect of another crucial market-specific heterogeneity based on the store's nearby demographics. We pose the questions: (5) *Are the effects of ESG news coverage on sales more severe at stores surrounded by high-age population compared to low-age population?* and (6) *Are the effects of ESG news coverage on sales more severe at stores surrounded by high-income households compared to low-income households?* When it comes to the firm's ESG incidents, the nature of the surrounding environment, the people within it and their interpersonal influence play a crucial role in shaping the dynamics of social influence (Shah and Asghar, 2023). These factors will likely manipulate individuals' perceptions and potentially impact consumers' purchase decisions.

To answer our research questions, we leverage data from multiple sources. First, we obtain a comprehensive dataset from a major U.S. retailer that sells a variety of brands and products at its stores. This dataset comprises transaction-level information with details at order, SKU, brand, basket, and store levels, among others. Second, we augment our transaction data with data on news coverage of ESG violations from RepRisk, a Zurich-based company. RepRisk employs a rigorous data collection process that searches over 80,000 news sources for any new information related to ESG violations. By merging these datasets, we construct a unique panel dataset that allows us to investigate the relationship between firms' ESG media publicity and brand-level sales at the retail level. Detailed explanations regarding the datasets utilized in our study are provided in Section 2.3.

2.1.2 Key Findings

Our study, to the best of our knowledge, is the first to analyze the effects of ESG violations through news coverage on brand sales at a large U.S. retailer. To estimate the impacts of ESG violations' news coverage on sales, we employ a fixed effects panel model that accounts for brand, store, and time fixed effects. We also establish the robustness of our results by addressing the endogeneity issue via employing the control function approach and alternative estimation strategies.

Our results document the negative effect of news coverage regarding ESG violations on brand sales. Additionally, we find that news coverage of social issues, such as human rights abuse and social discrimination, hurts sales. This effect is consistent with the public's increasing awareness and concerns regarding human rights and equity in recent years. Likewise, our results reveal the negative effect of news coverage related to cross-cutting incidents. RepRisk classifies violations that span multiple categories of ESG issues as cross-cutting. This type of issue includes the firm's broader supply chain incidents, violations of national legislation or international standards, and controversial products and services. Given the complexity and relatively large scale of the cross-cutting issues, when such an incident is disclosed, consumers tend to be more careful and opt not to trust the brand anymore.

Interestingly, we find that the news coverage of incidents related to environmental issues, such as pollution, waste, and impacts on ecosystems, has a positive effect on sales. We conjecture that this positive effect arises because the public's environmental concerns have gradually become normalized, leading to a tendency to overlook or ignore negative news regarding eco-impact. Additionally, we find a positive effect of news coverage regarding governance-related violations, including bribery, tax evasion, and fraud, on sales. This type of issue is oftentimes abstract and hard to connect to consumers' daily purchase decisions. Thus, rather than hurting the brand's sales, any news coverage on environmental and governance issues might function as supplementary publicity for the brand, thereby contributing to increased sales.

Taken together, our results indicate that firms' ESG efforts should go beyond enhancing any single aspect of the issues. With consumers' rising awareness regarding the overall welfare of the planet and society, brands should not underestimate the negative impact of various ESG-related news on product sales.

Our results also indicate that the overall negative effect of news coverage concerning ESG violations on sales is less severe for luxury brands when compared to non-luxury brands, which is consistent with earlier research that illustrates the exclusivity of luxury brands (Radón, 2012). Such an effective marketing strategy builds stronger customer loyalty and mitigates the negative impact of ESG incidents on brand sales.

We also underscore the crucial role of market-specific heterogeneities. Specifically, we highlight the significant influence of the political leanings of geographical regions on the relationship between ESG violations and brand sales. In particular, we find that the negative effect of news coverage related to ESG violations on sales is more severe at stores located in Democrat states compared to Republican states. This result is consistent with the fact that the Democratic party advocates for stricter regulations and higher ESG standards, while the Republican party takes a pro-market stance, prioritizing free-market economics over ESG concerns (Zahn, 2023). In addition, we find that the negative impact of negative

ESG news on brand sales is amplified in stores located in communities with higher age and household incomes. The interplay among store location, nearby demographics, political leanings, and the news coverage of ESG violations sheds light on the fact that businesses need to recognize the nuanced effects of ESG violations on different geographical regions.

The remainder of this paper is organized as follows. In Section 2.2, we summarize relevant research and position the contribution of our study. Section 2.3 describes the data sources and explains the data collection processes. Our primary econometric approach is presented in Section 2.4. We discuss robustness checks in Section 2.5 and further validate our results using a quasi-experimental approach in Section 2.6. Finally, we conclude and discuss managerial insights in Section 2.7.

2.2 Literature Review

Given the extensive studies in the ESG domain, we review the relevant literature from three facets to elaborate on the unique contribution of our paper. First, the aspects of ESG considerations; second, the outcome of interests regarding ESG-related activities; and third, the sources of ESG information.

The environmental component of ESG has driven the early development of ESG literature (Pérez et al., 2022; Vanderford, 2022), where extensive studies have highlighted the relationship between environmental and financial performance (e.g., Corbett and Klassen, 2006; Jacobs et al., 2010). In the wake of the public's rising awareness, however, attention has gradually shifted toward other ESG components such as social, governance, and cross-cutting issues (Dai and Tang, 2022). As Deshpande and Swaminathan (2020) underlines, while environmentally responsible operations are extremely important, social responsibility in operations is no less important. Taking the social dimension, for example, Edmans (2011) investigates the relationship between employee satisfaction and equity prices on stock return; Albuquerque et al. (2019) demonstrates that corporate social responsibility activities decrease systematic risk while increasing firm value. For supply chain issues under the cross-cutting category, Jacobs and Singhal (2020) employ a case study approach for the Volkswagen emissions scandal and suggest that firms should not only focus on selecting and monitoring responsible suppliers but also apply some of the same principles to developing responsible customers. Similarly, using the firms' glitch announcements, Hendricks and Singhal (2005) empirically documents the association between supply chain glitches and firm-level operating performance.

Unlike the prior literature focusing on a single aspect of ESG, our study adopts a holistic view and examines all dimensions of ESG-related issues. We aim to provide a comprehensive framework to enhance our understanding of the multifaceted nature of ESG issues and their implications for brand performance in today's socially conscious marketplace.

Second, literature in this domain has focused on analyzing the impact of firms' ESG-related activities on various outcomes. In particular, the impact of firms' ESG activities includes both the positive outcomes arising from ESG practices and the potentially negative outcomes resulting from ESG violations. Furthermore, existing studies have analyzed the impact of ESG activities on corporate-level financial measures (Corbett and Klassen, 2006; Jacobs et al., 2010), such as stock returns (Edmans, 2011; Lo et al., 2018; Jacobs and Singhal, 2020) and risk exposures (Bansal and Clelland, 2004; Albuquerque et al., 2019) while others explore the impact on organizational performance and accounting-based metrics such as corporate revenue growth (Lev et al., 2010; Eccles et al., 2014) and valuation of physical assets (Henisz et al., 2014).

Prior research explored the positive outcomes of firms' ESG activities primarily from stakeholders' perspective (Fombrun and Shanley, 1990; Lins et al., 2017). For instance, positive ESG performance can improve employee engagement and satisfaction, leading to greater productivity and retention rates (Barrymore and Sampson, 2021). Using firms' self-disclosed annual reports and press releases, other studies investigate the positive impact of corporate social responsibility initiatives such as sustainability practices (Lee and Faff, 2009; Eccles et al., 2014), social responsibility (Orlitzky et al., 2003; Flammer, 2015), and ethical behavior (Gino et al., 2013) on firm performance.

Meanwhile, previous literature has also analyzed the negative effects of ESG violations. For example, corporate irresponsibility is developed as a distinct theoretical construct in the strategic management domain that is operationalized by ESG violations of firms usually revealed by the media (Kölbel et al., 2017). To identify the negative impact of corporate irresponsibility, existing studies in this domain focus mostly on the outcome of a major event or a single type of incident. For example, the Volkswagen diesel emissions scandal has been studied from the perspective of green-washing behavior (Siano et al., 2017), business ethics (Rhodes, 2016), and the global automotive ecosystem (Jacobs and Singhal, 2020). While the ESG impact on corporate and firm performance has been widely studied, literature on the effects of ESG violations on downstream sales and customer response is limited. Furthermore, our study employs a longitudinal setting encompassing multiple types of ESG violations across 30 months. Doing so, our study provides key insights regarding the consequences of failing to abide by responsible corporate behavior.

Given that existing studies tend to focus on the corporate-level outcomes of ESG activities, the firms' related initiatives are mainly obtained from their annual reports or self-disclosed announcements. However, consumers are more likely to be aware of a firm's negative engagement through media coverage. Thus, to understand consumers' reaction to firms' violations and examine the potential sales volatility, our study aims to explore the consequences of ESG incidents that are being disclosed by news outlets. Extant marketing literature has shown that the consumer preference for products is often determined by factors such as brand reputation (Knittel and Stango, 2014), brand value (Hui, 2004), product quality (Qian, 2014; Guajardo et al., 2016), and price, among others. Furthermore, an individual's willingness to express a favorable or unfavorable reaction toward specific brands is based on the information obtained from various sources, including news outlets (Puzakova et al., 2013; Wang and Kim, 2020; Puriwat and Tripopsakul, 2022). Hence, consumers become sensitive when choosing sustainable brands, and negative ESG-related scandals are likely to influence consumers' purchase decisions. In fact, prior research has demonstrated the effects of negative ESG-related publicity on consumers' purchasing intentions (e.g., Hsu and Bui, 2022). However, the literature offers limited guidance regarding the effects of various types of ESG violations on actual customer purchases (i.e., brand sales), and our study aims to address this gap.

Table 2.1 summarizes the above relevant literature and the unique contribution of our paper. Evidently, ESG violations are shown to have a significant impact on firms' reputation (Knittel and Stango, 2014) and their financial performance (Lev et al., 2010; Edmans, 2011; Eccles et al., 2014; Lo et al., 2018; Jacobs and Singhal, 2020). Furthermore, such scandals may also affect consumers' purchase behavior (Puriwat and Tripopsakul, 2022). However, studying the impact on consumer behavior is not straightforward due to limitations in data availability. To overcome these limitations, we employ a unique transaction dataset and combine it with ESG violation data at the brand level, enabling us to directly examine the consequences of negative ESG violations on brand-level product sales. Our contribution to this important domain lies in documenting the effects of ESG violations on consumers' purchase behaviors in the retail industry. Additionally, our study also contributes to the existing ESG literature by quantifying the impact of different types of ESG violations, namely environmental, social, governance, and cross-cutting issues on brand sales.

2.3 Data and Variable Construction

In this section, we discuss our data and the operationalization of the key variables. To investigate the impact of news coverage regarding ESG violations on brand sales, we obtain data from two sources: (i) a major U.S. retailer and (ii) RepRisk.

2.3.1 Data Description

The source of the first dataset is a retailer that sells a wide range of products, including apparel, household decoration, accessories, and cosmetics, among others. This data includes information on in-store purchase transactions spanning 30 months from January 2014 to October 2016 from 311 stores in the U.S. Each transaction record in our dataset contains the purchase date, transaction value measured in U.S. dollars, the number of items involved in the transaction, brand information, store location, and

Table 2.1: Summarized Literature

Study	Aspect of ESG Consideration					Source of ESG Information				Outcome of Interest		
	General ESG Topics	Environmental-related	Social-related	Governance-related	Disruption	Company-reported ESG Information	Social Media	News Outlets	Others (Survey, Experimental design, Case Study, Conceptual paper)	Corporate-level measure (i.e., stock return, firm value, accounting rates of return, risk, reputation)	Employee-level measure (labor productivity, employee satisfaction)	Sales performance measure (i.e., sales, consumer purchase behavior)
Albuquerque et al. (2019)			✓			✓			✓	✓		
Barrymore and Sampson (2021)	✓							✓			✓	
Chang et al. (2019)			✓			✓			✓			✓
Corbett and Klassen (2006)		✓							✓	✓		
Dai and Tang (2022)		✓	✓	✓	✓				✓	✓		✓
Eccles et al. (2014)	✓					✓				✓		
Edmans (2011)			✓			✓			✓	✓	✓	
Flammer (2015)		✓	✓			✓				✓	✓	
Fombrun and Shanley (1990)			✓			✓				✓	✓	
Gino et al. (2013)			✓						✓	✓		
Hendricks and Singhal (2005)					✓	✓				✓		
Hendricks and Singhal (2005)					✓	✓				✓		
Henisz et al. (2014)			✓			✓				✓		
Hsu and Bui (2022)		✓	✓						✓	✓		✓
Jacobs and Singhal (2020)		✓			✓				✓	✓		
Jacobs et al. (2010)		✓				✓				✓		
Knittel and Stango (2014)			✓						✓	✓		
Kölbel et al. (2017)	✓							✓		✓		
Lee and Faff (2009)	✓					✓				✓		
Lev et al. (2010)			✓			✓				✓		
Li and Wu (2020)	✓							✓		✓		
Lins et al. (2017)			✓			✓				✓		
Lo et al. (2018)		✓				✓				✓		
Moss et al. (2023)	✓						✓	✓				
Orlitzky et al. (2003)		✓	✓						✓	✓		
Pu et al. (2022)	✓						✓	✓		✓		
Puriwat and Tripopsakul (2022)	✓								✓			✓
Rhodes (2016)			✓						✓	✓		
Siano et al. (2017)			✓			✓		✓	✓	✓		
Our study	✓	✓	✓	✓				✓				✓

specific information on the item type, among others.

Our second data comes from RepRisk, which operates a database to identify companies' ESG-related risk exposure by aggregating news articles related to firms' ESG violations. RepRisk uses a proprietary algorithm that searches over 80,000 sources to identify news coverage of firms' ESG violations.[1] This dataset has been previously utilized in the literature to study the reputational issues related to companies' ESG engagement and violations (e.g., Kölbel et al., 2017; Li and Wu, 2020). RepRisk considers violations across 28 core areas within the environmental, social, and governance categories. Apart from the three main ESG categories, RepRisk also collects data on violations related to "cross-cutting" issues, which include firms' supply chain violations, issues related to controversial products, and violations of international regulations or national legislation. Table 13 in the Appendix provides a summary of different violations considered by RepRisk. For each firm, RepRisk data contains monthly information on the number of articles covering news related to firms' ESG violations, the type of ESG violation, the severity of the news articles, the reach of the news sources, and a unique reputational risk index calculated by RepRisk's proprietary algorithm.

Next, we elaborate on how we combine the two data sources. The transactional data from the retailer is constructed at the brand-name level, while RepRisk data reports the count of news articles covering firm-level ESG violations. Notice that some brands are owned by the same company, we manually search for the parent company information for each brand, and then aggregate the brand sales at the parent company level. After merging the aggregated month-firm-store level transaction data with the month-firm level RepRisk data, we construct a unique panel dataset to examine the effects of ESG news coverage on the retail sales of each firm. Ultimately, we match 74 brands unique brands from the transaction dataset with 39 firms in the RepRisk dataset, which results in 690,420 (i.e., 311 stores $\times$ 39 firms $\times$ 30 months) observations. For some companies' brands, we observed zero sales at specific stores during the 30-month period, indicating that these brand names were not offered for sale in those particular stores. Hence, we exclude these firm-store observations from the main analysis to ensure that the analysis focuses on brands that were actively sold in stores. Doing so leaves us with 632,280 observations.

To supplement our main analysis, we collect voting data and additional demographic data for each store location. At the county level, we collect the electoral data from the election year of 2016. We also obtain information on the median age and average household income for each store in the nearby neighborhoods.

[1]Specific details on how this data is compiled by RepRisk is available at `https://www.reprisk.com/approach#scope-and-scale`.

2.3.2 Key Variables

In the rest of this section, we introduce the key variables employed in our models. As discussed earlier, our unit of analysis is at firm-store-month level.

2.3.2.1 Dependent Variable:

The outcome variable of interest is retail sales. Following Akturk et al. (2018), we measure sales by using the number of purchase transactions. We operationalize this dependent variable by counting the number of items customers purchase. Considering that news articles reporting negative ESG incidents can be published at different times within a month, the effects of such news on sales could either occur in the current month or spillover to the subsequent month. Furthermore, it is important to account for the fact that customers may not immediately react to ESG-related news about a firm and its associated brands, as there is a time lag before customers actually visit the store and make purchases. Therefore, to capture the potential impact of ESG news on sales, for each firm, we utilize the sum of sales for the current month and the subsequent month as the outcome variable in our main analysis, thereby capturing the immediate and subsequent effects of the news.

Thus, the dependent variable in the main model is denoted by $SumPurchase_{b,s,t} = Purchase_{b,s,t} + Purchase_{b,s,t+1}$, which represents the overall number of purchases for months t and $t+1$ for firm b at store s. We supplement our main analysis with several alternative dependent variables, which we discuss in Section 2.5.2. Next, we discuss our independent and moderating variables of interest.

2.3.2.2 Independent and Moderating Variables:

Our primary explanatory variable of interest is denoted as $ESG\_Total_{b,t}$, which represents the total number of news articles covering negative ESG-related violations for firm b in month t. To obtain this data, we follow the established literature (e.g., Kölbel et al., 2017) and collect aggregated information from RepRisk, which is recognized for its systematic screening of diverse public sources and stakeholders, enabling the identification and compilation of news items that disclose brands' ESG violations.

To examine the individual effects of different ESG violations on sales, we operationalize the following variables: $Environmental_{b,t}$, $Social_{b,t}$, $Governance_{b,t}$, and $CrossCutting_{b,t}$. The variable $Environmental_{b,t}$ captures the number of news articles related to environmental-related violations for company b in month t. Similarly, $Social_{b,t}$ and $Governance_{b,t}$ represent the counts of news articles addressing social and governance issues, respectively, pertaining to company b in month t. Finally, $CrossCutting_{b,t}$ accounts for the number of news articles mentioning cross-cutting issues. For a comprehensive overview of the classification of different issues within these four categories, please refer to

Table 13 in the Appendix.

In order to explore the influence of company-specific factors on the relationship between ESG violations and sales, we examine the moderating effect of the company's product value. Product value is a critical characteristic that is closely linked to a brand's positioning and customer base. We propose that the impact of ESG violations may be more pronounced for high-value (e.g., luxury) brands. To identify high-value brands, we calculate the average price of all items and brands sold for each firm over the analyzed time period. We then categorize a firm as a high-value if its average product price falls within the top 10 percentile of all sampled brands (i.e., $AvgProdPrice_b \geq \$96.53$). For the firm's brands meeting this criterion, we assign the value of 1 to the variable $HighValue_b$. For a complete list of high-value brands, please refer to Table 12 in the Appendix. Conversely, if a firm's brand does not meet the threshold, we assign the value of 0 to $HighValue_b$. By distinguishing between high-value and non-high-value brands, we can explore the potential variations in the impact of ESG violations on sales based on brand valuation.

To analyze the effects of market-specific heterogeneity, we utilize the store location and nearby demographics. First, we consider each store location's median age and average household income. Based on the sampled stores, we create categorical variables $HighAge_s$ and $HighIncome_s$ to indicate stores surrounded by high-age residents and high-income households, respectively. Specifically, $HighAge_s$ takes the value of 1 if the median age around store s falls within the top 25 percentile of all sampled stores (i.e., median age ≥ 38.3); otherwise, $HighAge_s = 0$. Similarly, $HighIncome_s = 1$ if store s is located at the top 25 percentile of the highest household income (i.e., household income $\geq \$66,504$).

Additionally, based on the store location, we incorporate the political party affiliation at the nearby county as a factor that may influence the relationship between ESG violations and brand sales, which is consistent with previous research (Green et al., 2023). To do so, we manually collect each store's zip code and county information through a publicly available website[2]. Since our study spans from 2014 to 2016, we employ the electoral data from the election year of 2016. The raw U.S. county-level is obtained from the data provided by Amlani and Algara (2021), which includes information on the county's name, the total number of votes, and the percentage of two-party vote share. We operationalize this market-specific variable by introducing a binary variable denoted as $Democrat_s$, where $Democrat_s = 1$ represents a store s where the nearby county was won by the democratic party; otherwise, a republican leaning store is denoted by $Democrat_s = 0$. This variable allows us to explore the potential effects of political leanings on the relationship between ESG news coverage and brand sales.

[2] https://www.unitedstateszipcodes.org/

2.3.2.3 Control Variables:

RepRisk data provides information related to the severity and reach of the news coverage on firms' ESG violations. The severity of incidents is categorized into three levels: low severity, medium severity, and high severity. Additionally, RepRisk classifies news sources into low-reach, medium-reach, or high-reach categories. News sources that fall into the low-reach category include local media, smaller non-governmental organizations (NGOs), and local governmental bodies. News published in national and regional media are classified as medium-reach. High-reach sources encompass globally recognized media outlets such as the New York Times and Wall Street Journal, among others.

To account for the severity and reach of the news articles, we follow the approach adopted by Kölbel et al. (2017) and include the following two control variables: the weighted average severity ($AvgSeverity_{b,t}$) and the weighted average reach ($AvgReach_{b,t}$). We operationalize these variables as follows:

$$AvgReach_{b,t} = \frac{1}{3} \times (3 \times HighReach_{b,t} + 2 \times MediumReach_{b,t} + 1 \times LowReach_{b,t}),$$

and

$$AvgSeverity_{b,t} = \frac{1}{3} \times (3 \times HighSeverity_{b,t} + 2 \times MediumSeverity_{b,t} + 1 \times LowSeverity_{b,t}),$$

where $HighReach_{b,t}$ ($MediumReach_{b,t}$, $LowReach_{b,t}$) represents the count of ESG news articles associated with firm b that were disclosed by high-reach (medium-reach, low-reach) media in month t. Similarly, $HighSeverity_{b,t}$ ($MediumSeverity_{b,t}$, $LowSeverity_{b,t}$) denotes the count of firm b's high-severity (medium-severity, low-severity) articles in month t.

Next, we will control each firm's current reputational risk exposure to isolate the specific impact of ESG news coverage on brand sales. The reputational score provided by RepRisk serves as a proxy to identify the risk exposure of the focal firm. By including this measure in our analysis (denoted as $RRI_{b,t}$), we can now account for the inherent differences in ESG-related risk exposure across firms and tease out the effect of news coverage on brand sales. Next, we account for any unobserved firm and store level heterogeneity through firm and store fixed effects. Finally, we include month-year fixed effects in our analyses to control for potential exogenous time-specific shocks. Table 2.2 reports the firm-store level summary statistics of the key variables used in the model.

2.4 Empirical Model and Results

We employ a fixed-effects panel model to assess the impact of news coverage related to ESG violations on retail brand sales, and the panel analysis is conducted at the firm-store-month level. In the

Table 2.2: Summary Statistics

Variable	Mean	SD	Min	Max
Dependent Variable				
SumPurchase	505	804	0	6,581
Independent and Moderating Variables				
ESG_Total	6	21	0	175
Social	2.9	12	0	105
CrossCutting	1.9	5.8	0	60
Environmental	0.61	2.8	0	30
Governance	0.67	3.5	0	35
HighValue	0.15	0.36	0	1
HighAge	0.25	0.44	0	1
HighIncome	0.25	0.43	0	1
Democrat	0.4	0.49	0	1
Control Variable				
AvgReach	0.13	0.25	0	1
AvgSeverity	0.094	0.19	0	0.89
RRI	94	97	0	375

rest of this section, we present our models and the key results.

2.4.1 Overall Impact of News Coverage of ESG Violations on Sales

Our main model focuses on the overall impact of ESG news coverage on retail brand sales, where $ESG\_Total_{b,t}$ is the key explanatory variable of interest and captures the total number of published news articles regarding ESG violations for firm b at month t. As discussed earlier, the main dependent variable is $SumPurchase_{b,s,t}$. Following the literature (Gallino and Moreno, 2014), we employ Ordinary Least Squares regression (OLS) and log transform the dependent variable.[3] We model the impact of news coverage regarding ESG violations as follows:

$$\log\left(SumPurchase_{b,s,t}\right) = \alpha_1 ESG\_Total_{b,t} + \mathbb{Z}\mathbb{C}_{b,s} + \theta_{b,s} + \lambda_t + \epsilon_{b,s,t}, \tag{2.1}$$

where the coefficient α_1 denotes the effect of the number of ESG-related news articles on brand sales. Vector $\mathbb{C}_{b,s}$ represents all the control variables discussed in Section 2.3.2.3, and $\mathbb{Z}$ denotes the parameter estimates for the control variables. We control for firm-store fixed effects with $\theta_{b,s}$ and time (year-month) fixed effects with λ_t. We report robust standard errors clustered at the firm-store level for all subsequent analyses. Since the number of purchases is a count variable, the literature suggests that the Poisson model is more appropriate to model count data and significantly outperforms log-linear models (Wooldridge, 2010; Mallipeddi et al., 2021); we also employ a Poisson model for estimation.

[3]To deal with zero values, we add 1 to all the values of the dependent variable before log transformation, i.e., $log(SumPurchase + 1)$.

Table 2.3 summarizes the results, where Model (1) is the estimation for the log-linear estimation and Model (2) reports the results for the Poisson Model. Taking the OLS results for example, we find that news articles on ESG violations have a negative and statistically significant impact on brand sales ($\alpha_1 = -0.001$, $p < 0.001$). Specifically, we find that each additional news article related to a firm's ESG violation leads to a 0.1% decrease in the number of purchase transactions, on average. Evidently, news coverage plays a pivotal role in disseminating information to consumers. When consumers are exposed to news about a brand's ESG violations, its credibility and trustworthiness are called into question, given that many consumers today prioritize ethical and sustainable practices in their purchasing decisions. As a result, this can lead to a change in consumers' perception, thereby making them less likely to buy from a brand committing ESG violations.

Table 2.3: Overall Impact of News Coverage of ESG Violations on Sales

	(1)	(2)
Dependent Variables	$\log(SumPurchase_{b,t,s})$	$SumPurchase_{b,t+1,s}$
Model	OLS	Poisson
ESG_Total	-0.001***	-0.001***
	(0.000)	(0.000)
Control variables	Yes	Yes
Year-month Fixed Effects	Yes	Yes
Firm-store Fixed Effects	Yes	Yes
Observations	611,088	611,088
R^2	0.920	-

Robust standard errors clustered by firm-store are in parentheses.
$.p < 0.1; *p < 0.05; **p < 0.01; ***p < 0.001$

2.4.2 Impact of Individual Type of ESG-related News

In the previous analysis, we demonstrated that news articles related to ESG violations have a negative and significant impact on brand sales. However, it is possible that customers may respond differently to different types of ESG-related incidents. As we described in Section 2.3, the ESG incidents are assigned into four main categories: environmental, social, governance, and cross-cutting. In this section, we use this classification to analyze whether different types of ESG violations, as depicted in news coverage, have a differential impact on brand sales. We model the impact of news coverage regarding different types of ESG violations as follows:

$$\begin{aligned}\log\left(SumPurchase_{b,s,t}\right) = \; & \beta_1 Environmental_{b,t} + \beta_2 Governance_{b,t} + \beta_3 Social_{b,t} \\ & + \beta_4 CrossCutting_{b,t} + \mathbb{Z}\mathbb{C}_{b,s} + \theta_{b,s} + \lambda_t + \epsilon_{b,s,t},\end{aligned} \tag{2.2}$$

where $Environmental_{b,t}$, $Governance_{b,t}$, $Social_{b,t}$, and $CrossCutting_{b,t}$, denote the number of news articles that are related to environmental, governance, social, and cross-cutting issues of firm b on month t, respectively. The coefficients β_1, β_2, β_3, and β_4 capture the effect of the number of environmental-, governance-, social-, and cross-cutting-related news articles, respectively. We include all the controls discussed in Section 2.3.2.3 in Vector $\mathbb{C}_{b,s}$. Furthermore, we account for firm-store Fixed Effects with $\theta_{b,s}$ and time (year-month) fixed effects with λ_t.

Similar to Section 2.4, we employ OLS and report the estimates of Equation 2.2 in Column (1) of Table 2.4. In the meantime, we supplement it with a Poisson regression and report the estimates in Column (2). Observing from the results of Model (1), we find a positive relationship between sales and news articles reporting environmental and governance issues ($\beta_1 = 0.008$, $\beta_2 = 0.007$), while news articles related to social and cross-cutting issues have a negative and statically significant effect on sales ($\beta_3 = -0.002$ and $\beta_4 = -0.006$).

Table 2.4: Impact of Different Types of ESG-related News on Sales

	(1)	(2)
Dependent Variables	$\log(SumPurchase_{b,t,s})$	$SumPurchase_{b,t+1,s}$
Model	OLS	Poisson
Environment	0.008***	0.017***
	(0.001)	(0.001)
Governance	0.007***	0.007***
	(0.001)	(0.001)
Social	-0.002***	-0.003***
	(0.000)	(0.000)
Cross.cutting	-0.006***	-0.004***
	(0.001)	(0.000)
Control variables	Yes	Yes
Year-month Fixed Effects	Yes	Yes
Firm-store Fixed Effects	Yes	Yes
Observations	611,088	611,088
R^2	0.920	-

Robust standard errors clustered by firm-store are in parentheses.
$.p < 0.1$; $*p < 0.05$; $**p < 0.01$; $***p < 0.001$

Interestingly, we find that environmental issues have a positive and significant impact on brand sales. The concept of eco-friendly and sustainable has developed rapidly in the past decades. In today's increasingly environmental-conscious consumer landscape and business environment, the threshold for environmental friendliness in conducting business has been raised significantly. In this case, heightened media attention to environmental concerns does not necessarily relate to a major boycott. Instead, it can incentivize future innovative and positive change within organizations, fostering transparency and a commitment to sustainability. Companies that effectively address environmental challenges highlighted in negative news coverage can utilize the publicity to emphasize their effort and differentiate themselves to enhance brand identity. By demonstrating such commitment to environmental responsibility in response to negative news coverage, companies have the potential to not only mitigate reputational damage but also cultivate a more loyal customer base that values sustainability, ultimately driving sales growth.

Our empirical results also indicate that news coverage of governance-related violations positively affects brand sales. Governance-related violations, including corruption, fraud, tax evasion, and anti-competitive practices, reflect the flaws in the company's ethical standards and corporate integrity. When making a decision about daily purchase activities, consumers may not find it relevant. Paradoxically, consumers may perceive the brand as transparent or honest in addressing governance issues publicly, thus fostering a sense of trust or authenticity. Additionally, this negative publicity can initially stimulate increased interest and engagement with the brand as consumers become more curious about the controversy surrounding it. This heightened attention can lead to a temporary spike in sales brought by consumers' curiosity, speculation, or even as a form of support for the brand during a challenging time following the firm's governance incidents.

Not surprisingly, we find the negative impact of news coverage of social issues on sales. This arises because consumers empathize with social issues, such as social discrimination and employee mistreatment. Moreover, the heightened societal awareness of Diversity, Equity, and Inclusion (DEI) in the workplace could also affect consumers' purchase behaviors. Thus, consumers may tend to react strongly if the company is reported to be involved in any of these violations, as evidenced by our findings.

We also report the sales decline related to cross-cutting incidents, such as violations of international standards, national legislation, supply chain failures, and controversial products. In particular, we demonstrate that for each additional news article covering a cross-cutting incident, there is a significant 0.6% reduction in brand sales. Unlike social issues, cross-cutting incidents may affect various stakeholders and involve multiple aspects of operations, which reveals severe potential to undermine the brand's trust and reputation across multiple dimensions simultaneously. The fact that this type of issue tends to involve more parties ultimately leads to a more impactful consequence, presenting more attention from the public and a more complex spectrum of challenges for businesses. Such complexity amplifies the negative public exposure of a firm's violation and, thus, results in a negative impact of cross-cutting issues on sales.

2.4.3 Mechanism Analysis

In this section, we conduct additional analysis that delves into brand- and store-level heterogeneity to explore the mechanisms through which ESG incidents impact brand sales differently. First, we consider the moderating effect of the perceived value of the firm's owned brand from the customers' perspective by calculating the average price of all the products being sold by the focal firm. Second, leveraging the store location and nearby demographic data, we examine the moderating effects of store-level characteristics.

2.4.3.1 Perceived Brand Value:

To measure consumers' perceived brand value, we screen all the products the firm offers and calculate the average listing price. Consumers are likely to respond differently to products and brands with different prices. To examine the moderating effect of the perceived brand value, we create a dummy variable, $HighValue_b$, to denote these brands with relatively high value. Specifically, $HighValue_b$ takes the value of one if the average price of firm b's products falls within the top 10 percentile of all the brands being sold at the retailer's stores; otherwise, $HighValue_b$ equals zero for those brands with relatively low prices. In particular, the following firms are identified as high-value brand owners in our sample: *Caleres Inc (formerly Brown Shoe Company), Coach Inc., Fossil Group Inc., Genesco Inc., Global Brands Group Holding Ltd., Hugo Boss AG, Michael Kors Holdings Ltd., The Timberland Co., Hermes International, Beiersdorf AG.*

Incorporating $HighValue_b$, we use the following specification to estimate the moderating effects of the perceived brand value on the relationship between a firm's ESG incidents and brand sales.

$$y_{b,s,t} = \alpha_1 ESG\_Total_{b,t} + \gamma_1 ESG\_Total_{b,t} \times HighValue_b + \mathbb{Z}\mathbb{C}_{b,s} + \theta_{b,s} + \lambda_t + \epsilon_{b,s,t}, \tag{2.3}$$

where $y_{b,s,t}$ represents our dependent variable, number of purchases. We again employ log-linear regression together with count data and Poisson estimation. After accounting for firm-store fixed effects and time fixed effects, the estimation results for Equation 2.3 are provided in Table 2.5.

Consistent with our findings in the main analysis, we find that the news articles related to ESG violations have a negative and statistically significant impact on sales. Furthermore, we find that this effect is significantly mitigated when it comes to the high-value brands ($\gamma_1 = 0.120$, $p < 0.001$). The rationale behind these results can be drawn from the following perspectives. First, high-value brands typically have established strong brand equity and trust among consumers over time. Regarding the firm's potential ESG violation, this deep-rooted trust acts as a buffer against negative publicity, which mitigates the immediate collapse of consumer confidence and minimizes the impact on sales. Second, high-value brands tend to have a dedicated customer base with strong loyalty and affinity. In particular, we are looking at the top 10% ranked luxury brands in our case. Even when faced with negative ESG news, loyal customers may remain committed in their support of the brand. Such a high level of loyalty then helps sustain sales levels despite the temporary negative publicity.

Third, high-value brands are often associated with premium quality and, more importantly, perceived as more stable and resilient compared to lower-valued brands. Consumers may perceive these brands as being held to higher standards across all aspects of their operations, including ESG performance. Consequently, negative ESG news may be viewed as a deviation from the brand's usual standards rather than a reflection of its own value or quality. In the meantime, consumers tend to believe that these brands have the resources, capabilities, and commitment to address ESG-related issues, if any. Thus, the combination of brand equity, trust, loyalty, and premium perceptions associated with high-value brands moderate the negative impact of negative ESG news on brand sales.

Table 2.5: Mechanism Analysis: Perceived Brand Value

	(1)	(2)
Dependent Variables	$\log(SumPurchase_{b,t,s})$	$SumPurchase_{b,t+1,s}$
Model	OLS	Poisson
ESG_Total	-0.001***	-0.001***
	(0.000)	(0.000)
$ESG\_Total \times HighValue$	0.120***	0.098**
	(0.021)	(0.019)
Control Variables	Yes	Yes
Year-month Fixed Effects	Yes	Yes
Firm-store Fixed Effects	Yes	Yes
Observations	611,088	611,088
R^2	0.920	-

Robust standard errors clustered by firm-store are in parentheses.
$.p < 0.1; *p < 0.05; **p < 0.01; ***p < 0.001$

2.4.3.2 Store-level Moderators:

Given that stores located in different areas are surrounded by a customer base with potentially different preferences and behaviors, we consider the moderating impact of demographic factors such as median age and household income on the relationship between news coverage of ESG violations and brand sales. Stores located in areas with higher median age and income levels may attract customers who prioritize ESG considerations, thereby being more sensitive to negative ESG news coverage. As described in Section 2.3.2.2, we operationalize this moderator by constructing two new indicator variables: $HighAge$ and $HighIncome$, which takes the value of one if the store nearby median age and household income fall within the top 25 percentile of all sampled stores.

In addition to customers' demographic differences, the political leaning of the neighborhood can shape nearby consumers' perceptions differently, which, in the meantime, impacts their attitude toward the firm's ESG incidents. Moreover, states and counties with varying political leanings may exhibit different standards and levels of tolerance towards ESG incidents, thereby influencing nearby customers' reaction and purchasing decisions toward ESG violations. To capture the moderating effect of political leaning, we introduce a categorical variable, $Democrat_s$, to indicate the political leaning based on the geographic location of the store s. Since we have each store's zip code, we can link each store to the county-level election voting data. We assign the value of 1 to $Democrat_s$ if the county in which store s is situated is Democrat-leaning. Conversely, we assign the value of 0 to $Democrat_s$ if the state is Republican-leaning.

Table 2.6: Mechanism Analysis: Store-level Moderators

Model	(1) OLS	(2) Poisson	(3) OLS	(4) Poisson	(5) OLS	(6) Poisson
ESG_Total	-0.001***	-0.001***	-0.001***	-0.001***	-0.001***	-0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$ESG\_Total \times Democratic$	-0.112***	-0.193***	-	-	-	-
	(0.019)	(0.020)	-	-	-	-
$ESG\_Total \times HighAge$	-	-	-0.155***	-0.272***	-	-
	-	-	(0.020)	(0.023)	-	-
$ESG\_Total \times HighIncome$	-	-	-	-	-0.089***	-0.161***
	-	-	-	-	(0.017)	(0.018)
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes
Year-month Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Firm-store Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	559,352	559,352	559,352	559,352	365,835	365,835
R^2	0.954	-	0.954	-	0.938	-

Robust standard errors clustered by firm-store are in parentheses.
$.p < 0.1; *p < 0.05; **p < 0.01; ***p < 0.001$

We follow the same procedures as presented in Section 2.4.3.1; the estimation results are provided in Table 2.6. Consistent with our findings in the main analysis, we find that the news articles related to ESG violations have a negative and statistically significant impact on sales across all six models. Furthermore, as shown in the first two columns of Table 2.6, this effect is amplified in Democrat counties. This result can be explained by the extant literature demonstrating the effects of political leanings on consumer attitudes and preferences (Ordabayeva and Fernandes, 2018). In Democratic-dominated areas, politicians tend to prioritize environmental concerns over economic development, ESG incidents may attract more attention and criticism from both consumers and local authorities. This heightened awareness could lead to stronger consumer backlash against brands associated with ESG incidents, potentially resulting in more severe declines in brand sales. In contrast, consumers located in Republican counties may be less inclined to penalize brands for ESG violations, viewing them as a consequence of over-regulation or as less relevant to their purchasing decisions. As a result, brands operating in Democratic-dominated areas may encounter more stringent repercussions for ESG violations, thereby resulting in a pronounced impact on their sales.

Next, observing from Model (3) and (4) in Table 2.6, negative ESG news coverage leads to a more severe effect on the stores that are surrounded by higher median age communities. It reveals that the older population places a greater emphasis on corporate responsibility and ethical conduct when evaluating brands. Consistent with the insights drawn from the theory of generativity and positive psychology of aging (Urien and Kilbourne, 2011; Wang et al., 2021), older people exhibit more environmentally responsible consumption behaviors due to their enhanced concern for the future and the need to contribute to the next generation. Moreover, given that older consumers perceive a stronger awareness of environmental risks, particularly their impact on human health (Witek and Kuźniar, 2020), they may be more sensitive to negative information and less willing to take chances. When it comes to the purchasing decision of irresponsible brands, this group of consumers tends to adhere to more traditional values and ethical standards. Thus, these factors collectively contribute to the observed severer negative impacts within these communities.

We also find the amplification of the negative impact of negative ESG news on brand sales in stores located in communities with higher household incomes. Prior literature suggests that many marketers segment their markets based on income (Ranzijn, 2002) due to the fact that wealthier households are more likely to spend on products committed to environmental and responsible practices (Cranfield and Magnusson, 2003). Households with higher incomes often have greater purchasing power, which allows them to have the affordability and flexibility to consider the brand's higher standards regarding corporate responsibility and ethical conduct. This group of consumers may also view their consumption choices as a reflection of their social status, values, and identity. In this case, negative ESG news can potentially challenge their self-image and perceived social standing, prompting them to disassociate from these brands.

2.5 Robustness Checks

In this section, we elaborate on the robustness checks that we conduct to further validate our empirical findings that establish the effects of news coverage regarding the ESG violations on sales. We find that our results are robust to the alternative models and specifications.

2.5.1 Endogeneity of News Coverage of ESG Violations

A potential concern in the model presented in Equation 2.1 may be endogeneity. While we control for time and firm-store Fixed Effects, the media attention to a brand's ESG violations may be influenced by unobserved factors such that $ESG\_Total_{b,t}$ variable in Equation 2.1 may be correlated with the error term. To address this concern, we employ the control function approach (Petrin and Train, 2010; Allon et al., 2023). While the two-stage least-squares (2SLS) method using instrument variables is suitable for models with a linear model, the endogenous variable in Equation 2.1 (i.e., $ESG\_Total_{b,t}$) is a count variable. In such a case, a control function approach is more viable as it allows us to use a non-linear estimator in the first-stage regression.

The control function approach involves two stages of regression. In the first stage, the endogenous variable (i.e., $ESG\_Total_{b,t}$) is regressed on the instrument variable (IV) and other exogenous variables to obtain control functions. More specifically, the control functions are residuals obtained from the first stage regression model employed to estimate the endogenous variable (i.e., $ESG\_Total_{b,t}$) with an IV as a predictor variable wherein the IV explains the exogenous variation in the endogenous variable. In the second stage, the control functions are included as additional regressors in the main regression equation, along with other exogenous variables. By doing so, the control functions capture the unobserved variation in the endogenous variable, thereby effectively controlling for endogeneity.

The validity of the IV in the first stage of a regression analysis depends on two essential conditions: relevance and exclusion. The relevance condition requires that the IV be correlated with the endogenous variable of interest. The exclusion condition requires that the IV be uncorrelated with the error term in the model. This implies that the IV must not directly affect the main dependent variable (i.e., $SumPurchase$) but only through its impact on the endogenous variable. We utilize a Hausman-type IV approach, which previous research has asserted to effectively meet the essential criteria for instrument relevance and exclusion (Xu et al., 2021; Allon et al., 2023; Xu et al., 2023). In particular, our IV is the average number of articles reporting negative ESG news over all brands in the same industry that have had at least one violation in the same month; in other words, the average number of ESG news of peer brands excluding the focal brand (denoted by $Peer\_ESG_{b,t}$). We use the type of products to define firms operating in the same industry. In particular, we classify three types of departments based on the retailer's brand assortment: cosmetics, home decoration, and apparel.

The Hausman-type IV, $Peer\_ESG_{b,t}$, satisfies the two conditions for the validity of an instrument variable. Specifically, consistent with the prior arguments for Hausman-style instruments, we posit that the average number of articles covering ESG violations of peer firms is a valid instrument for the number of articles of the focal firm, as peer firms may be subject to common shifters that influence media coverage across peer firms but are not correlated with sales at the retail market (Hausman, 1996). Furthermore, we verify the relevance criterion in the first stage regression – the coefficient of $Peer\_ESG_{b,t}$ is positive and statically significant (estimates of the first stage regression are provided in the Appendix, see Table 14).

The first-stage estimation for the endogenous variable, $ESG\_Total_{b,t}$, is presented below.

$$ESG\_Total_{b,t} = \phi Peer\_ESG_{b,t} + \mathbb{ZC}_{b,s} + \theta_{b,s} + \lambda_t + \upsilon_{b,s,t}, \tag{2.4}$$

where $Peer\_ESG_{b,t}$ captures the average number of reported ESG violations over all peer brands (i.e., excluding brand d) with at least one news during month t. We include all controls from the model in Equation 2.1, firm-store and time fixed effects. Given that the outcome variable in the first stage regression, $ESG\_Total_{b,t}$, is a count variable, we follow prior literature and adopt Poisson regression for model estimation (Kumar et al., 2018; Mallipeddi et al., 2021). We obtain the predicted residuals from the model in Equation 2.4 and denote them as $\hat{v}_{b,t}$ and use these predicted residuals, i.e., control functions, as an additional control variable to correct for endogeneity in Equation 2.1. Subsequently, the endogeneity-corrected main model is presented below.

$$y_{b,s,t} = \alpha_1 ESG\_Total_{b,t} + \rho\hat{v}_{b,t} + \mathbb{ZC}_{b,s} + \theta_{b,s} + \lambda_t + \epsilon_{b,s,t}, \tag{2.5}$$

where $\hat{v}_{b,t}$ is the term correcting for endogeneity and α_1 provides the endogeneity-corrected estimate for the effect of $ESG\_Total_{b,t}$. The other covariates are defined in Equation 2.1. The estimation results are provided in Columns (1) and (2) of Table 2.7 and are consistent with the model in Equation 2.1. Specifically, the results reveal a significant negative impact of the news coverage regarding ESG violations after addressing the potential endogeneity in the number of negative ESG news ($\alpha_1 = -0.001,\ p < 0.001$).

We also address the concerns of endogeneity related to the number of news articles for individual types of ESG violations in Equation 2.2. To address these endogeneity concerns, we again adopt the control function approach as discussed earlier. Specifically, we use the following IVs: $Peer\_Environmental_{b,t}$, $Peer\_Social_{b,t}$ $Peer\_Governance_{b,t}$, and $Peer\_CrossCutting_{b,t}$ to obtain control functions. The variables $Peer\_Environmental_{b,t}$, $Peer\_Social_{b,t}$, $Peer\_Governance_{b,t}$, and $Peer\_CrossCutting_{b,t}$, denote the average number of environmental, social, governance, and cross-cutting related violations, respectively, over all other brands with the same department (i.e., excluding brand d) that have had at least one related violation in month t. The relevancy and exclusion arguments for these Hausman-type IVs closely align with those discussed earlier for $Peer\_ESG_{b,t}$. Specifically, we postulate that the average number of articles covering individual-type violations of peer firms is a valid instrument for the number of articles related to the focal firm. This postulation is grounded in the idea that peer firms might experience shared external factors that influence media coverage, which are not correlated with brand sales. Formally, the first-stage regression models for all the endogenous variables are presented below.

$$\begin{aligned}
Environmental_{b,t} &= \phi_1 Peer_Environmental_{b,t} + \mathbb{ZC}_{b,s} + \theta_{b,s} + v_{1b,t},\\
Governance_{b,t} &= \phi_2 Peer_Governance_{b,t} + \mathbb{ZC}_{b,s} + \theta_{b,s} + v_{3b,t},\\
Social_{b,t} &= \phi_3 Peer_Social_{b,t} + \mathbb{ZC}_{b,s} + \theta_{b,s} + v_{2b,t},\\
CrossCutting_{b,t} &= \phi_4 Peer_CrossCutting_{b,t} + \mathbb{ZC}_{b,s} + \theta_{b,s} + v_{4b,t}.
\end{aligned} \tag{2.6}$$

In the above set of models, we first confirm the relevance of the instrument variables (i.e., $Peer\_Environmental_{b,t}$, $Peer\_Social_{b,t}$, $Peer\_Governance_{b,t}$, and $Peer\_CrossCutting_{b,t}$). The results of first-stage models estimated via Poisson models are reported in Table 15 of the Appendix. We find that the parameter estimates ϕ_1, ϕ_2, ϕ_3, and ϕ_4 are significant, thus confirming the relevancy of our instruments. The predicted residuals ($\hat{v_1}_{b,t}$, $\hat{v_2}_{b,t}$, $\hat{v_3}_{b,t}$, and $\hat{v_4}_{b,t}$) from the above set of equations are included in Equation 2.2 to account for endogeneity associated with each of the variables of interest (i.e., $Environmental_{b,t}$, $Social_{b,t}$, $Governance_{b,t}$, and $CrossCutting_{b,t}$). The endogeneity-corrected model is presented below.

$$\begin{aligned} y_{b,s,t} = \; & \beta_1 Environmental_{b,t} + \beta_2 Governance_{b,t} + \beta_3 Social_{b,t} \\ & + \beta_4 CrossCutting_{b,t} + \rho_1 \hat{v_1}_{b,t} + \rho_2 \hat{v_2}_{b,t} + \rho_3 \hat{v_3}_{b,t} + \rho_4 \hat{v_4}_{b,t} \\ & + \mathbb{ZC}_{b,s} + \theta_{b,s} + \lambda_t + \epsilon_{b,s,t}. \end{aligned} \tag{2.7}$$

The estimation results of the above endogeneity-correct model are summarized in Columns (3) and (4) of Table 2.7. The results remain consistent with those presented in Table 2.4, with one notable exception being the impact of governance-related news. After appropriately addressing the endogeneity of the number of negative ESG news for each issue type, the results still indicate the negative effects of news coverage related to environmental and social issues and the positive effect of news coverage related to cross-cutting issues on sales. However, we no longer observe a significant impact of news related to the firm's governance violations on brand sales.

2.5.2 Alternative Dependent Variables and Model Specifications

In Section 2.4, we log-transformed the dependent variable, $SumPurchase_{b,s,t}$ for ease of interpretation. We re-estimate the model in Equation 2.1 using a linear model (i.e., without log-transforming the dependent variable) to validate our results. The results of the linear fixed effects model are presented in Column (1) of Table 2.8. The results are substantively similar to those in Table 2.3.

While we employ the number of purchases of the current month and the following month as the dependent variable in our main analyses, we re-run the analyses by employing the sales of the month following news coverage as the dependent variable (denoted by $Purchase_{b,s,t+1}$). We report the results without log-transforming the dependent variable in Column (2) and log-transformed dependent variable in Column (3) of Table 2.8. The findings are consistent with our main results in Section 2.4.

In addition to our main dependent variable, the number of purchases, we also consider dollar sales as an alternative dependent variable. We re-run the analyses by employing the sum of dollar sales of the current month and the following month as the dependent variable (denoted by $SumDollarSales_{b,s,t}$),

Table 2.7: Impact of Firm's ESG-related News on Sales With Endogeneity Correction

	(1)	(2)	(3)	(4)
Dependent Variables	$\log(SumPurchase_{b,t,s})$	$SumPurchase_{b,t+1,s}$	$\log(SumPurchase_{b,t,s})$	$SumPurchase_{b,t+1,s}$
Model	OLS	Poisson	OLS	Poisson
ESG_Total	-0.001***	-0.002***	-	-
	(0.000)	(0.000)	-	-
$Environment$	-	-	0.004***	0.019***
	-	-	(0.001)	(0.001)
$Governance$	-	-	0.003*	0.011***
	-	-	(0.002)	(0.001)
$Social$	-	-	-0.002***	-0.005***
	-	-	(0.001)	(0.000)
$Cross.cutting$	-	-	-0.001	0.000
	-	-	(0.001)	(0.000)
$\hat{v}_{b,t}$	0.000***	0.001***	-	-
	(0.000)	(0.000)	-	-
$\hat{v_1}_{b,t}$	-	-	0.008***	0.002***
	-	-	(0.001)	(0.001)
$\hat{v_2}_{b,t}$	-	-	0.016***	-0.004***
	-	-	(0.002)	(0.001)
$\hat{v_3}_{b,t}$	-	-	0.003***	0.009***
	-	-	(0.001)	(0.000)
$\hat{v_4}_{b,t}$	-	-	-0.009***	-0.011***
	-	-	(0.001)	(0.000)
Control Variables	Yes	Yes	Yes	Yes
Year-month Fixed Effects	Yes	Yes	Yes	Yes
Firm-store Fixed Effects	Yes	Yes	Yes	Yes
Observations	611,088	611,088	611,088	611,088
R^2	0.920	-	0.920	

Robust standard errors clustered by firm-store are in parentheses.
$.p < 0.1$; $*p < 0.05$; $**p < 0.01$; $***p < 0.001$

and report the result in Column (4) and Column (5) of Table 2.8 The results indicate a negative and statistically significant impact of news coverage regarding ESG violations on dollar sales. In summary, our key result – the negative impact of news coverage of ESG violations on sales – is robust to these alternative models and measures.

Table 2.8: Impact of ESG-related News on Sales Using Alternative Dependent Variables

	(1)	(2)	(3)	(4)	(5)
Dependent Variables	$SumPurchase_{b,t,s}$	$Purchase_{b,t+1,s}$	$\log(Purchase_{b,t+1,s})$	$SumDollarSales_{b,s,t}$	$\log(SumDollarSales_{b,s,t})$
ESG_Total	-0.860***	-0.759***	-0.001***	-8.713***	-0.001*
	(0.064)	(0.035)	(0.000)	(1.609)	(0.000)
Control Variables	Yes	Yes	Yes	Yes	Yes
Year-month Fixed Effects	Yes	Yes	Yes	Yes	Yes
Firm-store Fixed Effects	Yes	Yes	Yes	Yes	Yes
Observations	611,088	611,088	611,088	611,088	611,088
R^2	0.937	0.900	0.919	0.965	0.850

Robust standard errors clustered by firm-store are in parentheses.
$.p < 0.1$; $*p < 0.05$; $**p < 0.01$; $***p < 0.001$

2.5.3 Inverse Hyperbolic Sine Transformation

While we use a log-transformed dependent variable for ease of interpretation in our main models, a potential drawback with log transformation lies in dealing with zero values. As discussed earlier, we deal with this scenario by adding 1 to all the values before the log transformation. We now replicate our analyses by using the hyperbolic inverse sine transformation, which is similar to the log transformation but can still retain zero-values in the dependent variable (Bellemare and Wichman, 2020). Table 2.9 shows that the findings of the models after the hyperbolic sine transformation are qualitatively similar to those discussed in Section 2.4.

Table 2.9: Analysis with Inverse Hyperbolic Sine Transformation

Dependent Variables	(1) $f(SumPurchase_{b,t,s})$	(2) $f(SumPurchase_{b,t,s})$
ESG_Total	-0.001***	–
	(0.000)	–
$Environment$	–	0.007***
	–	(0.001)
$Governance$	–	0.007***
	–	(0.001)
$Social$	–	-0.002***
	–	(0.000)
$Cross.cutting$	–	-0.006***
	–	(0.001)
Control variables	Yes	Yes
Year-month Fixed Effects	Yes	Yes
Firm-store Fixed Effects	Yes	Yes
Observations	611,088	611,088
R^2	0.910	0.910

Note: $f(\cdot)$ represents the inverse-hyperbolic sine function.
Robust standard errors clustered by firm-store are in parentheses.
$.p < 0.1; *p < 0.05; **p < 0.01; ***p < 0.001$

2.6 Supplementary Results

While we established the effects of ESG news coverage on brand sales, our analyses do not feature an experimental treatment, which can further establish the causal link between the variables of interest. Given the challenges of randomizing the real-world treatment – specifically, news coverage about ESG violations – through a field experiment, we opt for a quasi-experimental approach, leveraging a difference-in-differences (DID) with propensity score weighting. This approach helps us further validate the causal relationship between ESG news coverage and brand sales.

2.6.1 A Quasi-Experimental Approach

ESG violations can also be considered as external shocks for brands, which enables us to employ the DID methodology (Akturk and Ketzenberg, 2022). Since the date of the first ESG violation differs from brand to brand, the canonical DID models are not suitable as they do not allow for treatment time variation. Hence, we employ the generalized difference-in-difference (GDD) methodology proposed by Goodman-Bacon (2021), which accounts for treatment time variation.

Similar to the traditional DID methodology, the GDD methodology requires experimental units that are directly affected by reported ESG incidents as well as a control group that is not affected by the external shock. To do so, we screen the news articles of companies' ESG violations over time and assign companies to control and treatment groups using the following approach.

During our 30-month analysis period, only four companies had no negative ESG news reported by the media, and therefore, we assigned these companies to the control group. To construct the treatment group, we focus on companies that had at least one violation during the period of analysis and use a three-month pre-intervention and two-month post-intervention time window to construct a valid event for each company. We also ensure that no other negative ESG-related news is reported three months before and two months after a specific violation, since including those companies could confound our analyses. In particular, we drop the companies from the analysis if there is more than one violation during the consecutive six months (the actual violation month, three months before and two months after the violation). However, if the company has another violation after the six-month window, we keep that company in the analysis and treat the violation as another event for the same company. Doing so gives us 25 companies in the treatment group and four brands in the control group. Please note that 25 treated companies ultimately form 32 events over time due to multiple ESG violations by several companies.

A cursory glance at this initial screening process shows the imbalance in the number of companies for treatment and control groups. Furthermore, the DiD approach will lead to biased estimates if the choice of treated companies is not made in a random manner. In our case, a brand's potential involvement in ESG incidents and the likelihood of being disclosed by news outlets may be influenced by the popularity of the brand and the type of products are being sold under the brand name. Thus, we utilize a widely used approach, propensity score weighting (PSM), to address concerns about imbalanced samples and potential endogenous selection (Austin, 2011; Bell et al., 2018; Arslan et al., 2023; Delana et al., 2023).

The benefits of using PSM in our study is twofold. First, by matching on the propensity score, PSM ensures that the distribution of observed covariates is similar between our treatment and control groups. The balanced covariates enhances the validity of causal inferences, in other words, the differences in outcomes between the matched groups can be more confidently attributed to the treatment rather than underlying differences in characteristics. Second, unlike other methods that might discard unmatched units, PSM allows us to include the full sample, which is important for our case where only four companies consisting the control group.

We employ a two-stage procedure to utilize PSM. In the first stage, we estimate the propensity score, which is defined as the probability that a unit receives the treatment, conditional on its observed characteristics (Imbens, 2000). We then incorporate the propensity score as a weight to re-estimate our main model so that the treatment and control observations become comparable in terms of their observable covariates. As extensively adopted by prior literature (Bell et al., 2018; Arslan et al., 2023; Delana et al., 2023), we follow Hirano and Imbens (2001) and define the sampling propensity score weighting as

$$\omega(W, x) = \frac{W}{\hat{e}(x)} + \frac{1 - W}{1 - \hat{e}(x)},$$

where W is a dummy variable to indicate a treated company and $\hat{e}(x)$ denotes the estimated probability of being treated. To estimate the weights, we utilize a logistic regression and consider the following input variables: brand's average number of purchases, average selling price, domestic or international corporation, and types of products being sold (including cosmetics, home decoration, and apparel). After obtaining these estimated weights, we incorporate them into our main GDD analysis to examine the impact of the firm's ESG incidents on brand sales. Doing so decreases the imbalances of observable characteristics between our control and treatment groups.

We present the econometric model for the GDD methodology in Equation 2.8, where μ_b represents firm-store Fixed Effects and W_t denotes time fixed effects. The dependent variable $y_{b,s,t}$ captures the number of purchases of firm b at month t and store s. We use a dummy variable $TREAT\_POST_{b,t}$ to indicate the brand's post-incident period, where $TREAT\_POST_{b,t} = 1$ in the following two months after firm b had a violation, and 0 otherwise. Consistent with the panel data analysis presented in previous sections, we control for the news source's reach, the severity of the incident, and the firm's RRI in month t. We employ both OLS and Poisson models for the estimation.

$$y_{b,s,t} = \alpha_1 TREAT\_POST_{b,t} + \mathbb{ZC}_{b,s} + \theta_{b,s} + \lambda_t + \epsilon_{b,s,t} \tag{2.8}$$

We report the results in Table 2.10. The Poisson estimates in column (2) indicate that firms' ESG incidents have a significant and negative impact on the sales performance ($\alpha_1 = -0.187$, $p < 0.001$). This result provides additional evidence that, compared to sales of the control brands that never being reported for ESG incidents, sales for brands in the treatment group significantly declined after the news disclosure concerning the negative ESG incidents, which is consistent with the findings reported in Section 2.4.

2.6.1.1 Pretrend Analysis:

Note that one of the key assumptions of DID analysis is that the treatment and control groups follow parallel trends during the pre-intervention period. Because the treatment group brands in our study are exposed to the treatment effect in different periods, we adopted an event study DID approach to investigate the parallel trend assumption. Following Danaher et al. (2010), we employ relative time

Table 2.10: Generalized Difference-in-Differences Analysis with Propensity Score Weighting Adjustment

	(1)	(2)
Dependent Variables	$\log(SumPurchase_{b,t,s})$	$SumPurchase_{b,t+1,s}$
Model	OLS	Poisson
$TREAT\_POST$	-0.029.	-0.187***
	(0.016)	(0.013)
Control variables	Yes	Yes
Propensity Score Weighting	Yes	Yes
Year-month Fixed Effects	Yes	Yes
Firm-store Fixed Effects	Yes	Yes
Observations	133,010	128,135
R^2	0.930	-

Robust standard errors clustered by firm-store are in parentheses.
$.p < 0.1; *p < 0.05; **p < 0.01; ***p < 0.001$

dummies to measure the temporal proximity of the intervention (i.e., the firm's negative ESG news being reported by the media). The model specification of this DID event study is shown in Equation 2.9, where we focus on the three lagging months. In particular, $TimeToTreat_{b,k}$ is a set of relative time dummies for each firm b so that treatment is relative for all treated units, and the variable $Treat_b$ captures the treatment group brands (i.e., $Treat_b = 1$ denotes treatment group brands and $Treat_b = 0$ denotes control group brands).

$$y_{b,t,s} = \sum_{k=-3}^{-1} \delta_k Treat_b \times TimeToTreat_{b,k} + \mathbb{Z}\mathbb{C}_{b,s} + \theta_{b,s} + \lambda_t + \epsilon_{b,s,t} \tag{2.9}$$

We include both time and firm-store Fixed Effects as well as the exogenous covariates in the model. As we present in Table 2.11, there is no significant difference between treatment and control group brands during the pre-intervention period. This indicates that the treatment and control group brands follow parallel trends during the pre-intervention period.

2.7 Discussion and Conclusion

Although a growing body of literature has pointed out the significant connection between a firm's ESG involvement and financial performance, there is limited research that focuses on the impact of ESG violations from an operational perspective on brand sales. To fill this gap in the literature, we employ a unique transactional dataset from a major retailer in the U.S. along with the ESG information gathered by RepRisk, constructing a unique panel data to analyze the effects of ESG violations' news coverage on brand sales. Our study offers several key insights, which we briefly discuss in the following paragraphs.

Table 2.11: Pretrend Analysis

	(1)	(2)
Dependent Variables	$\log(SumPurchase_{b,t,s})$	$SumPurchase_{b,t+1,s}$
Model	OLS	Poisson
$Treat \times TimeToTreat_{-1}$	-0.079	-0.665
	(15,818.559)	(12,691.212)
$Treat \times TimeToTreat_{-2}$	0.091	-0.149
	(15,818.557)	(12,691.213)
$Treat \times TimeToTreat_{-3}$	0.253	0.088
	(15,818.557)	(12,691.215)
Control variables	Yes	Yes
Propensity Score Weighting	Yes	Yes
Year-month Fixed Effects	Yes	Yes
Firm-store Fixed Effects	Yes	Yes
Observations	52,791	48,297
R^2	0.969	-

Robust standard errors clustered by firm-store are in parentheses.
$.p < 0.1; *p < 0.05; **p < 0.01; ***p < 0.001$

Our results reveal that U.S. retail consumers are sensitive to environmental, social, and governance issues. In general, the firm's ESG incidents exhibit a significantly negative impact on product sales. Moreover, we find that negative news coverage of these different types of issues can affect brand sales in different ways. While the social and governance-related issues lead to a decrease in brand sales, the environmental and cross-cutting issues reveal positive impacts on brand sales. On the one hand, we provide empirical evidence of the increasing prominence of human justice and supply chain issues. On the other hand, our results challenge the conventional wisdom and demonstrate that consumers will not abandon brands immediately when it comes to environmental and governance-related issues. Instead, this news coverage leads to increased brand visibility and the potential for a more positive public perception.

Our findings not only confirm the overall negative effect of ESG violations on sales but also shed light on the role of brand identity and consumer demographics in moderating this impact. Specifically, we demonstrate that the impact of ESG violations on sales is not uniform across all brands. In particular, high-value brands are less vulnerable to the detrimental effects of ESG violations due to the deep-rooted premium brand image and stronger customer loyalty. Instead, these brands appear to benefit from consumers' innate preferences, which can mitigate the adverse consequences of ESG violations. This result underscores the importance of considering brand characteristics and consumer perceptions when assessing the consequences of ESG violations in different market segments.

We also find that the negative impact of ESG news coverage is amplified in Democrat states compared to Republican states, which can be attributed to differences in political leanings and the corresponding political advocacy. Similar amplification can be found in stores that are surrounded by older populations and higher household incomes.

While previous research has extensively explored the implications of ESG factors on corporate performance (e.g., market value of firms), these insights have primarily operated at a macro level. Our study contributes to this stream of literature by establishing the effect of ESG violations on brand sales, thereby shedding light on the intricate relationship between ESG violations and customer responses, specifically in terms of sales. Furthermore, our study also systematically examines the heterogeneous effects of various types of ESG violations on sales performance, which contributes to understanding how the ESG violations can result in heterogeneous market responses. We also establish how brand- and market-specific heterogeneities influence the effect of ESG violations on brand sales, thereby contributing to the literature on how different contextual factors shape the relationship between ESG violations and brand sales.

In conclusion, our analyses of the impact of ESG violations on brand sales have unveiled several novel and important insights for brands. More specifically, our findings underscore the nuanced dynamics influenced by consumer biases, brand characteristics, and political contexts. Our analyses reveal that the consequences of ESG violations are not the same; they vary based on brand origin, consumer expectations, and regional political leanings. These insights provide valuable guidance for brands and retail executives in understanding the intricate interplay between ESG violations and sales and the influence of brand origin, consumer expectations, and regional political leanings.

To successfully operate in a market with heightened ESG awareness, brands should develop strategies that monitor and assess their ESG practices to minimize the risk of violations and thereby reduce brand sales. These strategies may include proactively managing ESG compliance, considering regional variations based on political leanings, strengthening brand identity aligned with responsible practices, and continuously improving ESG initiatives to adapt to evolving consumer expectations and regulatory changes. By embracing these strategies, brands can effectively mitigate risks, enhance their reputation, and cultivate consumer loyalty within the context of ESG considerations.

From the perspective of retail executives, limited shelf space is a common challenge. Considering the substantial impact of ESG violations on brand sales, retailers may reassess their sourcing choices, particularly when it involves brands with perceived "irresponsible" ESG practices. These brands experience lower sales and can influence the performance of other brands at the same retailer. To optimize the allocation of shelf space and maintain a positive brand image, retailers may find it prudent to prioritize partnerships with brands committed to responsible business practices. This strategic shift not only aligns with consumer expectations but also safeguards against potential sales declines stemming from ESG-related issues.

Our study opens up several future research opportunities. First, while our analysis focuses on a particular retailer that mainly sells apparel, cosmetics, and home selections, future research could generalize these findings to different industries. Next, we examine the effects of ESG violations on brand sales as a proxy to understand consumer behaviors. Future research can build upon our findings and further investigate the consumers' decision-making process in responding to the brands' ESG violations using experiments or surveys. Finally, future research can also assess how brands should strategically respond to news coverage associated with ESG violations to mitigate the adverse effects of such coverage and examine how these responses, in turn, influence sales.

Appendices

Appendix A Brand Name and Parent Company

Table 12: High-value Brand

Brand Name	Parent Firm
COACH	Coach Inc
FOSSIL	Fossil Group Inc
FRYE	Global Brands Group Holding Ltd
HERMES	Hermes International
HUGO BOSS	Hugo Boss AG
JOHNSTON & MURPHY	Genesco Inc
LA PRAIRIE	Beiersdorf AG
MICHAEL KORS	Michael Kors Holdings Ltd
NATURALIZER	Caleres Inc (formerly Brown Shoe Co Ltd)
SAM EDELMAN	Caleres Inc (formerly Brown Shoe Co Ltd)
SOFFT	Caleres Inc (formerly Brown Shoe Co Ltd)
TIMBERLAND	The Timberland Co

Appendix B RepRisk Issues Explanation

RepRisk considers violations across 28 core areas within the Environmental, Social, and Governance (ESG) domains. Table 13 provides a summary of different violations considered by RepRisk.

Table 13: Violations by RepRisk

Category	Issues
Environment	Global pollution, Local pollution, Impacts on ecosystems and landscapes, Overuse and wasting of resources, Waste issues, Animal mistreatment
Social	Community Relations: Human rights abuses, Corporate complicity, Impacts on communities, Local participation Issues, Social discrimination Employee Relations: Forced labor, Child labor, Freedom of association and collective bargaining, Discrimination in employment, Health and safety issues, Poor employment conditions
Governance	Corruption, bribery, extortion, money laundering, Executive compensation, Misleading communication, Fraud, Tax evasion, Tax optimization, Anti-competitive practices
Cross-cutting	Controversial products and services, Products and services, Violation of international standards, Violation of national legislation, Supply chain

Reference: https://www.reprisk.com/content/static/reprisk-esg-issues-definitions.pdf

Appendix C Estimation Results of the Control Function

Employing the 2SLS method, we provide the estimation results of the first stage regression in Table 14. the control function approach

Table 14: Estimation Results of the 2SLS Control Function (Overall Impact)

Variables	ESG_Total
$Peer\_ESG$	0.000***
	(0.000)
Control variables	Yes
Year-month Fixed Effects	Yes
Brand-store Fixed Effects	Yes
Observations	632,160
AIC	2.413×10^6

Robust standard errors clustered by brand-store in parentheses.
$*p < 0.05; **p < 0.01; ***p < 0.001$

Table 15: Estimation Results of the 2SLS Control Function (Impact of Individual Type of ESG Incidents)

Variable	Social	CrossCutting	Environment	Governance
Peer_Social	0.000***	-	-	-
	(0.000)	-	-	-
Peer_CrossCutting	-	0.001***	-	-
	-	(0.000)	-	-
Peer_Environment	-	-	-0.005***	-
	-	-	(0.000)	-
Peer_Governance	-	-	-	0.002***
	-	-	-	(0.000)
Control variables	Yes	Yes	Yes	Yes
Year-month Fixed Effects	Yes	Yes	Yes	Yes
Brand-store Fixed Effects	Yes	Yes	Yes	Yes
Observations	632,160	632,160	632,160	632,160
AIC	1.436×10^6	1.302×10^6	5.523×10^5	6.580×10^5

Robust standard errors clustered by brand-store in parentheses.
$*p < 0.05; **p < 0.01; ***p < 0.001$

Chapter 3

Should Companies Take a Stance in the Political Issues? Insights from Nike's Advertising Campaign with Colin Kaepernick

Abstract

Corporate public stance on the sociopolitical controversy has the potential to impact the performance of other rival brands. In this study, we examine whether Nike's bold and controversial campaign, spurred by its partnership with Colin Kaepernick in 2018, leads to the sales volatility of other sportswear brands in comparison to the brands that should not be impacted by Nike's campaign. By employing a unique transactional dataset from a major U.S. department store, we examine how a prominent brand's public political stance affects sales across different departments. Our results show that Nike's political advocacy led to a significant sales decline in the sportswear department, compared to the control department, like furniture and home decor. We contribute to the literature on corporate political advocacy and political consumerism by providing empirical evidence of the broader retail consequences of a brand's public political stance. In the event of reputation collapse of a major brand, our findings highlight the significant role of a major brand as the foot traffic driver within brick-and-mortar stores.

Keywords: Corporate Political Advocacy, Sociopolitical Controversy, Retail Operations, Brand Sales.

3.1 Introduction

In recent years, corporations have increasingly been involved in social and political issues by taking public stances that match their brand values and customer base. A notable example is Nike's bold decision to integrate social justice themes into its marketing strategy, represented by the 2018 Colin Kaepernick campaign.[1] Although existing research investigates the net effect of such controversy on the focal firm's performance, such as market share (Hydock et al., 2020), impression and reputation (Baumeister et al., 2001), there is limited empirical evidence investigating the consequences of such a prominent brand's political advocacy on the retail-level performance.

Historically, in the corporate landscape, most companies avoid taking positions that may alienate

[1] Colin Kaepernick, a former NFL quarterback, began kneeling during the national anthem to protest against racial injustice in 2016. His gesture was followed by other players, and soon, an outbreak of disapproval for Colin Kaepernick's disrespectful behavior was heard throughout the nation. Despite the controversy surrounding his activism, in September 2018, Nike undertook a bold and controversial marketing strategy by featuring Colin Kaepernick as the face of a major new marketing campaign honoring the brand's 30th anniversary of its iconic "Just Do It" slogan (Draper et al., 2018). See `https://sites.psu.edu/burv/case-study-nike-colin-kaepernick-just-do-it-campaign/`

customers. However, in recent years, companies have faced pressure from consumers to take a stand on sociopolitical issues. Nike's "Just Do It" campaign, featuring the former NFL quarterback, Colin Kaepernick, known for his protest against racial injustice, sparked widespread debate and positioned Nike at the intersection of branding and political discourse. Essentially, Nike's decision departed from the risk-averse approach typically adopted by major public companies. Both news reports (Draper et al., 2018; Wang and Siegel, 2018) and prior literature (Wang and Lu, 2022; Liaukonytė et al., 2023) have pointed out the significant consequences on Nike's performance in the aftermath of this controversial movement. However, such an impact on Nike's attractiveness can go beyond the focal firm and be potentially devastating for the retail industry, in particular for some retailers (i.e., retailers specialized in selling sportswear products such as Foot Locker) who have long relied on this dominant brand to drive store visits and sales.

The industry-wise impact of a prominent brand can also be observed in other industries. Even though the rivals may benefit from the woes of others, the large-scale recall initiated by the major toy brand Mattel indeed brought concerns and fears that hurt almost all toy brands. As pointed out by the chief executive officer of MGA Entertainment, "People are going to be afraid of buying toys in general."[2] In the context of sociopolitical controversies, people lose faith in the major brand and refuse to be bound up with the brand name. Such a decline in the attractiveness of a prominent brand can lead to decreased visits in the entire department and results in a potentially industry-wide collapse within the retail context.

Furthermore, sociopolitical controversies are often intertwined with political discussion; customer demographics are also likely to moderate the impact of a brand's political stance. As a brand targeting young and urban audiences (Draper et al., 2018), Nike strategically supports Colin Kaepernick to establish a bold brand position. However, consumers across diverse geographic and demographic segments might react differently. Thus, we are also interested in uncovering the moderating impact of political leaning and demographics of different store locations.

In summary, our study seeks to examine the following research questions: (1) What is the sales impact of a major brand entering the political debate at the retail level? (2) How does the sales impact vary across store outlets that differ in political affiliations? Note that for the purpose of this dissertation, we focus on the first research question, and we provide the research plan for the second one.

In our context, Nike's campaign can be treated as an external shock, which enables us to construct a quasi-experiment setting and employ the difference-in-differences (DID) methodology. To answer our research question, we leverage a proprietary dataset from a national department store chain, which sells a wide range of products, including apparel, household decoration, accessories, and cosmetics,

[2] See "Mattel recalls may help some toy makers", `https://www.nbcnews.com/id/wbna20611115`.

among others. We focus on the impact of a major firm's political stance on real-world sales at the retail level, with a particular emphasis on the impact on the sportswear department in comparison to other departments, such as home decoration and furniture.

Recognizing the unconventional nature of Nike's campaign and observing the market-wise impact, we aim to understand the effects of a firm's deliberate disclosure of political stance and public association by quantifying the net sales outcome at the retail level. Our design of study and choice of dataset provides us with a unique opportunity to answer our research question for the following reasons: (1) the incident of Nike's partnership with Colin Kaepernick offers a unique lens through which to explore the contagion and competitive effects (Jacobs and Singhal, 2020) behind a major firm's deliberate disclosure of political stances; (2) our unique retail-level transactional dataset provides us with a suitable setting to uncover the multifaceted outcomes at the market level across different departments.

The rest of this paper is organized as follows. We first discuss the theoretical framework of the study and review related literature in Section 3.2. Then, we describe our data, explain the empirical models, and present our main results in Section 3.3. Finally, we discuss managerial insights and provide a plan for our follow-up study in Section 3.5.

3.2 Theoretical Framework and Literature Review

Our study is closely related to two streams of research: (1) corporate political advocacy and political consumerism, and (2) brand-clustering effect within the retail store.

3.2.1 Corporate Political Advocacy and Political Consumerism

Corporate political advocacy refers to a company's efforts to publicly support specific political or social issues (Dodd and Supa, 2015). Such a strategic move aims to align with the values of its target audience and build a stronger brand identity (Dodd and Supa, 2015; Wettstein and Baur, 2016), which can yield both positive and negative outcomes. For example, CMO survey[3] reveals that companies engaging in political advocacy can strengthen customer loyalty among supporters of the cause and attract a younger, more socially conscious customer base (CMO, 2018; Moorman, 2020). On the other hand, practitioners point out that concerned corporate political advocacy will have a negative effect on the brand's ability to attract and retain partners as well as customers (Eilert and Nappier Cherup, 2020). Using signaling and screening theories, Bhagwat et al. (2020) find that investors evaluate sociopolitical activism as a signal of a firm's allocation of resources away from profit-oriented objectives and toward

[3]Supported by Deloitte, the CMO Survey - conducted biannually since 2008 by Duke University's Fuqua School of Business marketing professor Christine Moorman — is a measure of how marketing leaders navigate this brave new world. The survey reports on their priorities and plans, enabling marketers to compare staffing, budgeting, and investment areas and identify potential trends. See `https://cmosurvey.org/`

a risky activity with uncertain outcomes. Overall, Baumeister et al. (2001) and Hydock et al. (2020) argue that the net effect of corporate political advocacy is likely to be negative as negative information is more effective in promoting boycotting than positive information in promoting purchases.

Although research in the corporate landscape has demonstrated the significant connection between the firm's social activities and its financial performance, such as investors' reactions and stock price, such effect may not stay the same when it comes to consumer purchase decisions due to the intrinsic difference between the stock market and consumer market. Political consumerism, on the other hand, involves consumers making purchasing decisions based on political or ethical considerations (Shah et al., 2007; Copeland and Boulianne, 2022; You and Hon, 2022). Studies have found that consumers increasingly use their purchasing power to support brands that align with their values and boycott those that do not (Stolle and Micheletti, 2013). As brands that engage in political advocacy must navigate the polarized responses of their customer base (Sen and Bhattacharya, 2001), public controversies can shape political consumerism behavior and significantly influence market dynamics.

3.2.2 In-store Brand Clustering Effects

To take advantage of shoppers' search patterns, similar products should be arranged within the same shelf or department (Ebster, 2011). This strategic arrangement of brands within a retail environment is referred to as brand clustering effects and retail agglomeration on shopping behavior (Oppewal and Holyoake, 2004), which is being widely used to enhance visibility and drive sales (Levy and Weitz, 2004) within a store. Additionally, prior literature also points out that effective store layout and the strategic placement of well-known brands can enhance the overall shopping experience (Levy and Weitz, 2004). Similarly, the presence and accessibility of a major brand within a brick-and-mortar store can serve as an attraction mechanism to drive foot traffic and sales for surrounding brands and stores (Oppewal and Holyoake, 2004; Moore et al., 2010).

Conversely, if a prominent brand within a cluster experiences a decline in its appeal — such as through a political controversy or in the event of boycott of a major brand — this can negatively impact the entire cluster. The decline in foot traffic arising from the boycott of major brand may translate into decreased visibility and lower sales volumes for other brands within the cluster (Levy and Weitz, 2004), especially if customers actively avoid the entire section of the store. Drawing similarities from the in-store brand clustering effects, we consider that if a prominent brand like Nike faces backlash and decreased sales due to its political stance, it might lead to a decline in the attractiveness and traffic to the sportswear department as a whole.

3.2.3 Contribution

Two recent studies are most closely related to our work. Following an involuntary revelation of the focal brand's political position disclosed by a highly influential celebrity's tweet, Wang and Lu (2022) evaluate the impact of corporate political positioning on sales by comparing the post-event performance between the focal brand and the other similar brand that the same company owns. Rather than looking at the consequences of involuntarily disclosed political position, our study investigates the outcome of a firm's deliberate disclosure of its stance on sociopolitical controversy. Additionally, instead of comparing the brands that are owned by the same focal company, our study generalizes the settings of Wang and Lu (2022) by comparing the associated brands within the sportswear industry and brands in other departments.

Another similar study by Liaukonytė et al. (2023) investigates the effects of boycott and buycott movements on actual consumption by examining the consequence of a brand with a very Democratic customer base actively sending a pro-Republican message. Our study is similar to Liaukonytė et al. (2023) in a sense that the focal brand actively announced its political stance by itself. However, methodologically, our study incorporates a quasi-experimental design and compares the sales performance of the sportswear brands before and after the event, whereas Liaukonytė et al. (2023) focus on a single brand and use the sales of the focal brand (i.e., Goya) in the previous year as a control.

The primary contribution of this study is to provide a deeper understanding of the consequences of a prominent brand's public political advocacy at the retail level. Our research builds upon the rationale behind corporate political advocacy and extends beyond the direct impact on the focal firm. Unlike existing studies that primarily address the corporate-level effects on the firm engaging in political advocacy, this paper quantifies the broader consequences by examining the sales impact across various departments within a multi-store retail chain. By doing so, we also contribute to the literature on political consumerism, and offer a comprehensive view of how a prominent brand's political stance can influence the overall retail environment.

Existing research on political consumerism has largely focused on understanding the types of consumers who participate and their motivations (Stolle and Micheletti, 2013; Endres and Panagopoulos, 2017; Copeland and Boulianne, 2022). We extend this stream of study by exploring how a prominent brand's political stance affects the entire retail ecosystem. In practice, a prominent brand often serves as a foot traffic driver for brick-and-mortar stores. The potential collapse of such a brand's image can deter customers, thereby hurting the sales of clustered brands within the same department. By examining the impact of a focal firm's political controversy on associated brands and comparing it to brands in other departments, we provide empirical evidence on the real-world sales impact of corporate political advocacy. To the best of our knowledge, this study offers some of the first empirical insights into the retail-level consequences of corporate political advocacy.

3.3 Empirical Setup

Our transactional data spans a multiperiod horizon, during which Nike launched its controversial advertising campaign featuring Colin Kaepernick. In our context, this event can be treated as an external shock for the retail brands, which enables us to construct a quasi-experiment setting and employ the difference-indifference (DID) methodology.

In this section, we explain the methodology and empirical setting. We start by describing our data and introducing propensity score matching in Section 3.3.1. Then, with a selected set of control and treatment groups, we explain the model setup and estimation strategy in Section 3.3.2. After presenting our results and analysis, we also test the parallel trend assumption in Section 3.3.4.

3.3.1 Data Description and Experimental Design

As a major brand in the sportswear industry, Nike's controversial campaign extends beyond the direct impact on the focal firm itself; it also has the potential to impact other sportswear brands that are sold in the same section within the department store. Hypothetically, given such a prominent brand in the sportswear industry, the impact of Nike's advertising campaign featuring Colin Kaepernick on brick-and-mortar stores would likely be more pronounced in the sportswear department compared to other industries like furniture.

To explore such impact and answer our research questions, we obtain a comprehensive dataset from a major U.S. retailer that sells a variety of brands and products. In addition to men's, women's, and children's clothing, this retail store offers shoes, accessories, cosmetics, home furnishings, and numerous other consumer products. Thus, the product assortment available at the department store provides us with a suitable setting to investigate the divergent consequences of a prominent brand's political advocacy concerning sales performance at the retail level.

Given Nike's advertising campaign in September 2018, we focus on three months before and three months following the event. Hence, our transactional data spans from June 2018 to November 2018. During this period, our dataset comprises a total of 1,114,233 purchase transactions of 2,035 brands from 298 stores in the U.S. Each transaction record in our dataset contains the purchase date, transaction value measured in U.S. dollars, the number of items involved in the transaction, brand information, store location, and specific information on the item type, among others. Note that for the purpose of the current study, we focus on the physical stores and exclude the online channel.

We design our study by first selecting a set of brands that were being directly impacted by Nike's movement, also referred to as the treatment group in the DID setting. As demonstrated by Jo and Na (2012); Dauvergne and Lister (2013); Wang and Lu (2022), the misleading behavior by a major player in the industry is likely to lead to an industry-wide collapse. In the context of our study, Nike's bold movement would hurt consumers' desire to buy Nike products, such as a decrease in in-store visits, resulting in a decline in store traffic and ultimately impacting the sales performance of the entire footwear department within the brick-and-mortar store. Thus, our treatment group consists of the major sportswear brands, but excluding the focal brand Nike itself: Adidas, ASICS, Champion, Columbia, Converse, Merrell, New Balance, Puma, Reebok, Skechers, The North Face, and Under Armour.

Second, we construct our control group by identifying brands from the other departments that are not directly impacted by Nike's campaign. Browsing through the retailer's assortments, we focus on the furniture and home decoration departments. To further establish a meaningful comparison, we utilize the Propensity Score Matching (PSM) approach to identify an equal number of 12 control brands from the home furnishing department that share similar characteristics with our 12 treated brands in the sportswear department. As a robustness test, we also pair our treated brands with other apparel brands in Section 3.4, and our findings are statistically consistent. We explain this methodology and our matching procedures in detail in the following subsection.

3.3.1.1 Propensity Score Matching

Given the fact that our treatment group consists of 12 major sportswear brands while we have 548 brands from the home furnishing department, this setting can cause concerns regarding unbalanced and biased estimation. Thus, we utilize the PSM (DeFond et al., 2017; Akturk and Ketzenberg, 2022) approach to address the selection bias. Note that our goal with this additional analysis is to minimize the differences in the matching characteristics (DeFond et al., 2017); thus, choosing variables that can reflect the brand features for the matching process is important. In this section, we briefly explain how we conducted the pairing process using PSM.

In the context of our study where we look at the retail brands within a department store, propensity score matching is used to balance the treatment and control brands so as to minimize concerns that treatment and control brands may have different economic scales or brand characteristics. To do so, we first estimate the propensity score for each brand in our sample using a logit model (Akturk et al., 2018). The dependent variable is a binary variable, which takes a value of one if brand b is in the treatment group and zero otherwise. To estimate the propensity score, our predictors are constructed from five observable brand-level variables that capture the features of each brand. Specifically, we create $AvgPurchases_b$, $AvgDollarSales_b$, $AvgPrice_b$, SKU_b, and $Store_b$ for each brand b. The explanation of each variable is summarized in Table 3.1. Note that our goal is to pair a set of brands with similar characteristics before the event actually happened; thus, these variables are measured based on each brand's data before the intervention (i.e., using data spanning from June, July, and August, 2018).

Table 3.1: List of Variables Used for PSM

Variable	Explanation
$AvgPurchases_b$	For a given brand b, the average number of purchase transactions per month during the pre-intervention period.
$AvgDollarSales_b$	For a given brand b, the average transactions value (in dollar sales) per month during the pre-intervention period.
$AvgPrice_b$	Considering all the SKUs being sold by brand b, the average selling price per item.
SKU_b	Total number of SKUs of brand b.
$Store_b$	The number of stores that displays brand b's products for sale.

We estimate each brand's propensity score using a logit model and then pair the treatment and control groups using the fitted values reported by the logit regression model. Note that 12 brands are selected in our treatment group; thus, we choose 12 brands from the control group of 548 home decor and furnishing brands by pairing them with brands in the treatment group. Table 3.2 presents the list of our selected brands. We also indicate the performance of our matching procedures by showing the mean difference improvement in the last column of Table 3.2. Therefore, the propensity score matching helps us prepare groups of brands with similar characteristics to proceed with the DID analysis.

Ultimately, we choose 12 most similar brands from the home furnishing department and provide the brand names in the second column of Table 3.2. To indicate the effectiveness of our matching process, we summarize the means of our treated and control brands before and after the matching process in Table 3.3. We can observe that employing PSM helps us reduce the differences between the treatment and control group brands. For example, before matching, the average brand price is 38.891 and 53.240 or the two groups respectively. After the matching, the average brand price is 38.891 and 39.551 for the treatment and control groups, which is around 95.4% improvement for the difference. Similar improvements can be observed from other variables in Table 3.3. In the following section, we use this set of paired brands obtained from the PSM process to construct our DID analysis.

3.3.2 Model Specification

In this natural experiment, we leverage a DID analysis using the matched brands obtained through PSM in Section 3.3.1.1. The major sportswear brands directly impacted by Nike's movement are being assigned into our treatment group. Note that we exclude Nike, the brand at the center of the political controversy, from our treatment group. By doing so, we attempt to isolate the impact of the focal brand. Meanwhile, Nike represents a much larger market share than other brands, and excluding it

Table 3.2: List of Treated Brands and Control Brands Obtained from Home Decor and Furnishing Department

Treated Brands	Control Brands (Home Decor and Furniture)
Adidas	Under the Canopy
ASICS	Pendleton
Champion	Nobility
Columbia	Vince Camuto
Converse	Highline Bedding Co.
Merrell	Southern Tide
New Balance	Original Penguin
Puma	Corkcicle
Reebok	Ted Baker London
Skechers	Marc New York
The North Face	Hugo Boss
Under Armour	DKNY

Table 3.3: Standard Mean Difference Improvement after Matching

Variable	Before Matching		After Matching		Std. Mean Difference
	Treated Brands	Control Brands	Treated Brands	Control Brands	Improvement
$AvgPurchases_b$	1,239,965.229	436,555.577	1,239,965.229	1,233,426.444	99.2
$AvgDollarSales_b$	2,082,114.417	1,080,548.244	2,082,114.417	1,652,904.750	57.1
$AvgPrice_b$	38.891	53.240	38.891	39.551	95.4
SKU_b	25,830.583	4,776.015	25,830.583	23,419.917	88.6
$Store_b$	261.083	137.745	261.083	260.250	99.3

helps to avoid skewing the analysis. Our control group is selected from the home furnishing brands, which do not sell sportswear items and are displayed away from the sportswear brands within a department store. The event month is set as September 2018, when Nike announced its "Just Do It" campaign featuring Colin Kaepernick.

We use subscripts b and s to denote the brand and store, respectively. Let $t \in \{-3, -2, -1, 1, 2, 3\}$ denote the month, where $t = 1$ represents the event month (i.e., September 2018), and $t = -1$ represents one month before the event month (i.e., August 2018). We present our econometric model for the DID estimation in Equation 3.1, where $\mu_{b,s}$ represents brand-store fixed effects and W_t denotes time fixed effects. The dependent variable is captured by $y_{b,s,t}$. Following the literature, we use both the number of purchase transactions (Akturk and Ketzenberg, 2022), denoted as $Purchase_{b,s,t}$, and dollar sales (Gallino and Moreno, 2014), denoted as $DollarSales_{b,s,t}$, to measure the sales performance of brand b at store s and month t. We use a dummy variable $TREAT_b$ to indicate treatment and control brands; another dummy variable $AFTER_t$ is equal to one of $t > 3$ and zero otherwise. The interaction term $TREAT_b * AFTER_t$ then captures the treated brand's post-incident periods. Following the literature (Gallino and Moreno, 2014; Akturk et al., 2018; Akturk and Ketzenberg, 2022), we employ Ordinary

Table 3.4: Estimation of the Sales Impact of Nike's Controversial Campaign on Retail Brands

Dependent Variables	$\log(Purchase_{b,t,s})$	$\log(DollarSales_{b,t,s})$
Model	(1)	(2)
$TREAT \times AFTER$	-0.406***	-0.248***
	(0.031)	(0.024)
Year-month Fixed Effects	Yes	Yes
brand-store Fixed Effects	Yes	Yes
Observations	30,768	30,768
R^2	0.788	0.867

Robust standard errors clustered by brand-store are in parentheses.
$.p < 0.1; *p < 0.05; **p < 0.01; ***p < 0.001$

Least Squares regression (OLS) and log transform the dependent variable.[4]

$$\log(y_{b,s,t}) = \alpha_1 TREAT_b * AFTER_t + \mu_{b,s} + W_t + \epsilon_{b,s,t}. \tag{3.1}$$

Our coefficient of interest is α_1, which represents the change in sales associated with the intervention. We report the results in Table 3.4. Column (1) presents the estimation of the number of purchase transactions, while Column (2) presents the estimation of dollar sales. After Nike's announcement of the campaign featuring Colin Kaepernick, for our treatment brands (i.e., $TREAT_b * AFTER_t = 1$), there is a negative and significant effect on sales in treatment brands compared to our control brands (i.e., $TREAT_b * AFTER_t = 0$). In other words, the prominent sportswear brand's (i.e., Nike) controversy reduces the sales of sportswear brands within the department store, we can estimate the drop in the number of purchase transactions to be about 40.6% ($\alpha_1 = -0.406$, $p < 0.001$) while the drop in dollar sales to be about 24.8% ($\alpha_1 = -0.248$, $p < 0.001$) compared to sales for home decor and furnishing brands.

This result provides us with evidence that, with comparison to sales of the control brands that are not impacted by Nike's campaign, the sales of brands in the treatment group (i.e., major sportswear brands) significantly decline after a prominent brand publicly declared its political advocacy on a controversial issue. For an additional robustness test, we select another set of 12 brands from the apparel department as our control group rather than focusing on the comparison with furnishing brands. To do so, we follow the procedures specified in Section 3.3.1.1 and conduct the PSM to identify an apparel control group. We present the results in Section 3.4 and show that the findings are consistent.

[4]To deal with zero values, we add 1 to all the values of the dependent variable before log transformation, i.e., $log(y+1)$.

3.3.3 Discussion

Our results demonstrate the industry-wise collapse driven by a prominent brand's controversial movement. The rationale behind this phenomenon can be comprehensively explained through the concept of brand clustering and the critical role that major brands play within retail environments. In the retail context, major brands and big names are introduced as instrumental in drawing significant customer foot traffic not only to their own products but also to the adjacent products within the same department. This clustering effect emphasizes the dependency of a department's overall performance on the attractiveness of its major brands.

When a prominent brand engages in controversial issues, it can generate polarized consumer responses (Wang et al., 2022). While supporters of the brand's stance may show increased loyalty, the detractors might choose to boycott the brand altogether. As demonstrated by prior literature (Baumeister et al., 2001; Hydock et al., 2020), the net effect of such controversy on the focal firm's performance is estimated to be negative. Thus, such actions can hurt the attractiveness of the controversial brand, which in turn affects the entire department. The decrease in foot traffic can result from both direct boycotts and a reduction in in-store visits by customers who might have been drawn to the sportswear department by the major brand. In contrast, customers shopping for other types of products like furniture are typically motivated by different factors such as design, functionality, and price rather than the sociopolitical stances of sportswear companies. Therefore, the furniture and home decoration department is less likely to experience significant fluctuations in foot traffic or sales due to Nike's advertising campaign. Collectively, these results demonstrate demonstrate how the performance of a single prominent brand can influence the sales dynamics of an entire department, leading to a potentially industry-wide collapse within that retail context.

3.3.4 Parallel Trend Assumption

DID analysis relies on the assumption of parallel trends. It requires that the treatment and control groups follow the same trend in the absence of the intervention (i.e., Nike's advertising campaign with Colin Kaepernick). To test that the pre-intervention trends between our treated and control brands are not different, we follow the literature (Gallino and Moreno, 2014; Akturk and Ketzenberg, 2022) and estimate the following model specification using the data from the pre-intervention period where $t = -3, -2, -1$ (i.e., June, July, and August of 2018).

$$\log(y_{b,s,t}) = \alpha_1 TREND_t + \alpha_2 TREND_t \times TREAT_b + \mu_{b,s} + \epsilon_{b,t},$$

Table 3.5: Test of Parallel Trend

Dependent Variables	$\log(Purchase_{b,t,s})$	$\log(DollarSales_{b,t,s})$
Model	(1)	(2)
$TREAT \times TREND$	-0.016	0.017
	(0.022)	(0.014)
Year-month Fixed Effects	Yes	Yes
brand-store Fixed Effects	Yes	Yes
Observations	15,023	15,023
R^2	0.848	0.922

Robust standard errors clustered by brand-store are in parentheses.
$.p < 0.1; *p < 0.05; **p < 0.01; ***p < 0.001$

where $TREND_t$ represents the numeric month indicator, and $TREND_1 = 1$ indicates June 2018. We present the results in Table 3.5. Observing from the insignificant coefficient of the interaction term, $TREAT_b \times TREND_t$, we provide evidence that there is no statistically significant difference between our treatment and control groups during the pre-intervention periods. Thus, our DID results derived above are not driven by different pre-intervention trends; in other words, they are reliable.

3.4 Robustness Test Using Apparel Brands

In the main analysis, we obtained our control brands from the home furnishing department. In this section, we test the robustness of our main model by comparing our treated sportswear brands with other apparel brands. To do so, we follow the matching procedures presented in Section 3.3.1.1 and select 12 apparel brands to form a valid control group.

We again focus on the five brand-specific variables (i.e., $AvgPurchases_b$, $AvgDollarSales_b$, $AvgPrice_b$, SKU_b, and $Store_b$) to estimate the propensity score of all the apparel brands. Then, we select a set of apparel brands that best match our treated brands. The list of our treated and control brands is presented in Table 3.6. With this set of brands, we estimate Equation 3.1 and summarize the results in Table 3.7. The results indicate that, using brands selling apparel-type products as a control group, we consistently observe the significant and negative impact of Nike's public political advocacy on sportswear brands within the department store chain.

3.5 Conclusion and Future Research Plan

In the aftermath of a major brand's public stance on the social controversy, consumer sentiments can significantly shape the narrative and their purchase behavior, and such impact will go beyond the focal brand itself.

Table 3.6: List of Treated Brands and Control Brands Obtained from Apparel Department

Treated Brands	Control Brands (Apparel)
Adidas	Diamond Supply
ASICS	UR
Champion	Little Me
Columbia	DKNY
Converse	Fit 4 U
Merrell	Rowm
New Balance	Flapdoodles
Puma	Retro Sport
Reebok	KUT from the Kloth
Skechers	Baby Essentials
The North Face	Buffalo David Bitton
Under Armour	Vince Camuto

Table 3.7: Robustness Test Using Apparel Brands

Dependent Variables	$\log(Purchase_{b,t,s})$	$\log(DollarSales_{b,t,s})$
Model	(1)	(2)
$TREAT \times AFTER$	-0.544***	-0.454***
	(0.033)	(0.025)
Year-month Fixed Effects	Yes	Yes
brand-store Fixed Effects	Yes	Yes
Observations	30,409	30,409
R^2	0.756	0.862

Robust standard errors clustered by brand-store are in parentheses.
$.p < 0.1; *p < 0.05; **p < 0.01; ***p < 0.001$

By providing insights into how public political positioning can impact consumer behavior and brand performance, our study provides important insights for both academics and industry practitioners. In particular, we offer a nuanced understanding of how socially charged advertising campaigns translate into sales volatility at the retail level. By examining the consequences of this controversial marketing approach, we seek to provide valuable perspectives to guide future marketing strategies and decision-making processes.

In response to increasing movements advocating for either boycotts or boycotts of politically engaged brands, limited empirical evidence exists regarding the effectiveness of such political consumerism campaigns on actual sales outcomes. Thus, this study aims to fill this gap by examining the consequences of a firm publicly taking a political stance and quantifying the resulting sales outcomes. We leverage empirical evidence from transactional data to provide a robust foundation for informed decision-making. When a major brand is actively engaged in political debate, brand managers who are operating within the same industry should take actions to protect their brands from the negative impact of the rival's controversy. For the retail executives, strategically displaying products and adjusting in-store assortments is important to cope with the dynamics in the aftermath of a major brands controversy so as to avoid the department-wise or even store-wise collapse.

Our findings enable retailers navigate the complexities of corporate political advocacy more effectively, enhancing the resilience and performance of the retail environment. These insights highlight the interconnected nature of brand performance within a retail context and reveal the importance of strategic planning and responsive management in the face of corporate political advocacy. By understanding and addressing the potential industry-wide impacts, retailers and brand managers can better position themselves to manage risks and ensure sustainable success in a dynamic market landscape.

Based on our current findings, in the next stage of this study, we plan to leverage additional store and customer data, which contains information regarding store location, customer ID, residential location, distance to the nearest store, and the customer's preferred store regardless of distance, among others. Meanwhile, we will be able to connect customer-level data with public demographic data. Understanding customer demographics and targeting appropriately is vital to studying consumer purchase behavior changes. The demographic profile of a brand's customer base plays a critical role in how corporate political advocacy is received. For instance, brands targeting a younger, urban audience may find that bold political stances strengthen customer loyalty and engagement. In contrast, brands with a broader, more diverse customer base may benefit from a more cautious approach to political advocacy to avoid alienating significant segments of their market.

Second, in addition to the purchase behavior, we are also interested in investigating consumers' return activities following the social event. Given the unique nature of product returns, we plan to pay extra attention to the online channel regarding customer returns. Third, we are aware of a major follow-up event. According to Washington Post (Wang and Siegel, 2018), on September 6^{th}, a Nike advertisement featuring Colin Kaepernick aired during the NFL season's opening game televised nationally on NBC. The next morning, President Trump delivered his review of the commercial on Twitter, saying it"sends a terrible message" and claiming that "Nike is getting absolutely killed with anger and boycotts." The widespread controversy surrounding the advertisement further triggered the debate; both Nike opponents and supporters held strong afterward by expressing their voices on social media and initiating boycotts or boycotts. We plan to extend our analysis to investigate the moderating impacts of additional news exposure and social media.

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