# The Rise of Ship-to-Store: Theoretical and Empirical Analyses of Its Impact on Online Sales

Necati Ertekin — Santa Clara University
Mehmet Gumus — McGill University
Mohammad Nikoofal — Ryerson University

**Abstract**

Fulfilling and shipping orders is at the core of online shopping world and it is taking on whole new meaning thanks to new fulfillment models launched by omnichannel retailers. In this paper, we consider an emerging fulfillment model called Ship-to-Store (STS) that enables customers to ship their online purchases directly to a nearby store. We first develop a customer choice model to generate theoretical predictions regarding the impact of STS on online sales for two types of products, namely online-exclusive products (i.e., products available only online) and hybrid products (i.e., products available both online and offline), as well as on overall online sales. Next, we empirically test our predictions using data from an omnichannel retailer that launched STS functionality at two different brand names. We find that, due to STS, online sales decrease at one brand name and increase at the other. We explain this controversy with our theoretical model and the supporting extensive empirical analysis. Theoretically, we demonstrate that STS has two effects: (i) the market expansion effect that is attributed to the convenience of STS in reducing shipping and return costs, and (ii) the channel shift effect that is attributed to the existing customers who switch from online to offline channel. The former has an increasing effect on the sales for both types of products whereas the latter has a decreasing effect on the sales of only hybrid products. We further extend our empirical analysis to examine the impact of STS on physical store sales.

Keywords: Retail operations, omnichannel retailing, in-store pickup services, empirical operations.

## 1 Introduction

Consumers' proficient use of digital technologies, combined with ever increasing demand for a tailored personal shopping experience, has drastically changed customer relationship management for retailers. Consumers now demand a seamless shopping experience in which they can utilize both online and offline channels to complete a transaction, a practice known as omnichannel shopping experience (Brynjolfsson et al. 2013, Bell et al. 2014). To stay competitive in this environment, many retailers have started omnichannel fulfillment initiatives to allow customers to pick up online orders in-stores, return online products at physical stores, have online orders shipped from stores, and access real-time in-store inventory information online. A Forrester Consulting study indicates that, among these initiatives, retailers consider in-store pickup of online orders to have the highest strategic priority for their companies (Forrester Consulting 2014). Consistent with this study, as of 2015, 41% of all retailers, including The Home Depot, Walmart, Target, Best Buy, Macy's, JCPenney and many others, have initiated in-store pickup services and this number is expected to reach 78% by 2018 (BRP 2015).

Order fulfillment for an in-store pickup of online orders can be either online (i.e., the product is shipped from a central warehouse to a store customer chooses, a practice known as *ship-to-store* (STS)) or offline (i.e., the order is fulfilled using in-store inventory, a practice known as *buy-online-pickup-in-store* (BOPS)) (Bell et al. 2017). Each of these services requires certain channel integration strategies related to inventory, supply chain, logistics, technology, and store capacity. Regardless of the service chosen, conventional wisdom suggests that in-store pickup services should be a win-win strategy for customers and retailers. From a customer perspective, in-store pickups are essential convenience. Customers who use in-store pickup services do not have to wait to receive their orders by mail. Rather, they can pick up their orders at a store they choose when they are available. In addition, for in-store pickups, shipping fees are typically waived and returns are low effort with no additional return shipping cost. From a retailer perspective, even though channel integration is a costly practice, convenience for online customers should be translated into more online sales as in-store pickup transactions are considered online transactions. Also, online customers who pickup their orders in-store generate additional traffic to physical stores. For retailers, this is another opportunity to increase physical store sales through cross-selling (Gallino and Moreno 2014) and improve customer experience.

In essence, despite their lateral effect on physical store sales, in-store pickup services particularly aim to influence online customer purchase behavior. As many major retailers offer this service, online customers are adopting it in growing numbers. An industry report indicates that the use of in-store pickup services has grown 30% within a year (Warner 2013). As such, as of February 2015, 48% of retail customers have used in-store pickup services (UPS 2015). As this number increases, online customers will be more likely to consider the availability of in-store pickup services an important factor when making online purchases (Warner 2013). In addition, it is projected that customers will likely decrease their in-store shopping frequency by 7% while online shopping will increase (UPS 2015). As such, online sales that account for about 10% of global multichannel retail sales today are expected to double to 20% over the next few years (Cisco 2015). When the trend in the use of in-store pickup services is coupled with the trend in online sales, the extent to which such services influence online store performance will likely be an indication of how they will impact the overall retail performance. This is not unwarranted as the literature already provides evidence that in-store pickup services do not necessarily increase overall sales for retailers (Gallino et al. 2017). This suggests that, beyond the sales shift (if any) between online and offline channels, in-store pickup services may not be able to lift sales in physical stores, leaving retailers with a costly initiative with no additional benefits. In such cases, the performance response of online channels to launching in-store pickup services may be critical for the success of those services. Thus, it is important for retailers (i) to understand how an in-store pickup service influences online channel sales, and (ii) to proactively develop strategies and customize in-store pickup services to maximize its impact on retail performance.

While the trend in offering in-store pickup services for online orders is visible for many retailers, our knowledge regarding the impact of such services on online sales is limited to industry claims and a few academic research. Surprisingly, we observe quite controversy between the two. Empirical studies in the literature demonstrate that, unlike the common wisdom suggests, in-store pickup services decrease online sales with both BOPS functionality (Gallino and Moreno 2014) and STS functionality (Akturk and Ketzenberg 2016) because some online customers shift to physical stores to complete their orders, henceforth referred to as *channel-shift effect*. In contrast, The Home Depot and Kohl's, the retailers that use both BOPS and STS functionality, report a 25% and 19% increase in online sales, respectively, mainly due to in-store pickup services (RIS-News 2015, MarketWatch 2017). Nordstrom (Market Realist 2015), Walmart (PYMNTS.com 2017), and Recreational Equipment Inc. (Outdoor Industry Association 2003) are among the other retailers that report an increase in online sales due to in-store pickup services of online orders. The controversy regarding the effect of in-store pickup services on online sales does not arise only across companies. As we will demonstrate later, even within the same company that runs multiple online channels under different brand names, in-store pick up services may increase sales for one online channel whereas they decrease sales for another online channel. Overall, these and similar contrasts between the literature and the practice lead to our first research question: "*Under which conditions do in-store pickup services increase or decrease online sales?*"

In this paper, we particularly focus on STS functionality and study how the introduction of STS affects a retailer's online sales. Drawing upon the operations management literature that demonstrates online channel sales performance depends on product selection of online stores relative to physical stores (e.g., Brynjolfsson et al. (2009, 2013)), we anticipate that product selection of online channels is a likely explanation for the impact of STS services on online sales performance. To illustrate this, consider in Figure 1 the two products offered online by a multichannel retailer that provides the STS service to its customers. While the STS option is available for both products, they differ based on channel availability. The product on the left, hereafter called a *hybrid product*, is available both online and in physical stores. In contrast, the product on the right, hereafter called an *online-exclusive product*, is available only online[1]. Theoretically, if a retailer offers STS only for online-exclusive products, the

[1] Hybrid products and online-exclusive products can be considered as "middle of tail" products and "long-tail" products, respectively (Brynjolfsson et al. 2013). Yet, we abstain from using these terms as they are defined based on the sales products generate whereas our terms are defined based on channel availability.

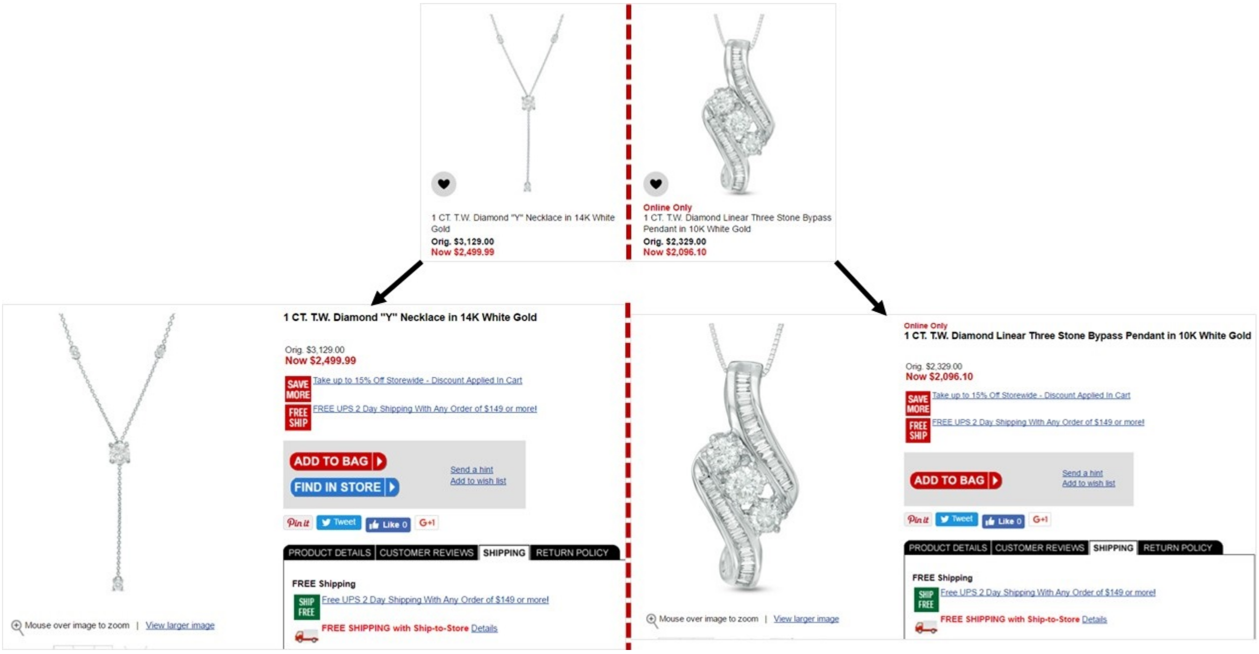



Figure 1: Hybrid product vs. online-exclusive product - For review purposes only

channel-shift effect should not exist since customers cannot find these products in-store. This implies that the effect of STS on online sales is likely to be contingent on the types of the products for which a retailer selects to offer STS[2]. Hence, explanations related to channel-shift effect as to whether STS services are profitable for retailers are incomplete without consideration of how such services affect online sales for hybrid vs. online-exclusive products. This leads to our second research question: "*How do STS services affect online sales for hybrid vs. online-exclusive products?*"

To explore our questions, we have partnered with a national jewelry retailer that operates more than 1,000 physical stores and multiple online stores under different brand names in the U.S. and Canada. A unique feature of our setting is that the retailer launched STS first in the U.S. and approximately one year later in Canada. Both STS introductions represent an exogenous shock to the customers' purchasing options because (i) the retailer announced the launch of STS in each country after operationalizing the service in that country, and (ii) Canadian customers were not exposed to the STS service in the U.S. due to the geographical distance and the different brand name used for the U.S. stores. From this perspective, both introductions provide a quasi-experimental setting for our research.

We follow a multi-methodology approach to examine the impact of STS services on online sales. First, we develop a stylized model that represents fundamental features of the STS functionality in an

[2]Considering that BOPS orders are fulfilled using in-store inventory, the channel-shift effect for BOPS can hold regardless of the product type. Even so, the argument related to the moderating role of product type can also hold for BOPS functionality, yet with a different categorization of products. In a theoretical paper that examines BOPS from a physical store perspective, Gao and Su (2017) demonstrate that BOPS services may not be suitable for products that are bestsellers in retail stores, suggesting the effect of BOPS on retailer overall performance may depend on the selection of in-store products made available for BOPS functionality.

omnichannel retail environment and derive theoretical predictions about how STS functionality affects sales for hybrid products, online-exclusive products, and overall online channel. Next, using the data including sales at the product level before and after the STS impementation at each brand name, we empirically test our theoretical predictions. We do so because the Canadian online store differs from the U.S. online store with respect to the mix of hybrid and online-exclusive products. Combined, the theory, the proprietary dataset, and the distinct features of the two online stores provide us rather a rare opportunity to observe two contradicting effects of STS on online sales within the same company. We explain this phenomenon with the following contributions of our study.

First, our theoretical model characterizes two different effects of STS on online sales: (i) the *market expansion effect* increases online sales by motivating previously non-shoppers to place online orders with STS due to its free shipping and return options, and (ii) the *channel shift effect* decreases online sales by motivating both existing and new online customers to switch to brick-and-mortar (BM) stores due to BM stores' immediate shopping experience. Hybrid product sales are subject to both effects whereas online-exclusive product sales are driven mainly by the former effect. Hence, as empirically supported, we find that STS unambiguously increases online-exclusive product sales. While the theoretical effect of STS on hybrid product sales depends on the magnitude of the two effects, we empirically demonstrate that STS decreases online sales for hybrid products. This suggests that the market expansion effect does not compensate the channel shift effect for hybrid products in our dataset. We support this explanation by empirically demonstrating that the impact of STS on online sales for hybrid products is positively moderated by the product price, an unambiguous prediction derived from our theoretical model. Our empirical findings are consistent between the two STS introductions at the subject retailer. Second, considering STS influences online sales for hybrid vs. online-exclusive products in different directions, we find that the overall effect of STS on online sales is contingent on how much online-exclusive products contribute to overall online sales relative to hybrid products do. When hybrid products dominate online sales, as is the case for the U.S. online store, we observe that STS decreases overall online sales as reported in the literature for in-store pickup services (Gallino and Moreno 2014, Akturk and Ketzenberg 2016). Yet, when online-exclusive products account for the majority of online sales, as is the case for the Canadian online store, we find STS increases overall online sales. Third, as theoretically predicted, we find that STS increases hybrid product sales in physical stores.

We further extend our analysis to examine how STS influences BM-exclusive product sales in physical stores. We find that STS does not have any measurable impact on BM-exclusive products. Also, we observe that even though hybrid product sales in physical stores increase at both brand names, when overall physical store sales are considered, this increase is not significant for Canadian stores whereas it is significant for the U.S. stores. Overall, STS functionality is profitable for both brand names, yet through a different process. For the U.S. brand name, the increase in physical store sales compensates the decrease in online store sales. For the Canadian brand name, even though physical store sales do not significantly change with STS, online store sales increase. The findings related to the Canadian brand name further justify our conjecture that the impact of in-store pickup services on the overall retail performance may depend on how such services influence online sales.

Our findings have implications for both retailers and academics. For retailers, our study highlights the importance of online product selection for the effect of in-store pickup services on sales. It also provides insights for retailers who strategically aim to influence online sales through implementing in-store pickup services. For academics, our study contributes to the understanding of an in-store pickup service that attracts growing attention in the retail operations literature and provides an explanation for a novel phenomenon related to omnichannel retailing.

We organize the rest of this paper as follows. In section 2, we position our work with respect to the relevant literature. In section 3, we develop our theory using a stylized model and derive analytical predictions regarding the impact of STS on sales. We empirically test these model predictions in section 4. We conclude the paper with managerial and theoretical insights in section 5.

## 2 Related Literature

Our study is closely related to two streams of the retail operations management literature: omnichannel retailing and online store assortment. We discuss both streams and position our work accordingly.

The omnichannel environment presents new challenges and opportunities for retailers and subsequently several academic studies have emerged recently. In this first stream, Rigby (2011), Brynjolfsson et al. (2013), and Bell et al. (2014) provide a good practical discussion regarding the challenges and opportunities associated with omnichannel retailing. Initial works on omnichannel retailing focus on issues related to marketing and information systems and explore the impact of marketing communication strategies on customer migration between channels (Ansari et al. 2008), cross-channel competition with product selection, geography, and location (Brynjolfsson et al. 2009, Forman et al. 2009), the change in pricing and store assistance level in the presence of consumer returns as a result of adding an online outlet (Ofek et al. 2011), self-matching pricing policy between channels in a competitive environment (Kireyev et al. 2017), and consumer channel choice in grocery stores (Chintagunta et al. 2012) as well as in health insurance customer support services (Jerath et al. 2015). Recent operations management papers explore omnichannel retailing with an emphasis on retail operations and study how several retail operational performance and efficiency metrics can be influenced by click stream information from the online channel (Huang and Mieghem 2014), the introduction of showrooms (Bell et al. 2017), the manufacturer's optimal product design strategy (Luo and Sun 2016), the change in return period policy (Ertekin and Agrawal 2017), and in-store pickup services of online orders (Gallino and Moreno 2014, Akturk and Ketzenberg 2016, Gallino et al. 2017, Gao and Su 2017).

Among these papers, ours is closely related to studies on in-store pickup services. In this sub-stream, Gallino et al. (2017) empirically demonstrate how launching STS increases a retailer's overall sales dispersion (i.e., the degree of equality in the sales contribution of different products). Gallino and Moreno (2014) and Akturk and Ketzenberg (2016) empirically examine the impact of BOPS and STS, respectively, on a retailer's aggregated online and BM store sales, and demonstrate that both functionalities decrease online sales and increase physical store sales due to the channel-shift effect. Our work differs from these papers as we focus on the impact of STS on hybrid vs. online-exclusive product sales, rather than on the aggregated sales. This way, we are able to demonstrate that the impact of in-store pickup services on online sales depends on the mix of hybrid vs. online-exclusive products in the online channel. In a theoretical paper, Gao and Su (2017) study the impact of the BOPS functionality on physical store inventory management and channel coordination for a multichannel retailer where (i) there is a single product, (ii) by definition, BOPS orders are fulfilled using in-store inventory, hence, a BOPS transaction can be completed only if the product is available in the selected store, and (iii) in-store product availability information is provided to online customers only after the BOPS implementation. Our setting is different as we study the impact of the STS functionality on consumer channel and product selection at a multichannel retailer where (i) there are two types of products (i.e., hybrid vs. online-exclusive), (ii) by definition, STS orders are fulfilled using online warehouse inventory, hence, a STS transaction can be completed even if the product is not available in the selected store, and (iii) in-store product availability information is present even before the STS implementation. Overall, we contribute to the omnichannel retailing literature by (i) developing a theoretical model to predict how the STS functionality influences consumer purchase behavior, and thus, retail sales, for hybrid vs. online exclusive products as well as aggregate online sales in an omnichannel retail environment, and (ii) empirically supporting our theoretical predictions.

In the second stream, the inventory management literature has heavily studied product variety (e.g., van Ryzin and Mahajan (1999), Rajagopalan (2013)) and assortment decisions (e.g., Cachon et al. (2005), Kok et al. (2009)) within the context of retail operations. Studies on product selection and assortment in online channel are related to our work. Motivated by the pioneering work that first analyzed the "long-tail products" (i.e., niche products that are typically unavailable in offline channel and account for a large share of online sales) (Brynjolfsson et al. 2003), we observe that this stream mainly categorizes retail products into long-tail, medium-tail, and popular products. Next, considering that long-tail (resp., popular) products are likely to be carried by online (resp., offline) channel and medium-tail products can be present in both channels, this stream focuses on the comparison of online and BM channels to document the presence of the long-tail phenomenon. Among them, Brynjolfsson et al. (2009) demonstrate that online channels face significant competition from BM stores when selling popular products, but are virtually immune from competition when selling long-tail products. Brynjolfsson et al. (2011) highlight that the long-tail phenomenon may also arise due to low search costs online channels offer relative to offline channels. Zentner et al. (2013) examine the impact of consumer channel shift from BM stores to online store on the consumption of long-tail and popular products. Our product categorization of hybrid vs. online-exclusive products is also related to the product categorization associated with the long-tail phenomenon. Along these lines, our research contributes to this stream by studying how the online channel product mix characterized by this categorization moderates the impact of the STS functionality on retail online sales.

# 3 Theory Development with Analytical Modeling

In this section, we develop a stylized model to establish theoretical foundations regarding the effect of STS strategy on retail sales for hybrid products and online-exclusive products. In the next subsection, we start with discussing the business context that motivates our analytical model. In the following two subsections, we define our modeling framework. Lastly, we analyze the analytical model and derive predictions to empirically test in section 4.

## 3.1 Business Context

The jewelry retailer operates its stores centrally such that the headquarters office makes operational decisions including inventory, pricing, and payroll. Pricing of a hybrid product does not vary across stores or channels, rather, once the pricing decision is made, it is held fixed at all channels.

Before the STS implementation, the retailer offered its online customers different fee- and free-based (only if the purchase amount is over a certain threshold) shipping options. These options are displayed along with product details (see Figure 3a). After the STS implementation, in addition to the same shipping options, a free STS option (regardless of the purchase amount) was made available to online customers for all online purchases (see Figure 3b). Customers choose the specific shipping option during the checkout, and if STS is chosen, enter their preferred store information (see Figure 4).

The BM store inventory availability information for a selected hybrid product was available to online customers before the STS implementation and this service remained the same after the STS implementation (see the red circles in Figures 5a and 5b). Customers can search whether or not a hybrid product is available in a BM store located within a selected distance (see Figure 6a)[3].

Customers who choose the STS option pay online, thus, all STS sales are considered online sales. By policy, STS orders are shipped within three business days from the distribution center. Yet, for

[3]From the perspective of providing in-store inventory availability information to online customers, our setting is similar to the BOPS setting empirically studied by Gallino and Moreno (2014) and different from the BOPS setting modeled by Gao and Su (2017).

most products, this delivery time does not include the processing time which can take up to four weeks (see Figure 6b). Thus, the time to receive an online order can be longer than three business days.

The retailer offers a full refund policy to protect their customers from potential dissatisfaction with their purchases. Online customers are allowed to return their products to either the distribution center by mail or to any BM store whereas BM store customers are allowed to return their purchases only to any BM store. If online customers decide to return to the distribution center, they have to prepay a return shipping fee before mailing the product.

To summarize, STS has offered two major novelties to online customers. First, STS has enabled online customers to have a free shipping option for all online purchases under certain threshold. Second, STS has decreased the return hassle and removed the return shipping fee since online customers already visit the store to pick their order and can return their order in-store if they do not like their products. We now proceed to define our modeling framework based on the business context discussed.

### 3.2 Modeling Framework

The model consists of a dual-channel retailer that sells two products denoted $o$ and $h$ for online-exclusive and hybrid products, respectively, at price $p_i$ where $i \in \{o, h\}$. Customer valuation is uncertain for both products. To simplify the model, we assume that the valuation for product $i$ can be either high $\bar{v}$ or low $\underline{v}$ with probability $\alpha$ and $1 - \alpha$, respectively. Without loss of generality, we normalize $\underline{v}$ to be 0. Customers are heterogenous with respect to $\alpha$ such that $\alpha \sim U[0, 1]$. Consistent with consumer returns literature (e.g., Anderson et al. (2009), Shulman et al. (2011)), customers make a purchase decision under uncertainty about product fit and resolve their uncertainty after the purchase. In the case of product misfit, the valuation is low and customers return their purchase to receive full refund $p_i$.

While in-store pickup services enable online customers to ship their orders to the closest store, as demonstrated by the prior research (Gallino and Moreno 2014), they can also increase awareness about the previously existing BM store inventory availability information. Indeed, considering that at the subject retailer, (i) online customers who choose the STS option during the checkout have to select their preferred store (as demonstrated in Figure 4) and (ii) they can readily access the inventory availability information in that store (see Figure 6a), such behavioral change is also very likely in our setting. Consequently, as demonstrated for BOPS services using cart abandonment data and an experiment (Gallino and Moreno 2014), STS services may also motivate online customers to abandon their virtual shopping carts and purchase a hybrid product directly from the preferred store if the product is available in the store inventory[4]. An industry survey with online customers indicates that as the order delivery time increases, customers are less likely to complete their online purchases (UPS

[4]The introduction of STS does not bring the store purchase option into the choice set of online consumers for online-exclusive products because by definition these products are not carried by BM stores.

2014). From this perspective, cart abandonment behavior due to the STS option is likely to be more prominent when (i) the delivery times are long, as with our setting for many products, or (ii) consumers are time-sensitive and thus, prefer to purchase in-store to avoid long waiting times.

To operationalize this feature, we define two parameters; namely $\beta$ and $\gamma$. The first parameter $\beta$ represents the store availability of a hybrid product[5]. The second parameter $\gamma$ represents the proportion of online customers who consider the BM store purchase option in their choice sets. Considering that STS is likely to increase cart abandonment behavior in favor of an in-store purchase for online consumers, we distinguish the values of $\gamma$ before and after STS is implemented and denote them by $\gamma^{before}$ and $\gamma^{after}$, respectively, where $\gamma^{after} \geq \gamma^{before}$.

### 3.3 Customer Decision Problem

We consider two types of online customers: (i) those who consider the store purchase option in their choice set, and (ii) those who do not. Figure 2 demonstrates the decision process for each type. The first type initially checks whether the product is available in the store. If available, she chooses among three options: (i) online purchase with direct shipping, (ii) online purchase with STS, and (iii) store purchase. Otherwise, she decides between the first two options. Similarly, the second type makes her purchase decision by comparing only the first two options as she does not consider the store purchase option (irrespective of in-store product availability). All customers are expected utility maximizers.

For the store purchase option, we assume customers incur a hassle cost $c_s$ to visit a store. Due to the touch-and-feel experience BM stores provide, customers can assess product fit before making a purchase. Hence, customers purchase the product only if the product fits. Therefore, product misfit related returns do not occur. To sum, customer's expected utility from a hybrid product purchase at the BM store can be written as $-c_s + \alpha(\bar{v} - p_h)$.

If the customer purchases the product via online channel, the hassle cost incurred by the customer takes different values depending on whether she uses direct shipping or STS. In the former case, the customer incurs a hassle cost in the form of shipping fee, which is denoted by $c_o$. In the latter case, she incurs a hassle cost to pick up the product in the store, which is equated to store visit cost $c_s$ for practicality and simplicity. The return cost also depends on whether the customer opts for STS or not. Since STS makes the return of online purchases free and relatively easy, we assume that the customer incurs zero (i.e., hassle-free) and non-zero (i.e., $r_o$) return costs in the case of STS and direct shipping, respectively. To sum, the expected utilities for the online purchase can be expressed as $-c_s - p_i + \alpha\bar{v} + (1-\alpha)p_i$ if the customer opts for STS, and $-c_o - p_i + \alpha\bar{v} + (1-\alpha)(p_i - r_o)$ if she opts for direct shipping. We summarize the expected utilities obtained from each option in Table 1.

[5] By its very definition, $\beta = 0$ for online-exclusive products.

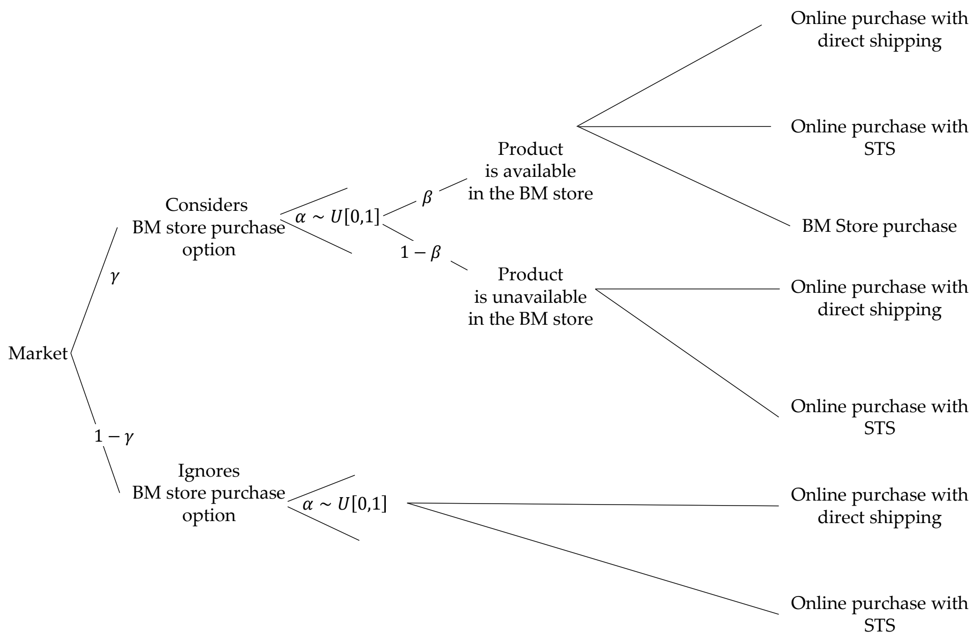



Figure 2: Customer choices after STS is implemented

Table 1: Customer's expected utility under each choice

| Choice | Customer's Utility | |
|---|---|---|
| Online Purchase ($i \in \{o, h\}$) | Use STS | $-c_s + \alpha(\bar{v} - p_i)$ |
| | No STS | $-p_i - c_o + \alpha\bar{v} + (1-\alpha)(p_i - r_o)$ |
| Store Purchase | $-c_s + \alpha(\bar{v} - p_h)$ | |

## 3.4 Impact of STS on Sales

Using the modeling framework and customer choice model presented above, we now characterize the impact of STS on retail sales. We first start with the impact of STS on online-exclusive product sales.

**Proposition 1** (Online exclusive product)**.** *STS increases the demand for online-exclusive product*[6]*. The demand increase due to STS for online-exclusive product is equal to*

$$\Delta_o^{STS} = \left[\frac{c_o + r_o}{\bar{v} + r_o - p_o} - \frac{c_s}{\bar{v} - p_o}\right]^+ \tag{3.1}$$

The first and second terms inside the parentheses in Equation (3.1) correspond to the valuations of the marginal customers who are indifferent between ordering online with direct shipping and no-purchase, and between ordering online with STS option and no-purchase, respectively. Therefore, the difference between these two terms captures the potential demand that arises from online consumers

[6]Throughout the paper, for the clarity of exposition, we use "increase" and "decrease" in the non-strict sense.

who, before the STS, do not consider the online channel due to its high shipping/return cost or due to its risk associated with the lack of touch-and-feel experience. We term this the *market expansion effect* of STS. Based on the characterization in Proposition 1, we predict:

**Prediction 1:** *STS increases sales for online-exclusive products.*

Next, we consider the impact of STS on hybrid product sales. As for the online-exclusive products, offering STS also expands the market for hybrid products. However, the ultimate effect of this market expansion on online and offline sales of hybrid products varies depending on online consumers' response to the STS offering. Recall that consumers do not have the store purchase option for online-exclusive products due to store unavailability (i.e., $\beta = 0$). Yet, this option is available for hybrid products so long as they are in store inventory. Thus, in addition to the market expansion effect, the STS option may also shift some of the online customers from ordering hybrid products via direct shipping method to buying them in the store. We term this the *channel shift effect* of STS. The following proposition characterizes the channel shift effect of STS on the BM store demand for hybrid products:

**Proposition 2** (Hybrid product - BM store sales)**.** *STS increases the BM store demand for hybrid products. The BM store demand increase due to STS for the hybrid product is equal to*

$$\Delta_{hs}^{STS} = (\gamma^{after} - \gamma^{before})\beta \left[\frac{c_o + r_o - c_s}{r_o} - \frac{c_s}{\bar{v} - p_h}\right]^+ \tag{3.2}$$

The channel shift effect in Equation (3.2) can be decomposed into three terms. The first term denotes the change in $\gamma$ due to STS since actively promoting STS triggers more online consumers to check in-store product availability. The second term represents the store availability of the hybrid product. Namely, among the online consumers who consider the store purchase option, $\beta$ of them find the hybrid product available in the store. Finally, some of these customers prefer visiting the physical channel to ordering online due to physical store's instant gratification. The third term represents those customers and is mathematically equivalent to the difference between the valuations of the marginal customers who are indifferent between store and online purchase, and between store and no purchase options, respectively. Motivated by Proposition 2 and ensuing discussion, we predict:

**Prediction 2:** *STS increases BM store sales for hybrid products.*

Finally, we discuss the impact of STS on the online sales of hybrid products. Unlike hybrid products at physical stores and online-exclusive products that are affected by either the market expansion effect or the channel shift effect of STS, hybrid products at online stores are influenced by both STS effects. More specifically, online hybrid product sales increase due to the market expansion effect and decrease due to the channel shift effect. Hence, the sign of the change in online demand for hybrid products due to STS depends on the relative comparison between the two effects as characterized below:

**Proposition 3** (Hybrid product - Online sales)**.** *STS decreases the online demand for hybrid products if the increase due to market expansion effect is overshadowed by the decrease due to the channel shift effect, i.e.,* $\Delta_{ho}^{STS} \leq 0$ *if and only if*

$$(\gamma^{after} - \gamma^{before})\beta \left[\frac{c_o + r_o - c_s}{r_o} - \frac{c_s}{\bar{v} - p_h}\right]^+ \geq (\gamma^{after}(1-\beta) + (1-\gamma^{after})) \left[\frac{c_o + r_o}{\bar{v} + r_o - p_h} - \frac{c_s}{\bar{v} - p_h}\right]^+ \tag{3.3}$$

The left hand side in the above condition (3.3) corresponds exactly to the expression (3.2) characterized for the channel shift effect in Proposition 2. The right hand side is derived by adjusting the expression (3.1) characterized for the market expansion effect in Proposition 1 with sum of two factors that represent two groups of customers: (i) $\gamma^{after}(1-\beta)$ and (ii) $(1-\gamma^{after})$. The first group represents previously non-purchasers who consider the store purchase option, yet opt for the STS option since the hybrid product is unavailable in the store. The second group represents previously non-purchasers who do not consider the store purchase at all even after STS, and thus purchase the hybrid product through STS. Considering the joint effects of market expansion and channel shift, we predict:

**Prediction 3(a):** *STS (i) decreases online sales for hybrid products if the negative channel shift effect dominates the positive market expansion effect and (ii) increases online sales otherwise.*

Condition (3.3) characterized in Proposition 3 is notably more complicated than its counterparts in Propositions 1 and 2. More importantly, the empirical justification of the theoretical condition that balances the market expansion effect with the channel shift effect is difficult to demonstrate using secondary data since the typical retail dataset includes the resulting sales, which commingle both STS effects. Yet, to provide support for our theory, we derive another prediction from our model through a sensitivity analysis on Condition (3.3) with respect to product price and later test empirically. We find that both market expansion and channel shift effects decrease in product price. Yet, in the next result, we show that the former decreases at a slower rate than the latter.

**Corollary 1** (Sensitivity analysis with respect to price)**.** *Consider two hybrid products* $H_1$ *and* $H_2$ *where* $p_{H_1} > p_{H_2}$*. Then, Condition (3.3) implies that* $\Delta_{ho}^{STS}(H_1) \geq \Delta_{ho}^{STS}(H_2)$*.*

The above result enables us to conjecture the following prediction:

**Prediction 3(b):** *The impact of STS on online hybrid product sales is positively moderated by* $p_h$*.*

The impact of STS on overall online sales depends on how STS influences online sales for online-exclusive products vs. hybrid products. For online-exclusive products, the direction is unambiguously positive whereas for hybrid products it can go either way. This implies that the overall change in the aggregate online sales depends on the composition of online-exclusive vs. hybrid products. Let $w$ denote the proportion of online-exclusive products in overall online sales. Then, we can state:

**Corollary 2** (Sensitivity analysis with respect to $w$)**.** *Consider two online channels with $w_1$ and $w_2$ where $w_1 > w_2$. Then, the positive market expansion effect on the sales of online-exclusive products and the negative channel shift effect on online sales of hybrid products collectively imply that the change in total demand due to STS is higher in online channel* 1 *than in online channel* 2*.*

We can make two inferences from Corollary 2. The presence of the negative channel shift effect for online hybrid product sales suggests that (i) if STS ever increases the aggregate online sales, the contribution should more likely come from the online-exclusive products rather than hybrid products and (ii) if STS decreases the aggregate online sales, the online sales increase for online-exclusive products is likely to be overshadowed by the online sales decrease for hybrid products. To summarize, we predict:

**Prediction 4:** *STS (i) decreases overall online sales if the decrease in online hybrid product sales dominates the increase in online-exclusive product sales and (ii) increases overall online sales otherwise.*

# 4 Empirical Analysis

In this section, we provide empirical support for the predictions of our analytical model. We start with explaining the empirical setting for the analysis. Next, we examine the STS effect on online channels and BM channels, respectively. Lastly, we deploy several robustness tests to validate our results and consider alternative explanations.

## 4.1 Empirical Setting, Analysis Design, and Data

The retailer operates several multichannels under different brand names in the U.S. and Canada. We are particularly interested in two brands, hereafter called *Alpha* and *Sierra*, for which STS was implemented at different times. In August 2011, the retailer enhanced the integration of online and BM channels for Alpha by adding a STS option for all online purchases. Approximately one year later, in September 2012, the retailer extended the STS option for all Sierra online customers.

Our aim is to identify the effect of the STS strategy on online and BM store sales for Alpha and Sierra separately. We measure this effect as the post-STS change in sales for a subpopulation that was exposed to the STS implementation (i.e., *treatment group*) relative to that for another subpopulation that was not exposed to the STS implementation (i.e., *control group*). This approach is called the difference-in-differences (DiD) estimation and has been used in the operations management literature (e.g., Caro and Gallien (2010), Gallino and Moreno (2014)). From an empirical identification standpoint, by estimating double differences between the treatment and control groups, the DiD approach addresses two concerns that are common to most empirical studies. First, by estimating the difference in sales across time but within each group, it eliminates any time-invariant unobserved heterogeneity (or omitted variable bias) concern (Card and Krueger 1994). Second, by estimating the difference between the differences obtained in the first step, it eliminates any time trend in sales. For interested readers, Goldfarb and Tucker (2014) provide a more detailed discussion about the DiD approach.

Considering that the STS was implemented at two different brand names with each having both an online channel and a BM channel, we conduct two channel-specific analyses (i.e., one for the online channel and one for the BM channel) for the STS implementation at Alpha and replicate the same analyses for the STS implementation at Sierra. Using two years of sales data between August 2010 and July 2012 (i.e., one year before the STS implementation at Alpha and one year after the STS implementation at Alpha) for Alpha and Sierra, we examine how the STS implementation influences online and BM store sales at Alpha. For this step, we consider the Alpha online channel and BM stores (for which the STS was implemented) as the treatment group and the Sierra online channel and BM stores (for which the STS was not an option throughout the data period) as the control group.

| **Variable** | **Definition** |
|---|---|
| **Product-level analysis** | |
| $Sales_{jt}$ | Log of total dollar sales for SKU $j$ in week $t$ |
| $PromotionPerc_{jt}$ | Ratio of sales with a promotion to all sales for SKU $j$ in week $t$ |
| $CustGender_{jt}$ | Ratio of all female customers to all customers who purchase SKU $j$ in week $t$ |
| $CustAge_{jt}$ | Average age of all customers who purchase SKU $j$ in week $t$ |
| $CustIncome_{jt}$ | Average household income of all customers who purchase SKU $j$ in week $t$ |
| $Price_{j}$ | Log of price for SKU $j$ |
| $ProductCategory_{j}$ | Indicator variables for the product category of SKU $j$ |
| $PrType_{j}$ | Whether SKU $j$ is an online-exclusive product (1) or hybrid product (0) |
| $SeasonalityControls_{t}$ | Indicator variables for both months and years |
| **Store-level analysis** | |
| $Sales_{it}$ | Log of total dollar sales for store $i$ in week $t$ |
| $PromotionPerc_{it}$ | Ratio of sales with a promotion to all sales at store $i$ in week $t$ |
| $CustGender_{it}$ | Ratio of all female customers to all customers who shop at store $i$ in week $t$ |
| $CustAge_{it}$ | Average age of all customers who shop at store $i$ in week $t$ |
| $CustIncome_{it}$ | Average household income of all customers who shop at store $i$ in week $t$ |
| $SeasonalityControls_{t}$ | Indicator variables for both months and years |

Table 2: Variable definition

Note that for the analysis of the STS implementation at Sierra, Alpha online channel and BM stores do not serve as an appropriate control group since the STS option had already been offered to Alpha online customers for almost a year by the time it was first offered to Sierra online customers. To overcome this limitation, we later contacted the retailer to obtain additional data from a third brand name, hereafter called *Foxtrot*, for which the STS strategy has never been implemented. To replicate the same analyses for the STS implementation at Sierra, we form two new datasets obtained from Foxtrot and Sierra online channels and BM stores, respectively, for the period between October 2011 and September 2013 (i.e., one year before the STS implementation at Sierra and one year after the STS implementation at Sierra). Hence, for this replication, we consider the Sierra stores as the treatment group and the Foxtrot stores as the control group[7].

| | | **Treatment Group** | | | | **Control Group** | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | **Pre-STS** | | **Post-STS** | | **Pre-STS** | | **Post-STS** | | **Correlation Matrix** | | | | |
| | **Variable** | **Mean** | **SD** | **Mean** | **SD** | **Mean** | **SD** | **Mean** | **SD** | **1** | **2** | **3** | **4** | **5** |
| Analysis for STS implementation at Alpha | 1.*Sales* | 5.44 | 0.95 | 5.60 | 1.05 | 5.11 | 1.03 | 5.15 | 1.00 | 1.00 | | | | |
| | | 5.42 | 1.00 | 5.38 | 0.98 | 5.18 | 0.96 | 5.29 | 0.97 | 1.00 | | | | |
| | 2.*PromotionPerc* | 0.65 | 0.19 | 0.67 | 0.16 | 0.63 | 0.46 | 0.62 | 0.37 | 0.08 | 1.00 | | | |
| | | 0.65 | 0.20 | 0.67 | 0.16 | 0.68 | 0.46 | 0.62 | 0.37 | 0.08 | 1.00 | | | |
| | 3.*CustGender* | 0.40 | 0.47 | 0.40 | 0.47 | 0.53 | 0.50 | 0.46 | 0.50 | -0.12 | -0.03 | 1.00 | | |
| | | 0.41 | 0.47 | 0.40 | 0.47 | 0.49 | 0.50 | 0.45 | 0.50 | -0.13 | -0.03 | 1.00 | | |
| | 4.*CustAge* | 5.75 | 3.76 | 5.66 | 3.86 | 5.89 | 3.57 | 5.77 | 3.55 | -0.02 | 0.01 | 0.04 | 1.00 | |
| | | 5.76 | 3.75 | 5.69 | 3.88 | 5.72 | 3.52 | 5.67 | 3.37 | -0.02 | 0.01 | 0.05 | 1.00 | |
| | 5.*CustIncome* | 5.28 | 2.17 | 5.23 | 2.19 | 5.54 | 2.37 | 5.48 | 2.32 | 0.00 | -0.01 | -0.03 | 0.19 | 1.00 |
| | | 5.26 | 2.17 | 5.21 | 2.20 | 5.35 | 2.27 | 5.23 | 2.17 | 0.01 | ***0.00*** | -0.02 | 0.19 | 1.00 |
| | *Sample Size* | 195,728 | | | | 640,432 | | | | | | | | |
| | | 681,824 | | | | 123,968 | | | | | | | | |
| Analysis for STS implementation at Sierra | 1.*Sales* | 5.12 | 0.98 | 5.26 | 1.03 | 3.34 | 0.62 | 3.39 | 0.65 | 1.00 | | | | |
| | | 5.27 | 0.96 | 5.19 | 0.94 | 3.23 | 0.58 | 3.27 | 0.60 | 1.00 | | | | |
| | 2.*PromotionPerc* | 0.63 | 0.36 | 0.65 | 0.38 | 0.53 | 0.37 | 0.52 | 0.37 | 0.05 | 1.00 | | | |
| | | 0.61 | 0.34 | 0.62 | 0.35 | 0.62 | 0.47 | 0.64 | 0.46 | 0.13 | 1.00 | | | |
| | 3.*CustGender* | 0.47 | 0.49 | 0.49 | 0.50 | 0.58 | 0.33 | 0.56 | 0.34 | -0.22 | ***0.03*** | 1.00 | | |
| | | 0.46 | 0.50 | 0.47 | 0.50 | 0.59 | 0.35 | 0.61 | 0.38 | -0.07 | 0.03 | 1.00 | | |
| | 4.*CustAge* | 5.75 | 3.54 | 5.71 | 3.53 | 4.92 | 2.15 | 4.80 | 2.03 | ***-0.00*** | -0.05 | ***0.02*** | 1.00 | |
| | | 5.69 | 3.41 | 5.66 | 3.39 | 4.88 | 2.11 | 4.82 | 2.07 | -0.06 | 0.06 | 0.04 | 1.00 | |
| | 5.*CustIncome* | 5.46 | 2.29 | 5.48 | 2.32 | 5.15 | 1.97 | 5.08 | 1.87 | 0.05 | ***0.00*** | ***0.03*** | 0.11 | 1.00 |
| | | 5.27 | 2.19 | 5.34 | 2.25 | 4.97 | 1.89 | 5.02 | 1.92 | 0.01 | 0.03 | 0.02 | 0.24 | 1.00 |
| | *Sample Size* | 674,232 | | | | 183,352 | | | | | | | | |
| | | 128,752 | | | | 35,586 | | | | | | | | |

Notes: (1) Except for cells in bold-italic, all correlations are significant at $p < 0.05$ level.

(2) For each variable, the first row indicates online-exclusive products and the second row indicates hybrid products.

Table 3: Product-level descriptive statistics and correlation matrix

Our reasoning to choose treatment and control groups is that customers visiting an online/BM store in the treatment group were exposed to the STS option, yet, customers visiting an online/BM store in the control group were not exposed to this option. A customer who shops at two different stores, one in the treatment group and one in the control group, would violate our reasoning and thus the DiD

[7]Note that, ideally, we would like to use Foxtrot as the control group to examine the STS implementation at Alpha. However, since the retailer keeps data only for the three most recent years, obtaining Foxtrot transaction data starting August 2010 was not possible when we contacted the retailer the second time.

settings. The data allow us to track a customer over time even if she shops at different stores/channels. Considering that jewelry purchases are rare, we observe the number of such customers is quite small and negligible. Nevertheless, we remove those customers to fully comply with the required DiD setting. We now proceed to the next section to identify the STS effect on online channels.

Consistent with our objective and theoretical grounding, we conduct two types of empirical analyses for online channels: (i) product-level analysis to establish the effect of STS on both online-exclusive and hybrid product sales, and (ii) store-level analysis to demonstrate the resulting change at the aggregate online sales. For both analyses, we include several time-variant and time-invariant variables as described in Table 2. For brevity, we provide descriptive statistics and correlation matrices only for the datasets used in the product-level analysis in Table 3.

## 4.2 STS Effect on Online Channels

We start our empirical assessment with product-level analyses and then move to store-level analyses. First, we assess the impact of STS on online-exclusive product sales to empirically test Prediction 1. To obtain an accurate estimate, we include in our analysis all stock keeping units (SKUs) that are offered throughout the study period and exclude all SKUs that are offered only some part of the study period. We identify a total of 8,040 online-exclusive SKUs for the assessment of STS on Alpha online channel and 8,246 online-exclusive SKUs for the assessment of STS on Sierra online channel.

We measure the dependent variable sales ($Sales_{jt}$) as the logarithm of the dollar value of all sales for SKU $j$ during week $t$. We note that the qualitative insights in all our analyses hold even if we use monthly sales. Since we have data on multiple time periods for each product, we specify the DiD model as longitudinal panel data regression model. In all analyses, we use fixed effect models as the Hausman tests suggest that the random effect formulations are not consistent. Thus, consistent with the formulation discussed by Wooldridge (2010), our model specification is the following:

$$Sales_{jt} = \beta_o + \beta_1 TreatmentSKU_j \times After_t + \beta_2 After_t + \boldsymbol{Controls_{jt}\beta_C} + u_j + \varepsilon_{jt} \tag{4.1}$$

where $After_t$ is a binary variable that equals to one for the time periods after the STS implementation and zero for the time periods before the STS implementation. $TreatmentSKU_j$ is another binary variable that indicates whether SKU $j$ is offered at the treatment online store ($TreatmentSKU_j = 1$) or at the control online store ($TreatmentSKU_j = 0$). The coefficient of interest to test our analytical prediction (i.e., the DiD estimator) is $\beta_1$ in Equation (4.1). Note that, in addition to time-variant control variables defined in Table 2, we also have time-invariant control variables including $Price$ and $ProductCategory$ for each SKU. However, the coefficients of these time-invariant variables are not estimated due to product fixed effects $u_j$ in our fixed-effects models.

The fact that STS was implemented at the brand-level means we should not assume that each SKU (or each store for later analyses) in our econometric specifications provides an independent draw from the population. Rather, customers, products, or operations of a given brand name may share observable and unobservable characteristics, making the data heteroscedastic at the observation level. Subsequently, we cluster standard errors at the channel-level in all of our analyses in order to avoid downward biases in our standard error estimates (Bertrand et al. 2004).

Table 4 summarizes the results of our model estimations for both Alpha and Sierra online channels. The columns named "Online-Exc." demonstrate the product-level analysis results for online-exclusive products. We find that the DiD estimators for the online-exclusive products at both Alpha online channel ($\beta_1 = 0.14$) and Sierra online channel ($\beta_1 = 0.15$) are positive and significant. This indicates that the STS implementation increases online-exclusive product sales by 14% at Alpha online channel and by 15% at Sierra online channel, supporting Prediction 1.

| | **STS implementation at Alpha** | | | | **STS implementation at Sierra** | | | |
|---|---|---|---|---|---|---|---|---|
| **Variable** | **Online-Exc.** | **Hybrid** | **Hybrid (T)** | **All** | **Online-Exc.** | **Hybrid** | **Hybrid (T)** | **All** |
| $After$ | 0.69*** | 0.80*** | 2.86*** | 0.79*** | 0.04 | 0.14*** | 0.15*** | 0.12*** |
| | (0.002) | (0.006) | (0.044) | (0.004) | (0.042) | (0.028) | (0.034) | (0.028) |
| $TreatmentSKU$ | 0.14*** | -0.12*** | -2.36*** | -0.11*** | 0.15*** | -0.15*** | -1.08*** | -0.23*** |
| $\times After$ | (0.002) | (0.006) | (0.043) | (0.005) | (0.020) | (0.005) | (0.013) | (0.033) |
| $After \times Price$ | | | -0.35*** | | | | -0.01*** | |
| | | | (0.009) | | | | (0.000) | |
| $After \times PrType$ | | | | -0.10*** | | | | -0.03 |
| | | | | (0.010) | | | | (0.028) |
| $TreatmentSKU$ | | | 0.38*** | | | | 0.07*** | |
| $\times After \times Price$ | | | (0.009) | | | | (0.004) | |
| $TreatmentSKU$ | | | | 0.25*** | | | | 0.38*** |
| $\times After \times PrType$ | | | | (0.010) | | | | (0.030) |
| $Controls$ | YES | YES | YES | YES | YES | YES | YES | YES |
| $R^2$ | 0.30 | 0.29 | 0.51 | 0.30 | 0.59 | 0.51 | 0.67 | 0.57 |
| Sample size | 836,160 | 805,792 | 805,792 | 1,641,952 | 857,584 | 164,320 | 164,320 | 1,021,904 |

*Notes*: (1) Standard errors clustered at the channel-level are presented in parentheses.
(2) *$p < 0.05$; **$p < 0.01$; ***$p < 0.001$

Table 4: Online channel product-level analysis results

Second, we estimate Equation (4.1) for hybrid products. We identify a total of 7,748 (resp., 1,580) hybrid products for the assessment of STS on Alpha (resp., Sierra) online channel, which are offered throughout the analysis period. In Table 4, the columns named "Hybrid" demonstrate the product-level analysis results for hybrid products. We find that the DiD estimators for the hybrid products at both Alpha online channel ($\beta_1 = -0.12$) and Sierra online channel ($\beta_1 = -0.15$) are negative and statistically significant. This indicates that the STS implementation decreases hybrid product sales by 12% at Alpha online channel and by 15% at Sierra online channel, supporting Prediction 3a.

From our theoretical analysis, a likely explanation for the decrease in online sales of hybrid products is that the decrease due to the channel shift effect dominates the increase due to market expansion effect. In our dataset, we are not able to quantify these two effects since we only observe the resulting overall sales. Yet, in the same line of thought, our theory also suggests that product price is a moderator for the effect of STS on hybrid product sales (i.e., Prediction 3b). Thus, to provide partial support for our theory, we deploy a difference-in-difference-in-differences (i.e., triple difference) estimation. The triple difference estimation enables us to assess whether the impact of STS implementation on hybrid product online sales is contingent on product price. We specify the triple difference model as follows:

$$\begin{aligned} Sales_{jt} = \beta_o + \beta_1 TreatmentSKU_j \times After_t + \beta_2 After_t + \beta_3 After_t \times Price_j \\ + \beta_4 TreatmentSKU_j \times After_t \times Price_j + \boldsymbol{Controls_{jt}\beta_C} + u_j + \varepsilon_{jt} \end{aligned} \tag{4.2}$$

The coefficient of interest to test Prediction 3b is $\beta_4$ in Equation (4.2). Due to the fixed effects specification, the coefficient of $Price_j$ is not estimated. The results from this specification are presented under the columns named "Hybrid(T)" in Table 4. We find that the triple difference estimators for Alpha online channel ($\beta_4 = 0.38$) and for Sierra online channel ($\beta_4 = 0.07$) are positive and significant. This supports Prediction 3b and strengthens our theoretical explanation for Prediction 3a.

The results from individual estimates suggest that STS decreases online sales for hybrid products and increases online sales for online-exclusive products. To empirically formalize this relationship, we specify the following difference-in-difference-in-differences (i.e., triple difference) estimation:

$$\begin{aligned} Sales_{jt} = \beta_o + \beta_1 TreatmentSKU_j \times After_t + \beta_2 After_t + \beta_3 After_t \times PrType_j \\ + \beta_4 TreatmentSKU_j \times After_t \times PrType_j + \boldsymbol{Controls_{jt}\beta_C} + u_j + \varepsilon_{jt} \end{aligned} \tag{4.3}$$

where $PrType_j$ equals to one if SKU $j$ is an online-exclusive product and zero if it is a hybrid product. The coefficient of interest is $\beta_4$ in Equation (4.3). Due to the fixed effects specification, the coefficient of $PrType_j$ is not estimated. The results from this specification are presented under the columns named "All" in Table 4. We find that the triple difference estimators for Alpha online channel ($\beta_4 = 0.25$) and for Sierra online channel ($\beta_4 = 0.38$) are positive and significant, supporting our theory that the impact of STS on online sales is moderated by the product type. When considered along with the negative coefficients for $TreatmentSKU_{ij} \times After_t$ in both analyses, the results of the triple interaction models support our individual product-specific analyses to test Predictions 1 and 3a.

One caveat of our analyses is that we use only SKUs that are offered throughout the analysis period. Even though, using these SKUs is likely to provide an accurate estimate for the product-level analysis, they represent only 37% (resp., 18%) of all SKUs at Alpha (resp., Sierra) online channel. It might be the case that online sales for these SKUs may be different from online sales for the SKUs excluded from the study and the estimated effects may not hold when the aggregate sales are considered. To address this, we conduct a store-level analysis using all SKUs and modify Equation (4.1) as follows:

$$Sales_{it} = \beta_o + \beta_1 TreatmentStore_i \times After_t + \beta_2 After_t + \boldsymbol{Controls_{it}\beta_C} + u_i + \varepsilon_{it} \tag{4.4}$$

Here, $Sales_{it}$ denotes the logarithm of the dollar value of all sales at online channel $i$ during week $t$. $TreatmentStore_i$ equals to one for the the treatment online store and zero for the control online store. We estimate Equation (4.4) for three different samples and demonstrate the results in Table 5. First, the columns named "Online-Exc." demonstrate the estimation results for the effect of STS on weekly sales of all online-exclusive products. The estimated effects for Alpha online channel ($\beta_1 = 0.13$) and Sierra online channel ($\beta_1 = 0.12$) are positive and significant, indicating that the STS implementation increases online weekly sales for online-exclusive products by 13% at Alpha and 12% at Sierra. Second, the columns named "Hybrid" demonstrate the estimation results for the effect of STS on weekly sales of all hybrid products. We find that the estimated effects for Alpha online channel ($\beta_1 = -0.23$) and Sierra online channel ($\beta_1 = -0.21$) are negative and significant, indicating that the STS implementation decreases online weekly sales for hybrid products by 23% at Alpha online channel and by 21% at Sierra online channel. The qualitative insights from the store-level analysis are consistent with those from the product-level analysis, supporting Predictions 1 and 3a also at the store-level.

| | **STS implementation at Alpha** | | | **STS implementation at Sierra** | | | **Alpha/Sierra** | |
|---|---|---|---|---|---|---|---|---|
| **Variable** | **Online-Exc.** | **Hybrid** | **All** | **Online-Exc.** | **Hybrid** | **All** | **Original** | **SCM** |
| $After$ | 1.99*** | 0.80 | -6.65*** | -0.34*** | 0.03 | 0.24 | 0.30* | 0.34* |
| | (0.368) | (0.378) | (0.663) | (0.025) | (0.259) | (0.181) | (0.140) | (0.163) |
| $TreatmentStore \times After$ | 0.13*** | -0.23*** | -0.16*** | 0.12*** | -0.21*** | 0.07*** | -0.15*** | -0.19*** |
| | (0.017) | (0.013) | (0.002) | (0.023) | (0.063) | (0.016) | (0.022) | (0.039) |
| $After \times OnlExc$ | | | | | | | 0.11 | 0.13 |
| | | | | | | | (0.067) | (0.084) |
| $TreatmentStore\times$ | | | | | | | 0.24*** | 0.29*** |
| $After \times OnlExc$ | | | | | | | (0.042) | (0.073) |
| $Controls$ | YES | YES | YES | YES | YES | YES | YES | YES |
| $R^2$ | 0.82 | 0.89 | 0.86 | 0.86 | 0.84 | 0.82 | 0.85 | 0.86 |
| Sample size | 208 | 208 | 208 | 208 | 208 | 208 | 416 | 416 |

*Notes*: (1) Standard errors clustered at the channel-level are presented in parentheses.
(2) *$p < 0.05$; **$p < 0.01$; ***$p < 0.001$

Table 5: Online channel store-level analysis results

Third, the columns named "All" present the results for the effect of STS on overall weekly online sales (i.e., both hybrid products and online-exclusive product sales). We find that the DiD estimator for Alpha online channel ($\beta_1 = -0.16$) is negative and significant, suggesting the STS implementation reduces online sales by 16% for Alpha. In contrast, the DiD estimator for Sierra online channel ($\beta_1 = 0.07$) is positive and significant, suggesting that the STS implementation results in a 7% increase for online sales at Sierra. To better understand the contradicting results at the store-level, we calculate the total sales generated by hybrid products and online-exclusive products for the treatment online channels before the STS implementation. We find that the online-exclusive product sales to hybrid product sales ratio is 0.26 for Alpha online channel and 5.14 for Sierra online channel, suggesting that hybrid (resp., online-exclusive) products dominate sales for Alpha (resp., Sierra) online channel[8]. To formally capture this feature in our econometric model and empirically test Prediction 4, we specify the following triple difference model for weekly online sales:

$$\begin{aligned} Sales_{it} = \beta_o + \beta_1 TreatmentStore_i \times After_t + \beta_2 After_t + \beta_3 After_t \times OnlExc_i \\ + \beta_4 TreatmentStore_i \times After_t \times OnlExc_i + \boldsymbol{Controls_{it}\beta_C} + u_i + \varepsilon_{it} \end{aligned} \tag{4.5}$$

where $OnlExc_i$ equals to one if pre-STS online sales are dominated by online-exclusive products and zero if pre-STS online sales are dominated by hybrid products. Due to the fixed effects specification, the coefficient of $OnlExc_i$ is not estimated. To estimate this model, we combine the dataset generated for the assessment of STS implementation at Alpha online channel with the dataset generated or the assessment of STS implementation at Sierra online channel. Since STS implementation dates are different, we normalize the STS implementation week to 0 and code the week index of each observation accordingly to align both panels[9]. We also recode unit index (i.e., the subscript $i$ in Equation (4.5)) such that Sierra online channel observations that belong to the control group in the first dataset have different unit index than Sierra online channel observations that belong to the treatment group in the second dataset. The coefficient of interest to test Prediction 4 is $\beta_4$ in Equation (4.5). The results from this estimation are presented under column "Alpha/Sierra Original" in Table 5. We find that the triple difference estimator ($\beta_4 = 0.24$) is positive and statistically significant. Considering that the coefficient of $TreatmentStore_i \times After_t$ is negative, these results suggest that, when hybrid product sales are dominant, STS decreases the overall online sales. In contrast, when online-exclusive product sales are dominant, online sales increase with the STS implementation. In conclusion, these results are consistent with our individually conducted analyses and support Prediction 4.

Even though combining the two datasets increases the statistical power of our analysis, one can argue that the resulting control group may not be appropriate since, despite belonging to different time windows, Sierra online channel serves as both one of the treatment subjects and one of the control subjects. We address this issue using synthetic control method. This method aims to identify the treatment effect when an unexposed group does not provide an appropriate comparison for an exposed

[8] The online-exclusive product sales to hybrid product sales ratio before the STS implementation is 5.12 for Foxtrot online channel.

[9] For interested readers, Autor (2003) demonstrates a similar normalization procedure for a DiD model setting in which the aim is to identify the effect of increased employment protection on the firm's use of temporary help workers and different states passed the protection at different points in time.

subject (Abadie and Gardeazabal 2003) and is used when the treatment group includes a single subject (Abadie et al. 2010) as well as multiple subjects (Cavallo et al. 2013). The premise is that a synthetic control group obtained through counterfactuals from a combination of the inappropriate control subjects provides a better comparison for the treatment group than any single subject in the control group alone. Using both observable covariates and pre-intervention outcomes, this method identifies the synthetic control group as the weighted average of all potential control group subjects that best resemble the characteristics of the treatment group subjects. Hence, the synthetic control group constructed through counterfactuals using the support of the data in our study can be considered to include two hypothetical online stores that have not implemented STS throughout the data period. Also, unlike large sample inferential techniques, synthetic control method is well suited to comparative case studies when the sample size is small. From this perspective, this method also serves as a robustness check for our store-level analysis in which the sample size is relatively small compared to the sample size of the product-level analysis. The "Alpha/Sierra SCM" column in Table 5 provides the DiD model results obtained from the comparison of the treatment group to the synthetic control group. We find that our qualitative insights remain the same with this approach, further providing support for Prediction 4.

To summarize, our exhaustive analyses on online channels highlight two novel phenomena regarding the impact of the STS implementation on online channel sales in our dataset: First, STS decreases online sales for hybrid products and increases online sales for online-exclusive products. Second, the impact of STS on overall online sales is contingent on the product mix. For an online channel that is dominated by hybrid product sales, STS is likely to decrease online sales and for an online channel that is dominated by online-exclusive product sales, STS is likely to increase online sales. We now proceed to the next section to empirically assess the impact of STS on BM store sales.

## 4.3 STS Effect on BM Channels

Ideally, we would like to replicate our online channel product-level analysis for BM stores as well. Yet, considering that the average inventory turn is quite low at BM stores, conducting a product-level analysis is infeasible since we do not observe sales for many SKUs for several time periods. Therefore, to measure the impact of STS implementation on BM stores, we only conduct the store-level analysis. In particular, we modify our DiD model to study weekly sales at BM stores as follows:

$$Sales_{it} = \beta_o + \beta_1 TreatmentStore_i \times After_t + \beta_2 After_t + \boldsymbol{Controls_{it}\beta_C} + u_i + \varepsilon_{it} \tag{4.6}$$

where $Sales_{it}$ is defined as the logarithm of the dollar value of all sales at BM store $i$ in week $t$. $TreatmentStore_i$ equals to one if BM store $i$ belongs to the treatment group and zero if it belongs to the control group. In this analysis, we use all BM stores that remain open throughout the analysis period and exclude those that are opened or closed during the analysis period. There are 930 stores for the assessment of STS on Alpha BM stores and 799 BM stores for the assessment of STS on Sierra BM stores. In addition to time-variant control variables defined in Table 2, we also have time-invariant control variables for BM stores including $StoreSize$ (i.e., the total hundred square feet of a store), $SAExperience$ (i.e., the average years of experience of all sales associates working in a store), $MallGrade$ (i.e., a categorical variable that demonstrates the quality and competitive environment of the mall store $i$ is located), and $MallSales$ (i.e., the average daily revenue per 100 square feet that any small-sized store (such as jewelry stores) makes in the mall in which a store is located). Again, the coefficients of these time-invariant variables are not estimated due to store fixed effects $u_i$.

We estimate Equation (4.6) for three different samples. Initially, we estimate the DiD model for weekly hybrid product sales at BM stores. The columns named "Hybrid" in Table 6 demonstrate the results. The estimated effect for Alpha BM stores ($\beta_1 = 0.09$) and Sierra BM stores ($\beta_1 = 0.07$) are positive and significant indicating that the STS implementation increases hybrid product sales by 9% at Alpha BM stores and by 7% at Sierra BM stores, supporting Prediction 2.

| | **STS implementation at Alpha** | | | **STS implementation at Sierra** | | |
|---|---|---|---|---|---|---|
| **Variable** | **Hybrid** | **BM-Exc.** | **All** | **Hybrid** | **BM-Exc.** | **All** |
| $After$ | 1.44*** | 1.21*** | 1.35*** | -0.43*** | -0.34*** | -0.37*** |
| | (0.028) | (0.038) | (0.021) | (0.033) | (0.025) | (0.025) |
| $TreatmentStore \times After$ | 0.09*** | -0.01 | 0.06*** | 0.07* | 0.02 | 0.04 |
| | (0.015) | (0.035) | (0.013) | (0.032) | (0.036) | (0.025) |
| $Controls$ | YES | YES | YES | YES | YES | YES |
| $R^2$ | 0.36 | 0.32 | 0.33 | 0.44 | 0.39 | 0.45 |
| Sample size | 96,720 | 96,720 | 96,720 | 83,096 | 83,096 | 83,096 |

*Notes*: (1) Standard errors clustered at the channel-level are presented in parentheses.
(2) *$p < 0.05$; **$p < 0.01$; ***$p < 0.001$

Table 6: BM channel store-level analysis results

There are two potential explanations for the increase in BM store sales for hybrid products. First, as our theory predicts, due to the channel-shift effect of STS, some existing online customers and previously non-purchasers switch to BM stores due to BM stores' immediate shopping experience. Subsequently, BM store sales for hybrid products increase. Second, as discussed by Gallino and Moreno (2014) for BOPS, the increase for hybrid products at BM stores can also be attributed to cross-selling effect (i.e., additional BM store sales that arise when customers who use STS functionality purchase extra items during their store pickup) because STS provides online customers with a shopping experience similar to what BOPS provides. Indeed, considering that online sales account for 7% of all sales at Alpha and 2% of all sales at Sierra, we find that, after launching STS, the increase in hybrid product sales at BM stores outweighes the decrease in hybrid products at online channels. This may suggest that cross-selling occurs for hybrid products at BM stores. We note that the type of the sales that occur in

BM stores due to STS is beyond the scope of our study[10].

As a second step in this section, even though not stated as one of the formal analytical predictions, we estimate Equation (4.6) for weekly BM-exclusive product sales. With this estimation, we aim to examine the potential impact of cross-selling effect due to STS functionality on incremental sales for BM-exclusive products. An advantage of our dataset is that we can differentiate hybrid products from BM-exclusive products. Since BM-exclusive products are not available to online customers, any increase in BM-exclusive product sales due to the STS implementation (if any) can be attributed to the incremental sales (not sales-displacement) of cross-selling effect due to STS functionality. The columns named "BM-Exc." in Table 6 demonstrate the estimation results for the effect of STS implementation on weekly BM-exclusive product sales. We find that the DiD estimator for Alpha BM stores ($\beta_1 = -0.01$) and Sierra BM stores ($\beta_1 = 0.02$) is not significant, suggesting cross-selling effect due to STS functionality is not present for BM-exclusive products at the subject retailer.

As a final step, we estimate Equation (4.6) using weekly sales for all products at BM stores to identify the overall effect of STS implementation on BM store sales. The columns named "All" in Table 6 present the estimation results. We find that the DiD estimator for Alpha BM stores ($\beta_1 = 0.06$) is positive and significant, suggesting STS increases BM store sales by 6%. In contrast, for Sierra BM stores, we find the estimated effect ($\beta_1 = 0.04$) is not significant, suggesting that STS does not have any substantial effect on Sierra BM store sales. A likely explanation for this result is that the proportion of hybrid product sales is less at Sierra BM stores than at Alpha BM stores. Thus, the increase in hybrid product sales at Sierra BM stores is not statistically significant when considering all store sales.

In summary, we find that the STS implementation decreases Alpha online sales, increases Sierra online sales and Alpha BM store sales, and does not change Sierra BM store sales. Overall, considering that online sales account for a small portion of all sales at Alpha, we conclude that the STS implementation results in an overall increase in sales for the subject retailer.

## 4.4 Robustness Checks

In this section, we conduct several robustness checks to ensure that (i) our model assumption is not violated, (ii) the results are not driven by systematic differences between treatment and control groups or by extreme values in the data, and (iii) alternative modeling approaches do not change our insights.

[10] As noted by Gallino and Moreno (2014), the cross-selling effect may include both the incremental sales (corresponding to sales that would not have occurred otherwise) and the sales-displacement (sales that would have occurred in the online channel or in the BM store, possibly at a different time). Assuming cross-selling incremental sales more likely arise for categories where purchases are unplanned, the authors demonstrate the cross-selling effect of BOPS by quantifying the sales increase in those categories. Yet, the authors note that they cannot precisely differentiate the incremental effect from the sales-displacement effect. Similarly, our dataset does not allow us to differentiate the two effects for hybrid products. The type of the cross-selling effect within hybrid products is beyond the focus of our study. Thus, we refer interested readers to Gallino and Moreno (2014) for a more detailed discussion.

First, the parallel trend assumption is the fundamental assumption of the DiD approach. The assumption states that (i) the difference in the mean of the outcome variable between the treatment and control groups has to be constant over time in pre-intervention period, and (ii) the outcome variable in both groups would follow the same trend during post-intervention in the absence of the treatment. Following Gallino and Moreno (2014), we test the parallel trend assumption of the DiD model using:

$$Sales_{it} = \beta_o + \beta_1 Treatment_i \times Trend_t + \beta_2 Trend_t + \boldsymbol{Controls_{it}\beta_C} + u_i + \varepsilon_{it} \tag{4.7}$$

where $Trend_t$ counts the number of weeks since the beginning of the dataset and $Treatment_i$ represents $TreatmentSKU_j$ (resp., $TreatmentStore_i$) in the product-level (resp., store-level) analysis. We estimate Equation (4.7) using only pre-STS data. Note that a statistically significant $\beta_1$ would indicate that the pre-intervention trends of the treatment and control groups are not parallel, violating the fundamental assumption of the DiD model. In all cases, we find that $\beta_1$ is not significant, indicating that the parallel trend assumption holds for our datasets.

| | | **Before Matching** | | | **After Matching** | | |
|---|---|---|---|---|---|---|---|
| Variable | Analysis | Control | Treatment | t-test | Control | Treatment | t-test |
| $Log(Price)$ | Alpha | 5.48 | 5.39 | 3.04 | 5.43 | 5.41 | 0.67 |
| | Sierra | 3.51 | 5.24 | -67.60 | 5.25 | 5.25 | -0.04 |
| $AvgPromotion$ | Alpha | 0.66 | 0.86 | -30.37 | 0.73 | 0.73 | 0.09 |
| | Sierra | 0.59 | 0.78 | -19.21 | 0.78 | 0.77 | 0.14 |
| $RejectPercent$ | Alpha | 0.04 | 0.09 | -7.87 | 0.08 | 0.08 | -0.29 |
| | Sierra | 0.03 | 0.07 | -5.63 | 0.06 | 0.05 | 0.84 |

Table 7: Propensity score matching for SKUs

Second, one may argue that since treatment and control groups represent two different brands, products and customer profiles may also be different between the two groups. Subsequently, the systematic differences between the two groups may drive the results. To assess this alternative explanation, we conduct propensity score matching within strata for online channel product-level analysis and BM channel store-level analysis. Propensity score is the conditional probability of receiving the treatment (i.e., being in the treatment group) rather than the control (i.e., being in the control group), given the observed covariates (Rosenbaum and Rubin 1983). The aim of propensity score matching is to construct a subsample of treatment group that is inherently similar to a subset of control group. For the product-level analysis on online channel, we match the SKUs in the two groups using log-transformed of $Price$, the ratio of promotional sales to all sales for a given SKU ($AvgPromotion$), and $RejectPercent$ (i.e., the percentage of rejected products of SKU $j$ based on the quality test conducted on each batch of newly procured products). We use $ProductCategory$ as the strata variable to ensure that a treatment group SKU in a specific product category is matched with a control group SKU in the same product category. We utilize radius matching without replacement and employ the common support restriction with a narrow caliper range of 0.01 (Dehejia and Wahba 2002). This process results in 3,359 matched SKUs for the assessment of STS on Alpha online channel and 2,271 matched SKUs for the assessment of STS on Sierra online channel. We assess the efficacy of propensity score matching in two ways. First, the average bias in covariates of unmatched SKUs before matching is 60.4% for the assessment of STS on Alpha online channel and 113.5% for the assessment of STS on Sierra online channel. With propensity score matching, the average bias decreases to 4% and 1.4%, respectively. Second, we compare the two groups of SKUs using t-tests for differences between means of covariates both before the matching and after the matching in Table 7. We observe that the two groups show statistically significant differences in their covariates before the matching. After the matching, the differences in covariates of the two groups are insignificant in all cases. Overall, we conclude that propensity score matching results in a subsample of SKUs that are inherently similar. Following this matching step, we repeat our product-level analysis specified in Equations (4.1–4.3) using the matched subset of SKUs. As presented in Table 8, we observe that the coefficients of interest are consistent with our main findings, indicating that our results are robust even when we restrict our analysis to SKUs that are inherently similar.

| | **STS implementation at Alpha** | | | | **STS implementation at Sierra** | | | |
|---|---|---|---|---|---|---|---|---|
| **Variable** | **Online-Exc.** | **Hybrid** | **Hybrid(T)** | **All** | **Online-Exc.** | **Hybrid** | **Hybrid(T)** | **All** |
| $After$ | -0.50*** | -0.28*** | -1.78*** | -0.29*** | 0.01 | -0.19** | -0.16** | -0.14*** |
| | (0.000) | (0.001) | (0.038) | (0.001) | (0.165) | (0.007) | (0.009) | (0.032) |
| $TreatmentStore \times After$ | 0.17*** | -0.13*** | -1.14*** | -0.10*** | 0.13*** | -0.11*** | -0.93*** | -0.17*** |
| | (0.000) | (0.004) | (0.039) | (0.003) | (0.032) | (0.015) | (0.012) | (0.043) |
| $After \times Price$ | | | -0.29** | | | | -0.01** | |
| | | | (0.008) | | | | (0.003) | |
| $After \times PrType$ | | | | -0.20** | | | | -0.02 |
| | | | | (0.076) | | | | (0.032) |
| $TreatmentStore\times$ | | | 0.33*** | | | | 0.08*** | |
| $After \times Price$ | | | (0.007) | | | | (0.005) | |
| $TreatmentStore\times$ | | | | 0.27*** | | | | 0.30*** |
| $After \times PrType$ | | | | (0.019) | | | | (0.036) |
| $Controls$ | YES | YES | YES | YES | YES | YES | YES | YES |
| $R^2$ | 0.28 | 0.30 | 0.43 | 0.30 | 0.54 | 0.48 | 0.59 | 0.50 |
| Sample size | 175,864 | 173,472 | 173,472 | 349,336 | 184,496 | 51,688 | 51,688 | 236,184 |

*Notes*: (1) Standard errors clustered at the channel-level are presented in parentheses.
(2) $*p < 0.05$; $**p < 0.01$; $***p < 0.001$

Table 8: Online channel product-level analysis results with matched SKUs

We repeat this procedure to match BM stores. For the store-level analysis, we match the stores in the two groups using $StoreSize$, $SAExperience$, $MallSales$, and $AvgPromotion$ measured as the ratio of promotional sales to all sales for a given store. We use $MallGrade$ as the strata variable to ensure that a treatment group store located in a mall with certain quality is matched with a control group store located in another mall with the same quality. This process results in 644 matched stores for the analysis on Alpha BM stores and 132 matched stores for the analysis on Sierra BM stores. The average bias in covariates of unmatched stores before matching is 109.4% for the assessment of STS on Alpha BM stores and 236.5% for the assessment of STS on Sierra BM stores. With propensity score matching, the average bias decreases to 9.8% and 10.5%, respectively. In addition, as presented in Table 9, propensity score matching results in subsets such that the differences in covariates of the two groups are insignificant for all covariates, implying that the matched stores are inherently similar.

| | | **Before Matching** | | | **After Matching** | | |
|---|---|---|---|---|---|---|---|
| Variable | Analysis | Control | Treatment | t-test | Control | Treatment | t-test |
| $StoreSize$ | Alpha | 1,625 | 1,801 | -3.78 | 1,579 | 1,729 | -0.97 |
| | Sierra | 1,034 | 1,526 | -17.82 | 941 | 1,103 | -1.12 |
| $SAExperience$ | Alpha | 6.50 | 4.81 | 6.11 | 5.09 | 4.93 | 0.16 |
| | Sierra | 3.62 | 6.69 | -12.48 | 5.63 | 7.19 | -1.52 |
| $MallSales$ | Alpha | 512 | 408 | 3.49 | 498 | 404 | 1.71 |
| | Sierra | 387 | 492 | -3.32 | 462 | 504 | -0.89 |
| $AvgPromotion$ | Alpha | 0.54 | 0.64 | -23.44 | 0.62 | 0.64 | -1.39 |
| | Sierra | 0.45 | 0.63 | -35.94 | 0.63 | 0.64 | -1.37 |

Table 9: Propensity score matching for BM stores

We estimate Equation (4.6) using the matched subset of stores and present the results in Table 10. Again, we observe that our qualitative insights from the entire data remain the same with the matched subset in which the systematic differences between the treatment and control groups are minimal.

| | **STS implementation at Alpha** | | | **STS implementation at Sierra** | | |
|---|---|---|---|---|---|---|
| **Variable** | **Hybrid** | **BM-Exc.** | **All** | **Hybrid.** | **BM-Exc.** | **All** |
| $After$ | 1.43*** | 1.25*** | 1.37*** | -0.36** | -0.28*** | -0.35*** |
| | (0.047) | (0.099) | (0.038) | (0.122) | (0.062) | (0.088) |
| $TreatmentStore \times After$ | 0.06*** | 0.00 | 0.06*** | 0.11* | 0.02 | 0.06* |
| | (0.012) | (0.041) | (0.014) | (0.049) | (0.049) | (0.024) |
| $Controls$ | YES | YES | YES | YES | YES | YES |
| $R^2$ | 0.39 | 0.32 | 0.34 | 0.41 | 0.36 | 0.42 |
| Sample size | 66,976 | 66,976 | 66,976 | 13,728 | 13,728 | 13,728 |

*Notes*: (1) Standard errors clustered at the channel-level are presented in parentheses.
(2) *$p < 0.05$; **$p < 0.01$; ***$p < 0.001$

Table 10: BM channel store-level analysis results with matched stores

Third, we have only two online stores. Our panels for the store-level analysis of online channels may better resemble time series cross-sectional (TSCS) data. For such data, using panel regression may not be appropriate due to potential correlation between online stores or autocorrelation within an online store over time. In such cases, Prais-Winston regression provides more consistent estimates for the standard errors compared to fixed-effects panel regression (Lapré and Tsikriktsis 2006). Thus, we estimate Equations (4.4) and (4.5) using Prais-Winston errors. Table 11 provides the results from the TSCS specifications. We find that, for our data, the fixed effect formulations provide very similar results and effect sizes for online stores compared to those obtained from the Prais-Winston regression.

| | STS implementation at Alpha | | | STS implementation at Sierra | | | Alpha/Sierra |
|---|---|---|---|---|---|---|---|
| **Variable** | **Hybrid** | **Online-Exc.** | **All** | **Hybrid** | **Online-Exc.** | **All** | **All** |
| $TreatmentStore \times After$ | -0.23** | 0.13*** | -0.17*** | -0.21*** | 0.10*** | 0.06** | -0.14*** |
| | (0.076) | (0.021) | (0.004) | (0.054) | (0.018) | (0.023) | (0.027) |
| $TreatmentStore\times$ | | | | | | | 0.21** |
| $After \times OnlExc$ | | | | | | | (0.064) |
| $Controls$ | YES | YES | YES | YES | YES | YES | YES |
| $R^2$ | 0.98 | 0.97 | 0.98 | 0.89 | 0.98 | 0.97 | 0.99 |
| Sample size | 208 | 208 | 208 | 208 | 208 | 208 | 416 |

*Notes*: (1) Panel corrected standard errors are presented in parentheses.
(3) *$p < 0.05$; **$p < 0.01$; ***$p < 0.001$

Table 11: TSCS model results for online channel store-level analysis

Fourth, the validity of standard error clustering relies on the asymptotic behavior of the estimator at the cluster rather than at the individual level. Given that there are only two brand names (i.e., treatment brand and control brand) in our analyses, it is likely to have downward bias in estimated standard errors due to the small samples. This might be particularly prominent for the online channel store-level analysis where we have relatively small number of observations. Thus, as proposed by Cameron et al. (2008), we introduce a finite correction to the estimated standard errors and implement the "cluster residual bootstrap-t" procedure in all of our model estimations to correct for the downward bias potentially induced in small samples. We find that, except one case, the coefficients in all models are significant at 5% significance level. The exception is for the estimated effect of STS implementation on hybrid product sales at Sierra BM stores (i.e., $\beta_1 = 0.07$ under the column named "Hybrid" for Sierra BM stores in Table 6). This coefficient is no longer significant when the cluster residual bootstrap-t procedure is used, suggesting Prediction 2 may not be supported for Sierra.

Fifth, we conduct a placebo test as suggested by Gallino and Moreno (2014). In particular, we use only pre-STS data and define January 2011 and March 2012 as the fake STS implementation dates for the assessment of STS functionality at Alpha and Sierra, respectively. We do not find any statistically significant effect on our variables of interest due to this fictitious STS implementation.

Lastly, it is possible that the recurrent spikes in sales during the Christmas season may affect our results. To test this alternative explanation, we estimate all models using a subset of our data without the peak season datapoints. We find that the effect of the STS implementation is consistent with our main analysis even when we censor the data for peak periods, ruling out this alternative explanation.

# 5 Conclusion

Order fulfilment to end customer is the crux of retailing function, offline and online alike. Ship-to-store is the new kid on the block thanks to omnichannel retailing where the boundaries between offline and online shopping experience for customers become more and more blurry. The benefits of STS to shoppers are well documented. Most notable ones are: (i) STS enables customers to pick up their products from the nearest location, which helps them reduce the shipping cost, and (ii) it ensures that customers can return easily if the product does not meet their expectations. Even though it is bonanza to customers, the impact of STS on omnichannel retail sales is less clear particularly for online channel. Do the above-mentioned benefits really help expand the market for omnichannel retailers by reducing the barriers to online shopping? Or do they only shift customers from online to offline channels resulting in win-lose for retailers due to the costly investment of channel integration? This paper seeks to investigate these questions from the benefit side of STS using analytical and empirical analyses on retail sales. More specifically, we first derive theoretical predictions regarding the impact of STS on sales for online-exclusive products (i.e., products available only online), hybrid products (i.e., products available both online and offline), and overall online channel, using a utility-based customer choice model where customers are heterogenous in two dimensions. Namely, customers differ in terms of (i) whether they consider the store purchase option at all or not, and (ii) how likely they return the product due to misfit. Next, using a set of difference-in-differences models on the proprietary dataset from an omnichannel retail that launched STS for two different brand names at different times, we empirically test our predictions to identify the effect of STS on retail sales performance.

A surprising observation, and a major motivation, for our study is that STS increases sales in one online channel and decreases sales in the other one. Our theoretical model supported by an exhaustive empirical analysis provides an explanation for this phenomenon. The analyses of the theoretical model enable us to characterize two opposing effects. The *market expansion effect*, which is associated with both online-exclusive and hybrid products, arises with the advent of new consumers who were non-shoppers before STS due to high shipping and return costs of online channels. The *channel shift effect*, which is associated with only hybrid products, arises when existing online customers switch to offline channel due to its immediate shopping experience. The former increases the online sales whereas the latter decreases on the behalf of offline sales. Thus, as empirically supported, our theoretical model unambiguously predicts that STS services increase the sales of online-exclusive products.

Unlike online-exclusive products, hybrid products are subject to both effects. Thus, theoretically, STS may either increase or decrease online sales for hybrid product depending on the contribution of each effect. Our empirical analysis demonstrates that online sales for hybrid products decrease with STS, suggesting the channel shift effect is likely to overshadow the market expansion effect at the focal company. The empirical comparison of the two effects for hybrid products using secondary data is not straightforward since a typical retail data compose sales transactions that arise as a result of both effects. Yet, as a supporting evidence for this explanation, we empirically demonstrate that the impact of STS on online sales for hybrid products is positively moderated by the product price, an unambiguous prediction derived from our theoretical model.

Considering that STS increases online sales for online-exclusive products and decreases online sales for hybrid products, as predicted by our theory, the overall effect of STS on online channel depends on the composition of online-exclusive and hybrid products. Our results show that when online-exclusive products account for the majority of online sales, STS increases online sales. In contrast, when hybrid products account for the majority of online sales, STS may decrease online sales.

We extend our empirical analysis to BM stores and find that STS increases BM store hybrid product sales, potentially due to the channel shift effect, as predicted by our theory, as well as the cross-selling effect. However, for BM-exclusive products, we do not observe any change in sales due to STS. When overall BM store sales are considered, we find that the increase in hybrid product sales is significant for one brand name whereas it is not significant for the other brand name. The latter finding suggests that the effect of STS on sales may be limited to only online channels and, in such cases, understanding how STS influences online channel sales might be critical for the success of launching STS.

Our results have key managerial implications for omnichannel retailers from both front-end and back-end vantage points. From the front-end perspective, our study suggests, if omnichannel retailers want to implement STS, they need to take into account that such strategy may not necessarily be a win-win value proposition when one takes product characteristics of online assortment into consideration. From this perspective, customizing the STS implementation strategy based on product characteristics may promise a more desirable outcome for retailers. For example, if the product offerings are composed of mostly online-exclusive products, STS may boost the overall sales. When online assortment is composed of mainly hybrid products, STS offerings targeted towards high-price products are likely to benefit retailers. Recall that STS is likely to lower return costs especially when it is offered for the products with potentially high mismatch risk. This suggests that omnichannel retailers should be cautioned to offer STS for hybrid products with low mismatch risk because the loss in sales due to negative channel shift effect may dissipate the benefit intended from the STS implementation.

Even though we focus on the impact of STS on sales, it has also some key implications for the back-end operations of an omnichannel retailer. A key benefit attributed to STS is the extra traffic generated in BM stores during the pickup of online orders. This may lead to benefits in other ways. For instance, as can be inferred from our finding, the additional BM store sales due to STS may likely arise in hybrid products. This may suggest that online customers are not familiar with BM-exclusive products since these products are not displayed online. From this perspective, in-store pickup of STS orders provides retailers an opportunity to expose online customers to BM-exclusive products, potentially through developing certain scripts for their salespeople who handle STS orders in stores.

While our study highlights the importance of product characteristics on assessing the efficacy of STS implementation, future research can focus on numerous other factors to extend our knowledge regarding in-store pickup services of online orders. First, for low priced-hybrid products with high shipping and handling (S&H) cost to price ratio, offering STS may not be beneficial to retailers because, not only the benefit of STS on sales is likely to be low due to the low price, but also the S&H costs incurred by customers with direct shipping will now be incurred by retailers with STS. Future research can examine the effect of the S&H costs on the STS implementation strategy. Second, retailers may forecast STS orders based on geographical locations and move their online inventory to downstream (e.g., local distribution center and physical store) in order to avoid the extra S&H cost of STS. Future research can study how retailers should optimize their downstream inventory to fulfill both local store demand and STS orders. Third, future research can identify how competition, the cost of actual implementation, and IT capabilities influence the success of launching in-store pick up services.

## References


Abadie, A., A. Diamond, J. Hainmueller. 2010. Synthetic control methods for comparative case studies: Estimating the effect of California's tobacco control program. *Journal of the American Statistical Association* **105**(490) 493–505.

Abadie, A., J. Gardeazabal. 2003. The economic costs of conflict: A case study of the Basque Country. *The American Economic Review* **93**(1) 113–132.

Akturk, M. S., M. Ketzenberg. 2016. Assessing the impact of ship-to-store service on sales and returns in omnichannel retailing: A data analytics study. *Working paper, Operations and Information Management Department, Mays Business School, Texas A&M University* .

Anderson, E. T., K. Hansen, D. Simester. 2009. The option value of returns: Theory and empirical evidence. *Marketing Science* **28**(3) 405–423.

Ansari, A., C. F. Mela, S. A. Neslin. 2008. Customer channel migration. *Journal of Marketing Research* **45**(1) 60–76.

Autor, D. H. 2003. Outsourcing at will: The contribution of unjust dismissal doctrine to the growth of employment outsourcing. *Journal of Labor Economics* **21**(1) 1–42.

Bell, D. R., S. Gallino, A. Moreno. 2014. How to win in an omnichannel world. *MIT Sloan Management Review* **56**(1) 45–53.

Bell, D. R., S. Gallino, A. Moreno. 2017. Offline showrooms in omnichannel retail: Demand and operational benefits. *Management Science* **Articles in Advance** 1–23.

Bertrand, M., E. Duflo, S. Mullainathan. 2004. How much should we trust differences-in-differences estimates? *The Quarterly Journal of Economics* **119**(1) 249–275.

BRP, Boston Retail Partners. 2015. Pos/Customer engagement survey. Tech. rep., Boston Retail Partners Company, Boston, MA.

Brynjolfsson, E., Y. J. Hu, M. S. Rahman. 2009. Battle of the retail channels: How product selection and geography drive cross-channel competition. *Management Science* **55**(11) 1755–1765.

Brynjolfsson, E., Y. J. Hu, M. S. Rahman. 2013. Competing in the age of omnichannel retailing. *MIT Sloan Management Review* **54**(4) 23–29.

Brynjolfsson, E., Y. J. Hu, D. Simester. 2011. Goodbye pareto principle, hello long tail: The effect of search costs on the concentration of product sales. *Management Science* **57**(8) 1373–1386.

Brynjolfsson, E., Y. J. Hu, M. D. Smith. 2003. Consumer surplus in the digital economy: Estimating the value of increased product variety at online booksellers. *Management Science* **49**(11) 1580–1596.

Cachon, G., A. Kumar, S. Netessine. 2005. Retail assortment planning in the presence of consumer search. *Manufacturing and Service Operations Management* **7**(4) 330–346.

Cameron, A. C., J. B. Gelbach, D. L. Miller. 2008. Bootstrap-based improvements for inference with clustered errors. *Review of Economics and Statistics* **90**(3) 414–427.

Card, D., A. B. Krueger. 1994. Minimum wages and employment: A case study of the fast-food industry in New Jersey and Pennsylvania. *The American Economic Review* **September** 772–793.

Caro, F., J. Gallien. 2010. Inventory management of a fast-fashion retail network. *Operations Research* **58**(2) 257–273.

Cavallo, E., S. Galiani, I. Noy, J. Pantano. 2013. Catastrophic natural disasters and economic growth. *Review of Economics and Statistics* **95**(5) 1549–1561.

Chintagunta, P. K., J. Chu, J. Cebollada. 2012. Quantifying transaction costs in online/off-line grocery channel choice. *Marketing Science* **31**(1) 96–114.

Cisco. 2015. Differentiating your retail store point of view with new delivery options. *Point of View* 1–4.

Dehejia, R. H., S. Wahba. 2002. Propensity score-matching methods for nonexperimental causal studies. *Review of Economics and Statistics* **84**(1) 151–161.

Ertekin, N., A. Agrawal. 2017. How does a return period policy change affect multichannel retailer profitability? *Working paper, Operations Management & Information Systems Department, Leavey School of Business, Santa Clara University* .

Forman, C., A. Ghose, A. Goldfarb. 2009. Competition between local and electronic markets: How the benefit of buying online depends on where you live. *Management Science* **55**(1) 47–57.

Forrester Consulting. 2014. Customer desires vs. retailer capabilities: Minding the omni-channel commerce gap. Tech. rep., Forrester Research, McLean, VA.

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

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

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

Goldfarb, A., C. Tucker. 2014. Conducting research with quasi-experiments: A guide for marketers. *Working Paper* .

Huang, T., J. A. Van Mieghem. 2014. Clickstream data and inventory management: Model and empirical analysis. *Production and Operations Management* **23**(3) 333–347.

Jerath, K., A. Kumar, S. Netessine. 2015. An information stock model of customer behavior in multichannel customer support services. *Manufacturing and Service Operations Management* **17**(3) 368–383.

Kireyev, P., V. Kumar, E. Ofek. 2017. Match your own price? Self-matching as a retailer's multichannel pricing strategy. *Marketing Science* **36**(6) 908–930.

Kok, A. G., M. L. Fisher, R. Vaidyanathan. 2009. *Assortment planning: Review of literature and industry practice*. Springer, New York, NJ.

Lapré, M. A., N. Tsikriktsis. 2006. Organizational learning curves for customer dissatisfaction: Heterogeneity across airlines. *Management Science* **52**(3) 352–366.

Luo, L., J. Sun. 2016. New product design under channel acceptance: Brick-and-mortar, online-exclusive, or brick-and-click. *Production and Operations Management* **25**(12) 2014–2034.

Market Realist. 2015. Strategies that boost online sales for department stores https://beta.marketrealist.com/2015/06/strategies–boost–online–sales–department–stores (accessed Dec 13, 2017).

MarketWatch. 2017. Kohl's gets a boost from selling more things people want to buy https://www.marketwatch.com/story/kohls–gets–a–boost–from–selling–more–things–people–want–to–buy–2017–08–10 (accessed Dec 13, 2017).

Ofek, E., Z. Katona, M. Sarvary. 2011. "Bricks and Clicks": The impact of product returns on the strategies of multichannel retailers. *Marketing Science* **30**(1) 42–60.

Outdoor Industry Association. 2003. REI store pickup lifts store and internet sales https://outdoorindustry.org/press–release/rei–store–pickup–lifts–store–and–internet–sales/ (accessed Dec 13, 2017).

PYMNTS.com. 2017. Walmart online sales explode https://www.pymnts.com/news/omnicommerce/2017/online–sales–sporting–goods/ (accessed Dec 13, 2017).

Rajagopalan, S. 2013. Impact of variety and distribution system characteristics on inventory levels at U.S. retailers. *Manufacturing and Service Operations Management* **15**(2) 191–204.

Rigby, D. 2011. The future of shopping. *Harvard Business Review* **89**(12) 65–76.

RIS-News. 2015. Home Depot's online sales see 25 percent boost https://risnews.com/home–depots–online–sales–see–25–percent–boost (accessed Dec 13, 2017).

Rosenbaum, P. R., D. B. Rubin. 1983. The central role of the propensity score in observational studies for causal effects. *Biometrika* **70**(1) 41–55.

Shulman, J.D., A.T. Coughlan, R.C. Savaskan. 2011. Managing consumer returns in a competitive environment. *Management Science* **57**(2) 347–362.

UPS. 2014. UPS pulse of the online shopper: A customer experience study conducted by comScore. Tech. rep., United Parcel Service of America, Atlanta.

UPS. 2015. UPS pulse of the online shopper: Empowered shoppers propel retail change. Tech. rep., United Parcel Service of America, Atlanta.

van Ryzin, G., S. Mahajan. 1999. On the relationship between inventory costs and variety benefits in retail assortment. *Management Science* **45**(11) 1496–1509.

Warner, S. 2013. Why in-store pick-up is the tip of the omnichannel iceberg. *Retail Info Systems News White Paper* .

Wooldridge, J. M. 2010. Econometric analysis of cross section and panel data. *MIT Press* **38** Cambridge, MA.

Zentner, A., M. Smith, C. Kaya. 2013. How video rental patterns change as consumers move online. *Management Science* **59**(11) 2622–2634.

# A Proofs of Propositions

**Proof of Proposition 1:** We first derive the demand without STS. Since the store purchase option is not available for online-exclusive products, we just need to derive the utility of the (marginal) customer who is indifferent between purchase and no-purchase options. Based on Table 1, the utility from online purchase without STS is $-p_o - c_o + \alpha\bar{v} + (1-\alpha)(p_o - r_o)$. Letting this equal to zero, and solving for $\alpha$, we find $\bar{\alpha}^{No-STS} = \frac{c_o + r_o}{\bar{v} + r_o - p_o}$. Next, we consider the case with STS. From Table 1, the utility from online purchase with STS is $-c_s + \alpha(\bar{v} - p_o)$. Letting it equal to zero and solving for $\alpha$, we obtain $\bar{\alpha}^{STS} = \frac{c_s}{\bar{v} - p_o}$. The demand increase due to STS follows directly by taking the difference between valuations of marginal customers who are indifferent between purchase and no-purchase options under no-STS and STS options. More specifically, $\Delta_o^{STS} = \left[\bar{\alpha}^{No-STS} - \bar{\alpha}^{STS}\right]^+ = \left[\frac{c_o + r_o}{\bar{v} + r_o - p_o} - \frac{c_s}{\bar{v} - p_o}\right]^+$ where $x^+ = \max(x, 0)$. The STS option decreases the valuation of the marginal customer. Hence, the demand for online exclusive products increases if $\bar{\alpha}^{STS} \leq \bar{\alpha}^{No-STS}$ and does not change otherwise.

**Proof of Proposition 2:** Similarly, we first derive the demand without STS. Note that for hybrid products, the store purchase option is feasible only for $\gamma$ types. Hence, we just need to derive the utility of the (marginal) customer who is indifferent between the store purchase and online purchase options. Based on Table 1, the utilities of a customer from online purchase without STS and from store purchase are $-p_h - c_o + \alpha\bar{v} + (1-\alpha)(p_h - r_o)$, and $-c_s + \alpha(\bar{v} - p_h)$, respectively. Letting them equal to each other, and solving for $\alpha$, we find that $\bar{\alpha}_1^{No-STS} = \frac{c_o + r_o - c_s}{r_o}$. On the other hand, by letting utility of a customer from the store purchase option equal to zero, and solving for $\alpha$, we derive the utility of the (marginal) customer who is indifferent between store purchase and no-purchase options, i.e., $\bar{\alpha}_2^{No-STS} = \frac{c_s}{\bar{v} - p_h}$. Finally, subtracting $\bar{\alpha}_2^{No-STS}$ from $\bar{\alpha}_1^{No-STS}$, considering the fact that $\gamma$ portion of customers choose the store purchase option only if the product $h$ is available in the store, we find the store demand for hybrid products before STS is $d_{hs}^{No-STS} = \gamma^{before}\beta\left[\bar{\alpha}_1^{No-STS} - \bar{\alpha}_2^{No-STS}\right]^+ = \gamma^{before}\beta\left[\frac{c_o + r_o - c_s}{r_o} - \frac{c_s}{\bar{v} - p_h}\right]^+$. Next, we consider the case with STS. Note that the demand derivation under STS is similar to that under no-STS. To prevent repetition, we provide the store demand for hybrid products after STS as follows: $d_{hs}^{STS} = \gamma^{after}\beta\left[\frac{c_o+r_o-c_s}{r_o} - \frac{c_s}{\bar{v}-p_h}\right]^+$. The increase in store demand for hybrid products due to STS follows directly by taking the difference between $d_{hs}^{STS}$ and $d_{hs}^{No-STS}$. More specifically, $\Delta_{hs}^{STS} = (\gamma^{after} - \gamma^{before})\beta\left[\bar{\alpha}_1^{No-STS} - \bar{\alpha}_2^{No-STS}\right]^+$. Substituting the expressions for $\bar{\alpha}_1^{No-STS}$ and $\bar{\alpha}_2^{No-STS}$, we can express the increase in store demand for hybrid products due to STS as follows:

$$\Delta_{hs}^{STS} = (\gamma^{after} - \gamma^{before})\beta\left[\frac{c_o + r_o - c_s}{r_o} - \frac{c_s}{\bar{v} - p_h}\right]^+$$

Finally, comparing $d_{hs}^{STS}$ and $d_{hs}^{No-STS}$, we can show that the store demand for hybrid products increases if $\frac{c_o+r_o-c_s}{r_o} \geq \frac{c_s}{\bar{v}-p_h}$, and does not change otherwise.

**Proof of Proposition 3:** Note that online demand of hybrid products is influenced by both the market expansion effect and the channel shift effect. The expression for the channel shift effect is exactly same as the one characterized in Proposition 2. Therefore, we restrict our attention to deriving the market expansion effect of STS for the online demand of a hybrid product. As opposed to the online-exclusive product, there are two sources of the market expansion effect for hybrid products. First one comes from the $\gamma^{after}$ proportion of customers who take the store purchase option into consideration. These customers opt for online purchase with STS only if the product is not available in the store, which occurs with probability $1 - \beta$. The second one comes from the customers who do not take the store purchase option into consideration at all. This constitutes $1 - \gamma^{after}$ proportion of the customer. To sum, the total market expansion effect due to STS can be expressed as follows: $(\gamma^{after}(1-\beta) + (1-\gamma^{after}))\left[\bar{\alpha}^{No-STS} - \bar{\alpha}^{STS}\right]^+ = (\gamma^{after}(1-\beta) + (1-\gamma^{after}))\left[\frac{c_o+r_o}{\bar{v}+r_o-p_h} - \frac{c_s}{\bar{v}-p_h}\right]^+$. Considering the joint effects of the channel shift and market expansion effects, we can now state the condition for online demand of hybrid products under STS. Namely, $\Delta_{ho}^{STS} \leq 0$ if and only if

$$(\gamma^{after} - \gamma^{before})\beta\left[\frac{c_o + r_o - c_s}{r_o} - \frac{c_s}{\bar{v} - p_h}\right]^+ \geq (\gamma^{after}(1-\beta) + (1-\gamma^{after}))\left[\frac{c_o + r_o}{\bar{v} + r_o - p_h} - \frac{c_s}{\bar{v} - p_h}\right]^+$$

**Proof of Corollary 1:** Note that both left- and right-hand sides of the condition in Proposition 3 decrease in price $p_h$. To conduct the sensitivity analysis of this condition with respect to $p_h$, we express $f(p_h) \geq \frac{\gamma^{after}(1-\beta)+(1-\gamma^{after})}{\gamma^{after}-\gamma^{before}}$ where $f(p_h)$ is given by:

$$f(p_h) = \frac{\frac{c_o+r_o-c_s}{r_o} - \frac{c_s}{\bar{v}-p_h}}{\frac{c_o+r_o}{\bar{v}+r_o-p_h} - \frac{c_s}{\bar{v}-p_h}}$$

Taking the derivative of $f(p_h)$ with respect to $p_h$ and simplifying the expression, we obtain:

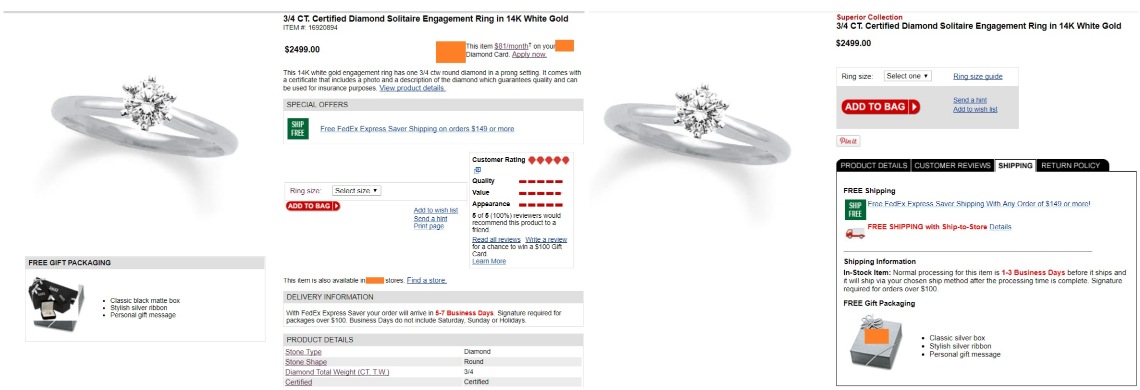
$$\frac{\delta f(p_h)}{\delta p_h} = \frac{r_o}{(p_h - \bar{v} - r_o)^2}$$

The above expression shows $f'(p_h) \geq 0$, which implies that the left-hand side of the condition in Proposition 3 increases at a faster rate than the right-hand side. This, in turn, means that the impact of STS on online demand for hybrid products is positively moderated by the product price.

**Proof of Corollary 2:** Note that the change in total online demand due to STS consists of two parts: (i) the change in online demand for online exclusive products (i.e., $\Delta_o^{STS}$), and (ii) the change in online demand for hybrid products (i.e., $\Delta_{ho}^{STS}$). Given that the proportion of online sales generated by online-exclusive products is equal to $w$, we can express the change in total demand due to STS as a weighted average as follows: $\Delta_{to}^{STS} = w\Delta_o^{STS} + (1-w)\Delta_{ho}^{STS}$. The change in total online demand due to STS increases with respect to $w$ if $\Delta_o^{STS} \geq \Delta_{ho}^{STS}$ and decreases otherwise.

# B Figures for the Review Team

The figures demonstrated here are for review purposes only. Due to the confidentiality agreement signed with the subject retailer, we are not allowed to publicly share these figures.




(a) Pre-STS implementation

(b) Post-STS implementation

Figure 3: The change on the website due to the STS implementation

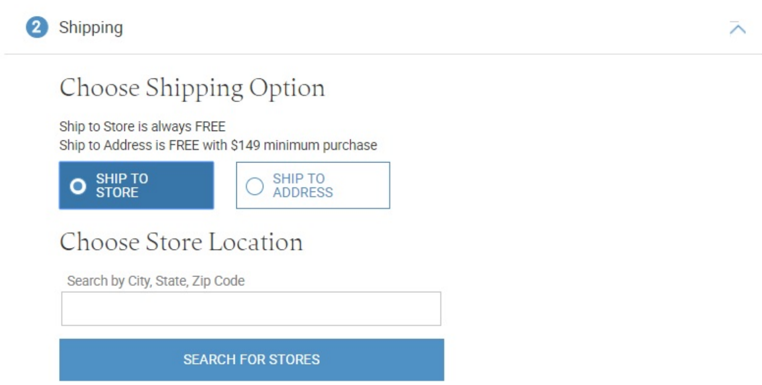
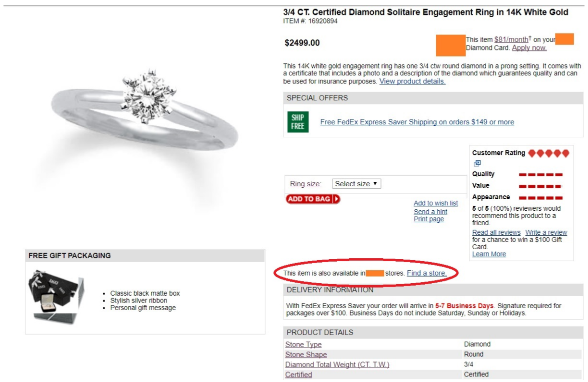
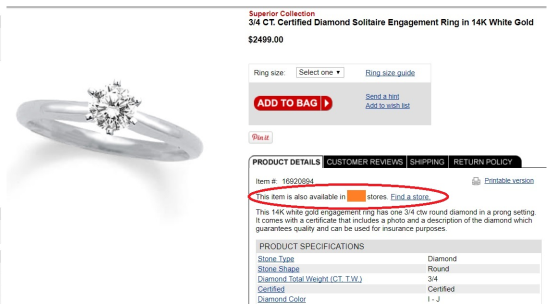



Figure 4: STS option during the checkout



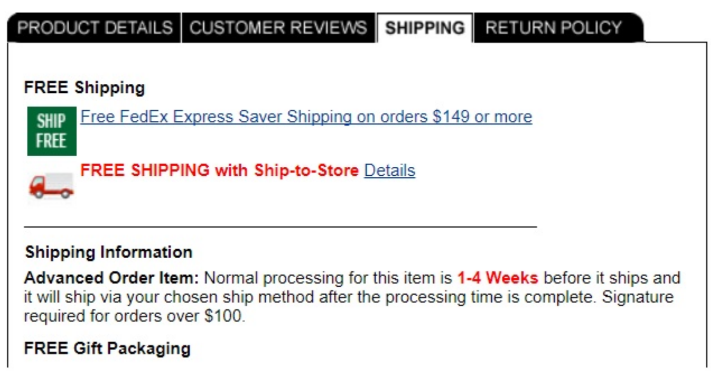

(a) Pre-STS implementation




(b) Post-STS implementation

Figure 5: BM store inventory availability information for online customers


(a) BM store inventory status




(b) Order shipping time

Figure 6: BM store inventory status and shipping times