Slow and Sure, or Fast and Furious? An Empirical Study about Omnichannel Demand Sensitivity to Fulfillment Lead Time

Stanley Frederick W.T. Lim

University of San Diego School of Business, San Diego, California, 92110, U.S.A.

stanleylim@sandiego.edu

Fei Gao

Kelley School of Business, Indiana University Bloomington, Bloomington, IN, 47405, U.S.A.

fg1@iu.edu

Tom Fangyun Tan

Cox Business School, Southern Methodist University, Dallas, Texas, 75275, U.S.A.

ttan@cox.smu.edu

Abstract

We examine a large transaction-level data set of an Italian omnichannel furniture retailer to study channel-specific effects of fulfillment lead time on demand. This omnichannel retailer sells the same products and has the same product fulfillment across three channels – showroom, online and catalog. A showroom channel carries no inventory but allows customers to touch and feel the products. An online channel provides a website for consumers to browse and order the products. A catalog channel sends a product catalog to all the households in Italy for them to place an order over the phone. We find that the showroom channel makes consumers less sensitive to fulfillment lead time than both online and catalog channels. In particular, a 10% increase in lead time (1.84 days from the sample mean of 18.35 days) causes a 0.85% reduction in the sales per order (~ EUR 7.6 from the sample mean of EUR 889.94) at the showroom, less than the reduction of 1.14% and 1.23% in the online and the catalog channels, respectively. This finding contradicts the common practical and theoretical assumption about homogeneous lead time sensitivity across channels. In addition, we find that niche products and experience goods accentuate the difference of lead time sensitivity between showroom and non-physical channels. We further develop a stylized model to study the implications of our empirical findings for the design of an omnichannel retailer's facility network. Given our finding that shows the showroom wait sensitivity is smaller than online wait sensitivity, retailers should build fewer but larger showrooms than the homogeneous wait sensitivity suggests.

Keywords: *omnichannel retailing, demand sensitivity to lead time, showrooms, online channel, catalog channel, facility network, empirical retail.*

1 Introduction

Over 12,000 brick-and-mortar retail stores were closed in the United States in 2018, including once formidable retailers like Sears and The Bon-Ton. The significant number of store closures may be attributed to the rise of e-commerce, the over-expansion of malls, and the shift in consumer preferences towards dining out over shopping. Such phenomenon is part of a global trend called "the retail apocalypse" (Peterson, 2018). To overcome this crisis and adapt to a new model, retailers have employed various omnichannel strategies. One effective strategy is the opening of showrooms. Similar to shopping at a traditional brick-and-mortar store, showroom customers can touch and feel the products, and consult expert store associates about the best fit. Online customers, however, cannot do that. Therefore, showrooms have been shown to increase demand overall, attract new customers, and decrease returns (Bell et al., 2017, 2019). Unlike the traditional physical store, showrooms carry no inventory, so customers either pick up the purchased products from the warehouse or wait for the order to be delivered. With little to no inventory retailers can have a smaller retail space and place showrooms in premium locations. Similar to virtual fitting and buy-online-pick-up-in-store (Gallino and Moreno, 2018; Gallino et al., 2017; Gao and Su, 2016; Akturk et al., 2018), showrooming has become part of the growing business models developing in an omnichannel retail era (Caro et al., 2020).

Previous research on the showroom channel has generally differentiated it from the online channel mainly in terms of information delivered and its impact on product returns and assortment (e.g., Bell et al. 2017; Gao and Su 2017b; Dzyabura and Jagabathula 2017). Few studies examine demand elasticity/sensitivity to fulfillment lead time[1] (a product fulfillment aspect). In fact, omnichannel research implicitly assumes that consumers have homogeneous preferences in product fulfillment across channels. That is to say, showroom demand is assumed to have the same elasticity/sensitivity to fulfillment lead time as the demand of other channels. None of the research has examined this important assumption, which is the basis of various omnichannel strategies, including the integration of supply chain network design and product fulfillment and distribution (Caro et al., 2020).

Our paper empirically studies the channel-specific effects of lead time on demand. We analyze 406,082 detailed order-level transactions from a leading national omnichannel furniture retailer in Italy, which operates three omnichannels – online, catalog, and showroom. We use a control function approach and Heckman selection modeling to address potential endogeneity due to unobserved customized order and channel selection bias. Our findings suggest that showrooms make customers less sensitive to lead time than either online or catalog channels. In particular, a 10% increase in lead time (1.84 days from the sample mean of 18.35 days) causes a 0.85% reduction in the sales per order (~ EUR 7.6 from the sample mean of EUR 889.94) at the showroom, less than the reduction of 1.14% and 1.23% in the online and the catalog channels, respec-

[1] In this paper, we use demand sensitivity to fulfillment lead time, and wait sensitivity or demand elasticity to order fulfillment time interchangeably.

tively. We do not find a statistically significant difference between online lead time sensitivity and catalog lead time sensitivity. These results are robust when we use propensity score matching to compare similar consumers and subsample analysis to compare the same products across channels. Furthermore, we study the moderating effects of product popularity and product uncertainty to support our proposed mechanisms. We then develop a stylized model to study the implications of our empirical findings for the design of an omnichannel retailer's facility network. Given that the wait sensitivity of showroom demand is less than the wait sensitivity of online demand, we show that the retailer should build fewer, but larger showrooms, than the homogeneous wait sensitivity suggests.

Our study makes three significant contributions. First, it examines an implicit and important assumption in the omnichannel retail literature; we present rigorous empirical evidence that consumers have lower sensitivity to lead time when shopping in the showroom than shopping online or through a catalog. This finding contradicts the common practical and theoretical assumption about homogeneous wait sensitivity across channels. Second, our research takes a preliminary step in answering the call by Caro et al. (2020) to complement the mainly empirical question about the value of physical stores with optimization-based prescriptions to determine optimal store network plans. We show that optimally designing the network can significantly reduce fulfillment costs. Third, our research highlights the previously-ignored fulfillment time sensitivity aspect of the physical store's value. The result is surprising, as people typically believe retailers should close more physical stores in the midst of "the retail apocalypse." We elaborate on our contributions to the related literature in the following section.

2 Literature Review

There is a growing body of literature on omnichannel retail operations, studying how a retailer should operate its online and offline channels in an integrated way (e.g., Rigby 2011; Brynjolfsson et al. 2013; Bell et al. 2014). Physical stores, which traditionally serve as a major selling channel, have gradually assumed new functions in an omnichannel environment (Gao and Su, 2019). One of the latest trends in the retail industry is to transform stores into showrooms, that is, physical locations with product displays but no inventory (Bell et al., 2018). In a showroom, customers can evaluate the product, but they do not receive the products there. Our paper focuses on the impact of the showroom channel on consumer shopping behavior.

The role of showrooms as a source of product information has been well studied. Bell et al. (2017) empirically demonstrate that a pure online retailer can benefit from the introduction of showrooms by reducing online product returns, because customers can visit the physical channel to touch and feel a product before purchase. Bell et al. (2019) further find that customers who have visited a showroom are likely to spend more, and shop more frequently, than those having only shopped online. As for a multi-channel retailer, however, Gao and Su (2017b) find that the implementation of a showroom strategy may backfire and lead to more product returns, due to the change of the retailer's inventory decisions. Dzyabura and Jagabathula (2017) incorporate the impact of physical evaluation on preferences into the consumer choice model and develop a heuristic algorithm to determine product assortment in the showroom channel. While previous work focuses on the effects of showrooms on sales, product returns and assortment, there is little research studying this new store format's impact on product fulfillment. Our paper fills this gap. Specifically, we empirically find that showroom customers tend to have a lower sensitivity towards fulfillment lead time compared to those who purchase online directly.

Product fulfillment has been identified as a critical operational decision for electronic retailing. Recent work empirically studies the impact of delivery speed on consumer demand. Fisher et al. (2019) collaborated with a U.S. apparel retailer and find that adding a distribution center to reduce fulfillment lead time leads to an increase in net profit. In a different setting, a Chinese online retail market, Cui et al. (2019) explore a natural experiment on Alibaba and show that the removal of a high-quality delivery option from the retail platform significantly reduces sales. Given customers' dislike of slow product delivery, the inconvenience of waiting has been incorporated in most demand models on "e-tailing". This stream of literature commonly assumes that consumers incur the same waiting cost for a product to be delivered, whether they shop online or offline (see e.g., Chen et al., 2008; Gao and Su, 2016, 2017b; Mehra et al., 2017). Our paper provides empirical evidence to directly challenge this assumption. Specifically, we find that consumers' sensitivity to fulfillment time when shopping online is greater than when shopping offline. Therefore, retailers should prioritize resources that reduce the lead time of online channels first.

Our paper also adds to the literature on the design of store networks in the retail industry. Cachon (2014) analyzes the impact of the layout of a retail supply chain on greenhouse gas emissions. Belavina (2019) studies the density of grocery stores and examines its effect on food waste generated at stores and households. Glaeser et al. (2019) develop an empirical method to determine when and where a retailer should operate its physical locations with the implementation of a buy-online-pick-up-in-store fulfillment strategy. Unlike these papers, we recommend showroom network strategies, which are increasingly important for omnichannel retail. Gao et al. (2018) analytically study retailers' decisions on the structure of the store network, including store density and size. However, they assume that consumers incur the same "hassle cost" (e.g., waiting cost for delivery) whether or not they have visited a showroom beforehand. Our empirical results test this assumption and find different waiting costs for delivery (i.e., demand sensitivity to lead time) across channels. We further build an analytical model to show the implications of our empirical results for the design of showroom networks. Provided the wait sensitivity of showroom demand is less than the wait sensitivity of online demand, we show that the retailer should build fewer, but larger showrooms, than the homogeneous wait sensitivity suggests.

3 Hypothesis Development

Our hypothesis development consists of three parts. First, we conjecture the strength order of the three channel-specific demand sensitivities to lead time (H1a and H1b). Second, we suggest the moderating effect of popular/niche products on the difference of demand sensitivity to lead time between showroom and other non-physical channels (H2). Finally, we propose the moderating role of experience/search goods in accentuating the gap of demand sensitivity to lead time between showroom and other non-physical channels (H3). We form H2 and H3 to explain the mechanism of the channel-specific lead time sensitivity.

3.1 Demand Sensitivities to Lead Time Across Sales Channels

Similar to price, lead time should be considered as a "time cost" for consumers. A longer lead time is associated with higher waiting costs for consumers, thus reducing their propensity of purchase. That is, the demand sensitivity to lead time should be negative. By contrast, a high expected value of the purchase should encourage purchase. Therefore, sales channels can affect the demand sensitivity to lead time through either the expected value derived from the purchase or the perceived cost in terms of lead time, controlling for everything else (e.g., price. return policy).

High expected value from a purchase is associated with low uncertainty of product quality or fit, especially for products with important non-digital attributes, such as apparel and furniture (Ofek et al., 2011). In other words, high product uncertainty creates strong impediments for consumers to adopt, try and purchase a product. This observation is supported by various empirical evidence. For example, Standifird (2001) shows that eBay sellers who provide extensive product descriptions, including pictures, help buyers reduce their uncertainty about a product's value, and increase their confidence of placing a bid with a higher bid amount. Consequently, those products having richer product descriptions received more bids and higher final bid amount. In addition, Kim and Krishnan (2015) and Gallino and Moreno (2018) conduct field studies showing that playing videos about products and providing a virtual fit technology, respectively, reduce product uncertainty and increase the probability of purchase. Similarly, both Musalem et al. (2019) and Lee et al. (2019) find that customers who use fitting rooms in an apparel store and consult store associates are more likely to make a purchase than those who do not. Furthermore, Bell et al. (2019) find after visiting a showroom, customers should purchase more and shop more frequently afterwards than those not having visited a showroom. Therefore, a sales channel that most effectively reduces the uncertainty about a product should create the highest expected value for a purchase.

High expected valuation of a purchase can also be achieved by the "endowment effect" (Kahneman et al., 1990). That is to say, people tend to assign more value to the products that they possess or they *feel* they own. For example, IKEA consumers are documented to have a higher valuation of the furniture when they assemble it themselves, which is referred to as the IKEA effect (Norton et al., 2012). If a sales channel can create a feeling of psychological ownership or high engagement of a product, such as a virtual fitting or home try-on, it may increase the expected value of the purchase (Bell et al., 2017).

Finally, low perceived cost regarding lead time may be managed by reducing anxiety during periods of waiting because anxiety makes waiting feel longer (Maister, 1984, pp. 4-5). Many practical examples suggest that reducing uncertainty about the product/service can reduce anxiety and make a waiting period appear to be shorter. For example, museums and theaters may show videos about the exhibition or the production to visitors waiting in line. Restaurant hosts provide menus and talk to customers waiting to be seated. Call centers announce expected waiting times (Yu et al., 2016). A sales channel that reduces product uncertainty should not only increase the expected value of the purchase but also reduce the anxiety of customers waiting for the products to arrive. Such customers would be more confident that their ordered product is likely to be an ideal fit compared to customers from other channels.

In our context, a showroom should maximize the expected value from the purchase because it reduces greater product uncertainty among the three sales channels. Furniture consumers generally acquire product information before purchasing from a sales channel. The showroom allows consumers to access multiple sources of information such as interacting with the sales employees on the floor and touching or feeling the products (even sitting on them). Online and catalog customers, however, have no such information for decision making. Therefore, showroom customers are more likely to have higher expected valuation of the purchase than either online or catalog customers. Furthermore, the showroom is more likely to create the "endowment effect" for its customers than the other two channels. Physically experiencing the furniture may evoke a feeling of ownership. Finally, the showroom should most effectively alleviate consumers' anxiety during their waiting period because it offers the richest product information of the three channels. Generally, a physical store traditionally differs from an online channel in terms of fulfillment. However, fulfillment is the same across channels in our omnichannel setting. Hence, controlling for everything else, we hypothesize that:

Hypothesis 1a: *Showroom sales are less sensitive to lead time than either online sales or catalog sales.*

The effectiveness of catalogs to provide product information is further limited by their size and number of pages (our partner retailer uses A5 page-size with an average of 150 pages per catalog). Moreover, unlike the typical online channel, catalogs usually do not provide consumer reviews as an additional source of information. Finally, searching for specific product information in a catalog is likely to be more difficult than online because the Internet browser, unlike the catalog, facilitates a quick search of any keyword on the screen.

Therefore, controlling for everything else, we further hypothesize that:

Hypothesis 1b: *Online sales are more sensitive to lead time than catalog sales.*

3.2 The Moderating Effect of Popular/Niche Products

The uncertainty of quality or fit varies from product to product. Popular products, defined as frequently sold items, have less uncertainty about their quality or fit than niche ones (infrequently sold item). Consumers learn about popular products from various sources, including word-of-mouth; more people are likely to know about popular products and talk about them as a social topic (Gu et al., 2013). Advertisements are another source for learning popular products, which typically have large advertising budgets. In other words, the relatively low search cost inherent in popular products significantly lowers the uncertainty about their quality. In addition, popular products tend to have mass appeal, further reducing the product fit uncertainty. However, niche products pose considerable uncertainty regarding their quality and fit for consumers. They do not have the same variety of information sources, such as word-of-mouth and advertisements, as that of popular products. They also attract a small niche segment of consumers, fueling the product fit uncertainty.

In sum, compared to popular products, niche products have greater uncertainty about quality and fit, which is a main mechanism of demand sensitivity to lead time across channels. We therefor conjecture:

Hypothesis 2 : *Niche products accentuate the difference of demand sensitivity to lead time between showroom and non-physical channels (i.e., online and catalog), compared to popular products.*

3.3 The Moderating Effect of Experience/Search Goods

Product uncertainty not only depends on popular/niche products, but also on experience/search goods. The product search process should significantly reduce product uncertainty for search goods, which require less effort in ascertaining their quality (Nelson, 1970; Hong and Pavlou, 2014). They generally have more digital attributes, such as technical facts, which can be readily found in any channel (Lal and Sarvary, 1999; Ofek et al., 2011). For example, a desk mainly has digital attributes, including its dimension, material, and its picture. This type of information can be equally effectively communicated in the online, catalog or showroom channels. By contrast, the uncertainty of product quality or fit remains high during search for experience goods, whose utility cannot be ascertained prior to experiencing it. Experience goods tend to have many non-digital attributes, such as the feeling of the texture, making it harder to assess either online or by catalog than at the showroom. For example, consumers typically do not know how comfortable a mattress feels until they actually sleep on it because people have idiosyncratic preferences for mattresses. A showroom experience is therefore more likely to reduce the uncertainty of experience goods like mattresses than both online and catalog channels.

Because product uncertainty is a major differentiating mechanism proposed in H1 for the channel-specific demand sensitivities to lead time, we posit:

Hypothesis 3: *Experience goods accentuate the gap of demand sensitivity to lead time between showroom and non-physical channels (i.e., online and catalog), compared to search goods.*

4 Data and Measures

4.1 Data Description

We collaborated with a large Italian furniture retailer for this study. This retailer updates its product assortment every three months, and sells the same product offerings across three channels – showroom, online, and catalog. First, in the 36 physical *showroom* stores, consumers can touch, feel, and try the products. They are also assisted by knowledgeable store associates with their purchases. Unlike in a traditional brick-and-mortar store, showroom customers cannot pick up their purchases immediately at the store because they do not inventory. Second, in the *online* store, consumers can browse and order the same product line on the web portal. Third, in the *catalog* channel, all of the households in Italy receive the catalog once every three months in their mail. They can speak with a representative by phone and place the order. For the fulfillment, the retailer does not offer ship-to-store option (Gallino et al., 2017; Akturk et al., 2018). Consumers across all the three channels have to place the order at the respective channel first, and either pick up the purchased item(s) from the warehouse or receive the delivery from the a sole third-party delivery company. In other words, all the three channels offer not only the same product offerings, but also the same order fulfillment methods. Specifically, we obtained detailed data of *all* of the 406,082 transactions across the three channels (showroom, online, and catalog) between January 1, 2015 and March 31, 2015, one entire catalog season. For each transaction, we observe the customer ID, transaction date and ID, the stock-keeping unit (SKU), the quantity (number of units) sold and the price. Each transaction also contains information about which of the three channels received the order, and the delivery mode (i.e. home delivery or warehouse pickup) chosen by the consumer.

Our data are ideal for us to study the channel-specific sensitivity to lead time for three main reasons. First, furniture is an important example of a non-digital product that has different levels of information uncertainty across the channels (Ofek et al., 2011). Second, similar to Brynjolfsson et al. (2011), our study period covers one entire catalog season (i.e. a quarter) to control for product offerings. Third, all three channels employ similar order fulfillment methods. In particular, all of the consumers can choose to have the products delivered or pick up their orders from a designated warehouse. Orders to these warehouses are assigned by the same centralized system. These data features account for the supply-side factors that may confound consumers' channel-specific sensitivity to order lead time. In other words, carrying no inventory at the physical store and having the same fulfillment across channels make our research setting "clean" to identify the channel-specific effect of information delivery on demand sensitivity to lead time.

Besides these transaction data, we collected demographic variables at the zip code level from the most recent Italian Census (2011) to control for consumer characteristics.[2] These covariates include *average age of household head*, *percentage with university degree*, *household size*, *percentage of home ownership*, and *status of residential building*. Finally, we excluded the instances that have no matching zip codes between the transaction data and the Census data (4% of the original data set). Our final sample contains 390,573

[2]Italian Institute of Statistics: http://www.istat.it.

observations (96% of the original full data set).

4.2 Variable Definitions

Approximately 77% of orders contain only one SKU. Similar to other work on omnichannel sales effect (e.g., Gallino and Moreno, 2018), we choose to conduct our analysis at the order level rather than at the SKU level. First, order-level analysis accounts for consumers' bundling decisions in one order. Second, the focal retailer does not split products in one order for delivery or customer pick-up. In other words, all of the items purchased in one order have the *same* fulfillment mode and the *same* lead time. Consumers cannot consider the lead time of each item independently. Rather, they consider order-level delivery time when making purchase decisions. Hence, we analyze the order-level lead time elasticity.

Table 1 presents the order-level variable definitions. On average, each order generates 889.94 euros, and takes 18.35 days to fulfill. Approximately 13% of the orders are picked up from the warehouse by customers. In addition, about 4% of the orders are later returned. Note that the zero fulfillment lead time does not mean that customers directly pick up the order from the showroom because the showroom has no inventory. Zero lead time means either same day warehouse pickup by the customer or same day delivery. In addition, the maximum lead time of 332 days is for specially customized items. As a robustness check, we limit our sample to those orders whose lead time is less than or equal to 60 days, and show that the results are consistent in Appendix A.

Table 2 further shows lead times, order sales and number of observations across the three channels, separately. The average lead time is 19.55 days in the showroom channel, compared to 9.09 and 9.42 days in the online and catalog channel, respectively. In addition, the average order sales is 939.27 euros in the showroom channel, higher than both 527.82 euros in the online channel and 527.98 in the catalog channel. In addition, the predominant sales channel is the showroom, which generates approximately 88.26% of total orders. This model-free evidence supports our hypothesis that consumers in the showroom channel may exhibit lower sensitivity to lead time. However, this evidence is only preliminary because it makes no attempt to control for other confounding factors, which could influence lead time. Moreover, it does not address potential endogeneity concerns that may bias our elasticity estimations. We elaborate on how we address these issues through our empirical modeling and identification strategy in Section 5.

Table 1: Variable Definition and Descriptive Statistics

Type	Variable	Description	Min	Max	Mean	Std. Dev.
Dependent Variable	Order Sales ($SALES_{ij}$)	Euro amount of order *i* placed by consumer *j*.	28.00	34,572.00	889.94	988.03
Independent Variables	Lead Time ($LEADTIME_{ij}$)	Fulfillment lead time (in days) for order *i* placed by consumer *j*. This variable measures the duration between order placed date and order received date by the consumer.	0.00†	332.00	18.35	22.59
	Channel ($CHANNEL_{ij}$)	A categorical variable indicating the channel where order *i* was placed by consumer *j*, o = Online, s = Showroom, and c = Catalog.				
Order-level Control ($\mathbf{X}_i$)	Return ($RETURN_i$)	An indicator of whether the order was returned (in full or partial), 1 = yes, and 0 otherwise.	0.00	1.00	0.04	0.19
To control for order characteristics, including fulfillment, product popularity, return, location and temporal factors.	Fulfillment Mode ($FULFILLMENTMODE_i$)	An indicator of whether the order was fulfilled to a warehouse for pick up (warehouse pickup) or to a zip code (home delivery), 1 = warehouse pick up, and 0 otherwise. Consumers can only choose one fulfillment mode regardless of number of items in an order.	0.00	1.00	0.13	0.33
	Store Age ($STOREAGE_i$)	Number of years the showroom store (where order was placed or nearest to the consumer's address) was in operation.	1.00	24.00	8.43	4.53
	Product Factor ($PRODUCT_i$)	Dummy variable, one for each of the 429 SKUs to control for time-invariant product attributes (e.g. size and color). For orders including multiple products, we control for the unique combination of these product fixed effects.				
	Week Factor ($WEEK_i$)	Dummy variable, one for each of the 13 weeks to control for temporal shocks or seasonality effects.				
Demographic Control ($\mathbf{W}_j$)	Average Age of Household Head	Average age (in years) of household head.	34.27	65.14	45.22	2.48
To control for household characteristics that may influence shopping activity.	University Degree	Percentage of population in the zip code with a university degree qualification.	0.01	0.37	0.71	0.07
	Household Size	Average number of members in household.	1.34	2.47	2.38	0.26
	Home Ownership	Percentage of home ownership in the zip code as opposed to being leased.	0.16	0.98	0.71	0.07
	Residential Building Status	Percentage of residential buildings in the zip code with excellence status.	0.00	0.29	0.01	0.01

† : Zero values reflect same-day delivery or pick up from the warehouse. Consumers cannot receive the purchase immediately at the store because showrooms carry no inventory.

Table 2: Channel-specific Descriptive Statistics of Key Variables

	Channel	Min	Max	Mean	Std. Dev
Lead Time (in days)	Online	0†	234	9.09	11.09
	Showroom	0	332	19.55	23.34
	Catalog	0	245	9.42	13.26
Order Sales (in euros)	Online	28	4,829	527.82	512.55
	Showroom	28	34,572	939.27	1,010.80
	Catalog	28	26,880	527.98	779.70
Number of Observations	Online	15,514 (3.97% of all orders)			
	Showroom	344,721 (88.26%)			
	Catalog	30,338 (7.77%)			
	Total	390,573			

† : Zero values reflect same-day delivery or pick up from the warehouse. Consumers cannot receive the purchase immediately at the store because showrooms carry no inventory.

5 Empirical Modeling and Identification

5.1 Log-log Sales Model

Our main objective is to test the hypothesis of whether or not consumers have channel-specific preferences in fulfillment lead time. We employ a log-log model, which is similar to estimating price elasticity of demand in the literature (e.g., Granados et al., 2012; Ito, 2014). In particular, we estimate the following specification:

$$\begin{aligned} \ln SALES_{ij} &= \beta_0 + \eta_0 \ln LEADTIME_{ij} + \gamma_k CHANNEL_{ij} + \\ &\quad \eta_k \ln LEADTIME_{ij} \times CHANNEL_{ij} + X_i\beta + \boldsymbol{W}_j\Theta + \varepsilon_{ij}. \end{aligned} \tag{1}$$

We specify channel $k = s$ (showroom) as our base for all model estimations. Hence, η_0 captures the lead time sensitivity (elasticity) of sales in the showroom channel, while $\eta_0 + \eta_o$ and $\eta_0 + \eta_c$ measure the lead time sensitivities of sales in the online channel and the catalog channel, respectively. These estimates should be negative, similar to negative price elasticity. In order to identify them, ideally we want to examine the same customers who purchase the same products across the three channels. In practice, few customers make repeated furniture purchases within three months, let alone purchasing the same products across the three channels. To overcome this identification challenge, we take a three-pronged approach. First, we include an extensive list of control variables of order-level characteristics ($\boldsymbol{X}$) and demographic characteristics ($\boldsymbol{W}$).

They are meant to adjust for the observable product-related and consumer-related confounding factors of sales. Note that we also include the SKU fixed effects to account for unobserved product heterogeneity in each order, which essentially allows us to compare the same product across channels. Second, we use a control function approach and a Heckman selection model to address customers self-selecting within the channels. Third, we conduct robustness checks by applying a propensity score matching technique of similar consumers and examining subsamples of same purchased products across all three channels. All of these robustness checks yield consistent results (see Subsections 6.4.1 and 6.4.2 for details). Moreover, in all of our analyses, we use cluster-robust standard errors at the consumer province (i.e. the province where the consumer resides) level for robust estimation.

5.2 Endogeneity and Control Function Approach

Model 1 is prone to a potential simultaneity bias between order sales and fulfillment lead time. Specifically, a high sales amount order may very well be associated with customization (e.g., purchasing a kitchen set). A customized order typically lengthens the fulfillment lead time, causing an upward bias of the lead time elasticity. Such factors as customization are unobservable to researchers in our data. To address this endogeneity issue due to the unobservables influencing both lead time and order sales, we adopt a control function approach (Wooldridge, 2015). The control function approach is similar to the two-stage least squares (2SLS) estimator for our linear models. It disintegrates the correlation between the endogenous explanatory variables (*LEADTIME,* and *LEADTIME*×*CHANNEL*) and unobservable factors affecting the outcome using instrumental variables (IVs) that do not appear in Model 1 (Wooldridge, 2015). Accordingly, we estimate the residuals, $\hat{v_1}$, $\hat{v_2}$, and $\hat{v_3}$, which represent any unobserved sales factors that are independent from the endogenous variables, from the first-stage equations specified as follows:

$$\begin{aligned} \ln LEADTIME_{ij} &= z_1\pi_1 + v_1 \\ \ln LEADTIME_{ij} \times CHANNEL_{ij} &= z_2\pi_2 + v_2, \quad CHANNEL = o \\ \ln LEADTIME_{ij} \times CHANNEL_{ij} &= z_3\pi_3 + v_3 \quad CHANNEL = c. \end{aligned} \tag{2}$$

In these models, z_1, z_2, and z_3 include all control variables (***X, W***) and four IVs. The four IVs are:

1. The number of warehouses located in consumer's region per square kilometer (*WAREHOUSE*, mean

= 0.001, SD = 0.0004);

2. Weekly average lead time of the same products at other channels (*OTHERLEADTIME*, mean = 18.35, SD = 2.68);

3. Distance (in miles) between the warehouse assigned to fulfill the order [3] and the consumer (*DIST_WC*, mean = 23.14, SD = 26.65); and

4. Distance (in miles) between the warehouse assigned to fulfill the order and the showroom nearest to the consumer (*DIST_WS*, mean = 13.78, SD = 19.82).

Are these IVs valid? First, our instruments should be individually correlated with the lead time variable (aka relevance condition) because: (1) a higher number of warehouses within a consumer's region (*WAREHOUSE*) increases product availability and therefore reduces overall lead time; (2) lead times at other channels (*OTHERLEADTIME*) may correlate with the lead times for the focal channel due to shared logistical capabilities and resources, such as trucks and movers; (3) a shorter distance between warehouse and consumer (*DIST_WC*) reduces the lead time for delivery due to proximity; and (4) a shorter distance between warehouse and showroom (*DIST_WS*) increases the likelihood of same-day pick-up for products available in the warehouse, thus reducing lead time. In addition, the average correlation between our set of four IVs and *LEADTIME* is 0.44, while the average correlation between four IVs $\times$ *CHANNEL* and *LEADTIME* $\times$*CHANNEL* is 0.31 (p-values are both < 0.001). We also show first stage results to support the relevance condition in Subsection 6.2.

The second criterion of a valid instrument is exclusion restriction condition, which states that the IVs should affect the sales only through the endogenous variables (i.e., lead time). We argue that our IVs should satisfy this condition because customers cannot and will not use the information about warehouse to make the purchase decisions. First, customers typically do not know the quantity of warehouses in the region or about the lead time of the same products in other channels. Second, the existence of a warehouse cannot alleviate product uncertainty and is only for product fulfillment. It therefore should not affect purchase decisions other than through fulfillment lead time. We also conduct Hansen-Sargan over-identification test in Subsection 6.2 to support the exclusion restriction aspect of our IV validity (Angrist and Pischke, 2008).

[3] Only one warehouse is assigned to fulfill one customer's order. If an item in an multi-item order is unavailable at the assigned warehouse, a nearby warehouse with the available item will route the item to the assigned warehouse.

After the first stage, we include the estimated residuals, $\hat{v_1}$, $\hat{v_2}$, and $\hat{v_3}$ (equation 2), as correction terms into our second-stage equation defined as:

$$\begin{aligned}\ln SALES_{ij} \quad = \quad & \beta_0 + \eta_0 \ln LEADTIME_{ij} + \gamma_k CHANNEL_{ij} + \eta_k \ln LEADTIME_{ij} \times CHANNEL_{ij} + \\ & X_i\beta + \boldsymbol{W}_j\Theta + \rho_1\hat{v_1} + \rho_2\hat{v_2} + \rho_3\hat{v_3} + \varepsilon_{ij}, \end{aligned} \tag{3}$$

and apply bootstrapping 100 times to obtain the robust standard errors (Mooney et al., 1993).

5.3 Channel Selection and Heckman Selection Model

Although we use an extensive list of demographic control variables and incorporate the control function approach in our main model (Model 3), we may still be prone to a channel-selection bias. That is, if all of the lead time-insensitive consumers choose to shop at the showroom as opposed to the other two channels, they will artificially inflate our estimation coefficient. To alleviate this channel-selection bias, we adopt a Heckman selection model method (Heckman, 1976, 1979). In addition, we apply a propensity score-matching algorithm to ensure comparable customers across the channels as a robustness check in Subsection 6.4.1. For the Heckman model, we follow Lee's generalized approach (Lee, 1983), and obtain the channel-specific correction term ratio (λ) from a first-stage multinomial Logit model of channel selection. The model is specified as $Pr(CHANNEL_{ij} = k) = exp(\mathbf{X}_{2ijk}\beta_2)/\sum_{m=1}^{K} exp(\mathbf{X}_{2ijm}\beta_2)$, where $k = o$, s and c, and $\mathbf{X}_{2ij}$ and β_2 denote the vector of variables in the selection model and their corresponding coefficients, respectively. These variables include: average product price (in EUR) in order i placed by consumer j, an indicator of whether or not consumer j is a high spender (his/her total expenditures of all transactions greater than sample median, EUR 718); distance between consumer j and the nearest showroom store;, demographic controls $\mathbf{W}_j$ same as in Table 1; and week factors $WEEK_i$. Let $F()$ be the logistic distribution function, $F(\mathbf{X}_{2ij}\beta_2)$ the predicted probabilities of each channel given $\mathbf{X}_{2ij}\beta_2$, and the transformation $J = \Phi^{-1}F$. We then compute the correction term ratio via:

$$\hat{\lambda_{ij}} = \lambda(\mathbf{X}_{2ij}\hat{\beta}_2) = \frac{\phi(J(\mathbf{X}_{2ij}\hat{\beta}_2))}{F(\mathbf{X}_{2ij}\hat{\beta}_2)}, \tag{4}$$

where $\phi(.)$ is the probability density function of a standard normal. In the second stage, we bring the computed ratio into Model 3 as an additional control variable of consumers' channel selection decision. The ratio, like the inverse mills ratio in the traditional Heckman selection model, is prone to collinearity, which may lead to incorrect standard errors in the second stage (Leung and Yu, 1996). To circumvent this problem, we impose an exclusion restriction in the second-stage equation to increase the variation in λ. Specifically, we include the same four instruments (*WAREHOUSE*, *OTHERLEAD*TIME, *DIST_WC*, and *DIST_WS*) as used in our control function approach in the first-stage selection model.

6 Empirical Results

6.1 Lead Time Elasticity

Table 3 shows the results of lead time elasticity across channels. Column 1 shows the OLS estimation results of Model 1. Then, we provide control function estimations of Model 3 in Columns 2 and 3. In Column 2, we exclude the week and product fixed-effects, and add them in Column 3 to show the transparency of our estimation results. Finally, we present the full model results using both our Heckman selection modeling approach and the control function approach in Column 4. The OLS coefficient of ln(*LEADTIME*) is significant and positive (0.188), which would erroneously suggest that longer lead time cause higher sales. However, this endogenous overestimation is corrected downwards by the control function approach. The coefficients are significant and negative in Columns 2 through 4 (-0.182, -0.188, -0.085). We interpret the coefficients from Column 4 because it addresses both the endogeneity and the channel selection biases, and because it has the higher adjusted R^2 (0.656). For every 10% increase in lead time (1.84 days from the sample mean of 18.35 days), the sales per order at the showroom is expected to decrease by 0.85% ($\sim$ EUR 7.6 from the sample mean of EUR 889.94). This effect size is not only statistically significant, but also economically relevant. It is comparable to the estimate reported in Fisher et al. (2019), which finds that reducing delivery time by one day from a baseline of seven days (14.28% reduction) increases sales by 1.45% for an apparel retailer. In addition, the coefficients of the interaction terms with the other two channels are consistently significant and negative (-0.029 and -0.038 in Column 4). The negative interactions terms suggest that the showroom channel sales are more lead time *inelastic* than either the online channel sales or catalog channel sales. This result supports H1a. In other words, consumers are less sensitive to lead time when shopping at a showroom than when shopping at either of the other two channels. The showroom channel effectively reduces the uncertainty of product fit and quality, increasing the expected valuation of the purchase and reducing the perceived cost of lead time. The showroom also gives consumers a chance to experience the furniture, likely producing an "endowment effect," which further increases the expected value of the purchase. Moreover, the lead time elasticity of the online channel ($-0.085 - 0.029 = -0.114$) turns out to be statistically indifferent from that of the catalog channel ($-0.085 - 0.038 = -0.123$). Therefore, we find insufficient support for our H1b. Although the page size in a catalog limits the product information presentation, catalog sales representatives on the phone tend to be knowledgeable about the products. These two competing effects may mitigate the difference in information uncertainty between the online channel and the catalog channel.

Table 3: Lead Time Elasticity

Variable	(1) Model 1 Estimated by OLS	(2) Model 3 Estimated by Control Function	(3) Model 3 Estimated by Control Function	(4) Model 3 Estimated by Heckman + Control Function
ln*LEADTIME*	0.188*** (0.006)	-0.182*** (0.009)	-0.188*** (0.009)	-0.085*** (0.006)
ONLINE	-0.258*** (0.020)	-0.349*** (0.022)	-0.275*** (0.018)	-0.100*** (0.013)
CATALOG	-0.262*** (0.022)	-0.391*** (0.028)	-0.269*** (0.023)	-0.155*** (0.018)
ONLINE ×ln(*LEADTIME*)	-0.049*** (0.012)	-0.028* (0.012)	-0.052*** (0.012)	-0.029*** (0.0067)
CATALOG ×ln(*LEADTIME*)	-0.060*** (0.013)	-0.041* (0.015)	-0.064*** (0.013)	-0.038** (0.010)
Control variables				
RETURN	-0.018 (0.017)	0.021 (0.025)	-0.260* (0.100)	-0.217** (0.066)
FULFILLMENTMODE	-0.318*** (0.027)	0.2835*** (0.050)	-4.694* (1.759)	-2.860* (1.173)
STOREAGE	-0.003 (0.002)	-0.006** (0.002)	-0.003 (0.004)	-0.003 (0.002)
ABC = B	0.032** (0.009)	0.029* (0.011)	-0.097 (0.0942)	-0.077 (0.056)
ABC = C	0.058** 0.017)	0.145*** (0.011)	-1.111* (0.517)	-0.700 (0.0342)
RESIDUAL1		0.780*** (0.024)	-5.655* (2.220)	-3.423* (1.489)
RESIDUAL2		-0.3780*** (0.026)	-0.438 (0.636)	0.279 (0.353)
RESIDUAL3		-0.139*** (0.033)	3.382** (0.946)	2.034*** (0.672)
$\hat{\lambda}_{ij}$				3.178*** (0.019)
Demographic Controls	Yes	Yes	Yes	Yes
Week Effects	Yes	No	Yes	Yes
Product Effects	Yes	No	Yes	Yes
No. of observations	390,573	390,573	390,573	390,573
Adj. R^2	0.367	0.157	0.369	0.656

Notes. Cluster robust standard errors are reported in parentheses.
** $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.*

6.2 Validity of Instruments

The results in Table 3 suggest that the instruments manage to correct the endogenous variables (i.e., channel-specific lead time elasticities) from being positive to negative, in the expected direction. Correcting the bias in the expected direction supports our IV design as argued in Subsection 5.2. To provide a firmer assurance of the validity of our instruments, we examine additional statistical tests of relevance and exclusion restriction conditions.

Table 4 shows the first-stage estimation for $\ln LEADTIME_{ij}$. As can be seen, all of the coefficients of the instruments are significant and have the expected signs. For example, the more warehouse in the customer's region, the shorter the lead time, which is consistent with the negative sign of *WAREHOUSE* (-0.005). In addition, Angrist-Pischke multivariate F-test of excluded instruments is 2,614.23, well above 10, a rule of thumb for weak instruments. These results alleviate the weak instrument concern and support the relevance condition (Angrist and Pischke, 2008; Staiger and Stock, 1994). To check the exclusion restriction condition, we conduct a Hansen-Sargan over-identifying restriction test (Hansen, 1982). The Sargan statistic is distributed as χ^2 with degrees of freedom equal to the number of exclusion restrictions less the number of endogenous variables. We find $\chi^2_{(1)} = 6.202$ which is less than the critical value of 7.815 at 0.05 significance level. We therefore fail to reject the null hypothesis that the error term of the second-stage model is uncorrelated with the instrumental variables.

Table 4: First-stage Regression Estimates

Variable	First-stage
WAREHOUSE	-5.532* (2.779)
ln*OTHERLEADTIME*	0.950*** (0.001)
DIST_WC	0.056*** (0.005)
DIST_WS	0.023* (0.010)
Control variables	
RETURN	-0.058*** (0.012)
FULFILLMENTMODE	-1.072*** (0.003)
STOREAGE	-0.000* (0.000)
ABC = B	-0.044*** (0.008)
ABC = C	-0.082*** (0.013)
Demographic Controls	Yes
Week Effects	Yes
Product Effects	Yes
F-Statistic	2,614.23
No. of observations	390,573
Adj. R^2	0.752

Notes. Cluster robust standard errors are reported in parentheses.
** p < 0.05, ** p < 0.01, *** p < 0.001.*

6.3 Moderating Effects of Popular/Niche Products and Experience/Search Goods

To test the hypotheses of the two moderating effects, we employ the following regression models:

$$\begin{aligned}
\ln SALES_{ij} \quad = \quad & \beta_0 + \eta_0 \ln LEADTIME_{ij} + \gamma_l CHANNEL_i + \\
& \eta_l \ln LEADTIME_{ij} \times CHANNEL_i + \Pi_{1,m} MODERATOR_i + \Pi_{2,m} MODERATOR_i \times \ln LEADTIME_{ij} + \\
& \Pi_{3,m} MODERATOR_i \times CHANNEL_i + \Pi_{4,m} MODERATOR_i \times \ln LEADTIME_{ij} \times CHANNEL_i + \\
& X_{\mathbf{ij}}\beta + W_i\Theta + \rho_1 \hat{v_1} + \rho_2 \hat{v_2} + \rho_3 \hat{v_3} + \varepsilon_{c,ij}. \qquad (5)
\end{aligned}$$

In these models, we replace *MODERATOR* with *ABC* and *EXPERIENTIAL,* respectively. Categorical variable *ABC* is used to measure product popularity. To operationalize this variable, we set A = Class A (top 20% of SKUs that account for 70% of total sales), B = Class B (30% of SKUs that account for 25% of sales), and C = Class C (50% of SKUs that account for 5% of sales) (Silver et al., 1998). For orders with multiple SKUs, we compute the weighted average value based on each SKU's contribution to the total order sales amount. Class A has a value of 1, Class B a value of 2, and Class C a value of 3. Then, an order with a weighted average value closest to 1 is assigned as Class A, closest to 2 as Class B, and closest to 3 as Class C. We set ABC = A as the base in this regression model.

Furthermore, we define binary variable *EXPERIENTIAL* = 1 for those product categories whose quality/fit is largely unknown until a customer experiences it by touching and feeling. In particular, we follow a rater's approach by Hong and Pavlou (2014) and ask two independent assistants to rate each product category by three criteria of experiential goods on a scale between 1 (pure search good) and 7 (pure experiential goods)[4]. We average the ratings of the three dimensions for each product category and classify it as experiential (i.e., *EXPERIENTIAL* = 1) if the average value is ≥ 3.5, and non-experiential, otherwise. The Cohen Kappa coefficient shows a high inter-rater reliability score of 0.811, suggesting high consistency between the two raters (Cohen, 1960). For those orders having more than one item, we use the same weighted average approach to measure this variable as we define variable *ABC*. In the end, we code product categories of bed, couch and sofa, mattress, chair, and wardrobe as experiential products. Examples of non-experiential product categories include mirror, bookcase, and bedside table.

[4]We provide the following texts and the three criteria of experiential goods to each of our two raters: "For a product, an experience attribute cannot be ascertained before purchase, while a search attribute can be ascertained before purchase. The more experience attribute a product has, the harder it is for you to evaluate it before purchase. Based on your understanding, please answer the following questions: (1) It is important for me to see/touch/hear (whichever applies) this product to evaluate its attributes (1-7); (2) I can adequately evaluate this product using only information provided by the retailer or manufacturer about this product's attributes and features (1-7); and (3) I can evaluate the quality of this product simply by reading information about the product (1-7)" (Hong and Pavlou, 2014).

Table 5: Moderating Effects of Popular/Niche Products and Experience/Search Goods

(a) Moderating effect of Popular/Niche Products

Variable	ABC
ln*LEADTIME*	-0.176** (0.008)
ONLINE	-0.333** (0.024)
CATALOG	-0.313*** (0.014)
ONLINE ×ln*LEADTIME*	-0.029* (0.012)
CATALOG ×ln*LEADTIME*	-0.054*** (0.010)
B	-0.093 (0.060)
C	-0.755* (0.323)
B ×ln*LEADTIME*	0.003 (0.003)
C ×ln*LEADTIME*	-0.009* (0.004)
B ×*ONLINE*	0.172** (0.051)
C ×*ONLINE*	0.227*** (0.046)
B ×*CATALOG*	0.171*** (0.040)
C ×*CATALOG*	0.146*** (0.026)
B ×ln*LEADTIME* ×*ONLINE*	-0.041 (0.025)
C ×ln*LEADTIME* ×*ONLINE*	-0.061* (0.025)
B ×ln*LEADTIME* ×*CATALOG*	-0.036** (0.012)
C ×ln*LEADTIME* ×*CATALOG*	-0.030* (0.014)
Control variables	
RETURN	-0.171** (0.059)
FULFILLMENTMODE	-3.227** (1.062)
STOREAGE	-0.000 (0.003)
RESIDUAL1	-3.771* (1.325)
RESIDUAL2	0.022(0.454)
RESIDUAL3	2.523*** (0.523)
Demographic Controls	Yes
Week Effects	Yes
Product Effects	Yes
No. of observations	390,573
Adj. R^2	0.378

Notes. Cluster robust standard errors are reported in parentheses.
** p < 0.05, ** p < 0.01, *** p < 0.001.*

(b) Moderating Effects of Experience/Search Goods

Variable	Experiential
ln*LEADTIME*	-0.202*** (0.008)
ONLINE	-0.311*** (0.023)
CATALOG	-0.343*** (0.034)
ONLINE ×ln*LEADTIME*	-0.034* (0.017)
CATALOG ×ln*LEADTIME*	-0.044* (0.019)
EXPERIENTIAL	0.619*** (0.067)
EXPERIENTIAL ×ln*LEADTIME*	-0.021** (0.006)
EXPERIENTIAL×*ONLINE*	0.0451 (0.030)
EXPERIENTIAL ×*CATALOG*	0.104*** (0.023)
EXPERIENTIAL ×ln*LEADTIME* ×*ONLINE*	-0.018 (0.019)
EXPERIENTIAL ×ln*LEADTIME* ×*CATALOG*	-0.020* (0.010)
Control variables	
RETURN	-0.033 (0.017)
FULFILLMENTMODE	-0.852*** (0.090)
STOREAGE	-0.003* (0.001)
RESIDUAL1	-0.790*** (0.138)
RESIDUAL2	-0.802*** (0.164)
RESIDUAL3	1.320*** (0.240)
Demographic Controls	*Yes*
Week Effects	*Yes*
Product Effects	*Yes*
No. of observations	390.573
Adj. R^2	0.369

Notes. Cluster robust standard errors are reported in parentheses.
** p < 0.05, ** p < 0.01, *** p < 0.001.*

Table 5a presents the results of the moderating effect of popular/niche products. The coefficients of the interaction terms of Class C with channel-specific lead time elasticity are significant and negative (-0.061 and -0.03). The negative signs suggest that consumers are less sensitive to lead time when purchasing niche products in the showroom than in either the online or catalog channel. This result supports our H2. The extra product uncertainty about niche products allows the showroom to more effectively moderates the negative sales effect of lead time than both online and catalog channels. In addition, the coefficients of the interaction term of Class B with the catalog channel is also significant and negative (-0.036), consistent with our hypothesis. However, the interaction term with the online channel turns out to be insignificant (-0.041), probably because: (1) the information uncertainty gap between Class A and Class B is smaller than that between Class A and Class C, and (2) the catalog channel with its page size limitations is probably even less effective in reducing information uncertainty than the online channel. In addition, the coefficients of channel-specific lead time elasticity are both significant and negative (-0.029 and -0.054), which are congruent with our main results in Table 3.

Table 5b shows the results of the moderating effect of experience/search goods. The coefficient of the experiential product interaction term with the catalog channel lead time elasticity is significant and negative (-0.02), supporting our H3. Consumers are more sensitive to lead time when purchasing an experiential product from the catalog than at the showroom because experiential products require more touch and feel than non-experiential ones. The coefficient of the interaction term with the online channel lead time elasticity (-0.018) turns out to be insignificant, likely because the catalog channel is even more restrictive than the online channel in reducing the information uncertainty of experiential products. Furthermore, the coefficients of channel-specific lead time elasticity are both significant and negative (-0.034 and -0.044), which are again consistent with our main results.

6.4 Robustness Checks

6.4.1 Propensity Score Matching

In addition to the extensive list of demographic control variables and the Heckman selection model, we apply propensity score matching to ensure the three channels have comparable consumers matched on a set of observables (Rosenbaum and Rubin, 1983; Bell et al., 2019). In particular, we use our full set of zip code level demographic variables (i.e., *Average Age of Household Head, University Degree, Household Size, Home Ownership, Residential Building Status*) as the matching covariates. Unlike the conventional matching between two groups (control vs. treatment), our setting has three channels. Since the large sample properties for propensity score matching are still preliminary for matching more than two groups (Abadie and Imbens, 2006), we implement pair-wise channel matching and comparison. That is, we estimate Model 3 of two different channels at a time, and repeat for three unique pairs.

Table 6a shows the results. The three columns present the results of the comparisons between showroom and online, showroom and catalog, and online and catalog, respectively. The coefficients of $\ln LEADTIME$ are all significant and negative (-0.076, -0.082, and -0.065). They are consistent with our main results that suggest lead time inhibits order sales in the showroom and the online channels. In addition, the coefficients of the interaction terms are all significant and negative (-0.025, -0.024, -0.093) They also support our main finding that the showroom makes consumers the least sensitive to lead time, followed by online and catalog channels. We further verify that our matching procedure properly balance our data by following Guo and Fraser (2014) to carry out the validation procedure detailed in Part B of the appendix.

6.4.2 Subsample Analysis

Products purchased in the showroom may be distinct from those purchased in the other two channels. These possibilities may create an alternative explanation of our results, which would be unrelated to channel environment. In the main analysis, we address this concern by explicitly including *Product Effects* (product SKU fixed effects). As a robustness check, we use the same control function approach to conduct a subsample analysis. We limit our sample to a set of common products purchased across the three channels, which total 204 SKUs. In essence, we control for the same products that consumers purchase from different channels.

Table 6b shows the subsample analysis results. All of the coefficients of lead time elasticity ($-0.194, -0.055, -0.069$) have the same signs as our main results in Table 3, supporting our finding that the showroom channel will make consumers less sensitive to lead time than both online and catalog channels.

Table 6: Robustness Checks

(a) Propensity Score Matching

Variable	(1) Showroom vs. Online	(2) Showroom vs. Catalog	(3) Online vs. Catalog
ln*LEADTIME*	-0.076***	-0.082***	-0.065***
	(0.008)	(0.006)	(0.008)
CHANNEL = o and s	-0.180***		
	(0.023)		
CHANNEL = s and c		-0.3404***	
		(0.018)	
CHANNEL = o and c			-0.025 (0.014)
CHANNEL = o and s	-0.025**		
×ln*LEADTIME*	(0.009)		
CHANNEL = s and c		-0.024***	
×ln*LEADTIME*		(0.007)	
CHANNEL = o and c			-0.093***
×ln*LEADTIME*			(0.006)
Control variables			
RETURN	0.050 (0.049)	0.005 (0.034)	-0.021 (0.0353)
FULFILLMENTMODE	-0.057 (0.184)	-1.510***	-1.339***
		(0.146)	(0.141)
STOREAGE	-0.000 (0.001)	0.004***	-0.000 (0.001)
		(0.001)	
ABC = B	0.125***	-0.011 (0.016)	0.155***
	(0.026)		(0.019)
ABC = C	0.141* (0.071)	-0.7342***	-0.006 (0.049)
		(0.045)	
RESIDUAL1	0.264 (0.222)	-1.626***	-1.460***
		(0.188)	(0.184)
RESIDUAL2	-0.136 (0.153)		
RESIDUAL3		1.125***	0.930***
		(0.126)	(0.123)
Demographic Controls	Yes	Yes	Yes
Week Effects	Yes	Yes	Yes
Product Effects	Yes	Yes	Yes
No. of observations	15,514	30,338	15,514
Adj. R^2	0.567	0.531	0.498

Notes. Cluster robust standard errors are reported in parentheses.

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

(b) Subsample Analysis

Variable	Common Products
ln*LEADTIME*	-0.194***
	(0.010)
ONLINE	-0.228***
	(0.028)
CATALOG	-0.226***
	(0.021)
ONLINE	-0.055**
×ln*LEADTIME*	(0.016)
CATALOG	-0.069***
×ln*LEADTIME*	(0.012)
Control variables	
RETURN	-0.199* (0.090)
FULFILLMENTMODE	-3.878* (1.627)
STOREAGE	-0.002 (0.003)
ABC = B	-0.059 (0.087)
ABC = C	-0.888 (0.480)
RESIDUAL1	-4.731* (2.054)
RESIDUAL2	0.272 (0.592)
RESIDUAL3	2.921**
	(0.882)
Demographic Controls	Yes
Week Effects	Yes
Product Effects	Yes
No. of observations	188,864
Adj. R^2	0.433

Notes. Cluster robust standard errors are reported in parentheses.

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

7 Showroom Network Design

Given the increasing popularity of the omnichannel strategy, Caro et al. (2020) recently call for analytical models to complement empirical research to determine optimal store network plans in such a new retailing environment. We intend to answer this call in this section. Specifically, our goal is to study how an omnichannel retailer should design its showroom network, given our empirical findings presented.

The availability of touch-and-feel experience has been touted as one of the key advantages of physical stores compared to their online counterparts (Gao and Su, 2017b; Gao et al., 2018). Our empirical analysis discovers a new impact of the physical channel on customers' preference for lead time. Specifically, showrooms make customers less sensitive to lead time than both online and catalog channels, two alternative channels in the virtual world. How should omnichannel retailers change their operational decisions given this new insight? We focus on one specific operational decision – designing the network of showrooms which have gained increasing popularity in today's retail industry (Bell et al., 2018). Previous showroom network design models typically do not consider the channel-specific lead time elasticity of sales. Our empirical results find each channel has its idiosyncratic effect on lead time preferences, thus the same lead time preferences across channels may not realize the full potential of analytical models. Hence, in this section, we develop a stylized model that incorporates our empirical findings to study its implications for showroom network design. Of course, analyzing a sophisticated full-blown showroom network design model requires a full paper. Our paper uses some assumptions to build a relatively simple and yet insightful model to demonstrate the potential value of the channel-specific sales effect of lead time.

We build the model based on the framework proposed by Gao et al. (2018). A retailer sells products through an online channel[5] and also operates showrooms (physical stores without any inventory) in a city area. A city area is modeled as a circle of unit circumference with customers uniformly distributed upon it (Salop, 1979). Assume that the retailer can offer an entire set of distinct products, denoted by I, in the online channel. The retailer needs to determine the number of showrooms n, and what products $I_s \subseteq I$ to display in these showrooms. For simplicity, we consider a symmetric case where the n showrooms are evenly located on the circle, and each showroom carries the same set of products $I_s \subseteq I$. Accordingly, $|I_s|$ can be interpreted as the showroom size, where $|\cdot|$ denotes the cardinality of a set.

[5] We do not distinguish between online and catalog channels in the analytical model for two reasons. First, customers largely face similar tradeoffs in these channels (i.e., they can easily place an order but they cannot physically check the product before purchase.). Second, our empirical results find no significant difference between customer wait sensitivity in both online and catalog channels.

A customer is interested in only one specific product. This assumption should be reasonable in our empirical context because the majority of orders (approximately 77%) contain only one SKU. We label the customers interested in product $i \in I$ as class-i customers. The size of customer class i is $d_i > 0$. Customer valuations are ex-ante uncertain. Specifically, with probability $\gamma \in (0,1)$, a class-i customer dislikes the product and has zero value. With probability $1-\gamma$, the customer likes the product and has a positive value v_i. Customers can learn their valuations before purchase only if they inspect the product in a showroom; otherwise, customers learn valuations after purchase.

Suppose a class-i customer purchases product $i \in I$ online without visiting a showroom. She will first incur a waiting cost $w_o\tau$ for online delivery, where w_o is the wait sensitivity (i.e., lead time elasticity) and τ is the fulfillment lead time. Once the customer receives the product, she can realize her valuation. Specifically, if she likes the product (which happens with probability $1-\gamma$), she keeps it and obtains a payoff $v_i - p_i$, where p_i is the product price; if she dislikes the product (which happens with probability γ), she returns it to the retailer and incurs a return hassle cost denoted by h_r. Therefore, the customer's expected utility from purchasing product i directly through the online channel is given by

$$u_{i,o} = -w_o\tau + (1-\gamma)(v_i - p_i) - \gamma \cdot h_r \tag{6}$$

For product $i \in I_s$ displayed in the showrooms, a class-i customer can also choose to first visit the showroom to evaluate the product. As a result, with probability $1-\gamma$, she likes the product and then makes a purchase. In this case, she still needs to incur some waiting cost $w_s\tau$ for fulfillment, where w_s is showroomers' wait sensitivity. Note that the fulfillment lead time continues to be τ since both showrooms and online channels have the same fulfillment method. With probability γ, the customer does not like the product and decides not to purchase it. In either case, customers have to incur a travel cost tx to visit the showroom (x denotes the distance between a customer's location on the circular city and her nearest store, and t the unit travel cost), but it allows them to avoid the return hassle cost. Accordingly, customer's expected utility from visiting a showroom is given by

$$u_{i,s}(x) = (1-\gamma)(v_i - p_i - w_s\tau) - tx \text{ for } i \in I_s. \tag{7}$$

In the spirit of omnichannel choice, consumers are willing to consider both channels, thus we assume v_i

is large enough so that $u_{i,o} \geq 0$ and $u_{i,s}(0) \geq 0$. On the one hand, for products not offered in the showrooms ($i \notin I_s$), all class-i customers will buy the product directly through the online channel, and thus the total demand for the online channel for product i is d_i. On the other hand, for a product displayed in showrooms ($i \in I_s$), customers will decide whether to visit the showroom or not by comparing their expected utilities given in (6) and (7). It is straightforward to find that a class-i customer will choose to visit a showroom store as opposed to buying the product directly online, if and only if $u_{i,s}(x) \geq u_{i,o}$ or equivalently $x \leq \frac{w_o\tau-(1-\gamma)w_s\tau+\gamma h_r}{t}$. Denote the demand from customers who purchase a product directly online and the number of customers who visit showrooms as $d_{i,o}$ and $d_{i,s}$ respectively. In particular,

$d_{i,o} = d_i$ and $d_{i,s} = 0$ for $i \notin I_s$;

$d_{i,o} = d_i - 2\min\left\{\dfrac{w_o\tau-(1-\gamma)w_s\tau+\gamma h_r}{t}, \dfrac{1}{2n}\right\} nd_i$ for $i \in I_s$;

$d_{i,s} = 2\min\left\{\dfrac{w_o\tau-(1-\gamma)w_s\tau+\gamma h_r}{t}, \dfrac{1}{2n}\right\} nd_i$ for $i \in I_s$.

In the showroom channel, on average a total of $(1-\gamma)d_{i,s}$ units of product i will be sold with no returns, because a customer only purchases the product if she likes it, which occurs with probability $1-\gamma$. In contrast, for products purchased by customers online (i.e. $d_{i,o}$), on average $(1-\gamma)d_{i,o}$ units will be eventually kept by the customers and $\gamma \cdot d_{i,o}$ units will be returned to the retailer. The total sales of product i across the two channels is thus $(1-\gamma)d_{i,s} + (1-\gamma)d_{i,o} = (1-\gamma)d_i$ and the total number of product i returned is $\gamma \cdot d_{i,o}$. If we use m_i to denote the retailer's per-unit profit of selling product i, and k_i as the amount of net loss for each returned product i due to repackaging and restocking, then the expected profit earned by the retailer from product i is given by

$$\pi_i = m_i(1-\gamma)d_i - k_i\gamma d_{i,o}. \tag{8}$$

The retailer has to invest capital in building showrooms. We model the total facility cost of building n showrooms with a size $|I_s|$ as $c \cdot n \cdot |I_s|$, where c is the facility cost factor. The retailer's total expected profit is then given by the profit earned from all of the products, less the total facility cost, namely,

$$\pi = \sum_{i \in I} \pi_i - nc|I_s|. \tag{9}$$

We solve the retailer's problem to maximize its expected profit by choosing the number of showrooms n and subset of products to display in the showroom $|I_s|$. We use the superscript * to denote the optimal decisions, n^* and I_s^*. The following proposition gives the equilibrium outcome. All of the proofs are given in Part C of the appendix.

Proposition 1. $I_s^* = \left\{ i \in I : 2k_i \gamma \frac{w_o \tau - (1-\gamma) w_s \tau + \gamma h_r}{t} d_i > c \right\}$. *Moreover, if* $|I_s^*| \neq \emptyset$*, then* $n^* = \frac{t}{2[w_o \tau - (1-\gamma) w_s \tau + \gamma h_r]}$*; otherwise,* $n^* = 0$.

Denote $\delta = w_o - w_s$ as the impact of the showroom on consumer's wait sensitivity, which is commonly assumed to be zero in literature (e.g., Gao and Su (2017b); Gao et al. (2018)). In contrast, our empirical findings suggest $\delta > 0$, and its implications on retailer's optimal decisions are summarized in the following proposition. Denote $n^*(\delta)$ and $I_s^*(\delta)$ as the optimal showroom decisions given δ.

Proposition 2. *Given* w_o*, suppose* $n^*(0) > 0$*. If* $\delta > 0$*, then*

(i) $n^*(\delta) < n^*(0)$*;*

(ii) $|I_s^*(\delta)| \geq |I_s^*(0)|$.

Proposition 2 shows that δ has a significant impact on an omnichannel retailer's facility network design. Compared to the case when $\delta = 0$ (as commonly assumed in practice and in literature), and given our empirical result showing $\delta > 0$, retailers should build fewer showrooms (i.e., $n^*(\delta) < n^*(0)$), but make them larger in size (i.e., $|I_s^*(\delta)| \geq |I_s^*(0)|$). The reason is as follows. Contrary to conventional belief, our empirical results show that customers have a stronger dislike for waiting for product fulfillment when they shop online compared to the case where they visit a physical location. This finding implies that customers have a stronger-than-expected preference for the offline channel. As a result, the density of a showroom network (which determines customers' offline shopping hassle/travel cost) is not as important in attracting customers to a physical location as it is touted. The retailer can therefore build fewer stores to reduce facility costs. Instead, Proposition 2 shows that retailers should build larger showrooms and display more products so that more customers are able to physically examine the products of interested. In doing so, the retailer can take better advantage of the beneficial impact that a physical location has on consumer's preference regarding fulfillment lead time.

8 Conclusions

Our study examines an implicit and important assumption in the omnichannel retail literature about the demand sensitivity to lead time. We find that a showroom channel reduces consumers' demand sensitivity to lead time, compared with either an online or catalog channel. In particular, a 10% increase in lead time

(1.84 days from the sample mean of 18.35 days) causes a 0.85% reduction in the sales per order (~ EUR 7.6 from the sample mean of EUR 889.94) at the showroom, less than the reduction of 1.14% and 1.23% in the online and the catalog channels, respectively. These numbers suggest that retailers should prioritize resources to reduce the lead time of non-physical channels first. In addition, we find that niche products and experience goods accentuate the difference of lead time elasticity between showroom and non-physical channels. This is a result of niche products and experience goods having a disproportionately higher level of uncertainty about quality or fit than popular products and search goods. These moderating effects support our proposed mechanism of the main empirical result. That is, the showroom effectively reduces the uncertainty of product fit and quality, thus increasing the expected valuation of the purchase and reducing the perceived cost of lead time. As a result, showroom customers are content with "slow and sure" lead times, while online or catalog customers expect "fast and furious" fulfillment. As a limitation of our data, however, we cannot track customers' cross-channel search behavior. In other words, we do not observe whether or not a consumer goes to a showroom first and then places an order online or through the catalog channel. Given that the showroom experience is more effective in reducing product uncertainty than the other two channels, this unobserved cross-channel product search path would only make our results more conservative. Hence, this paper primarily contributes to the empirical retail literature, which uses data to document important insights that can be used as the basis for future modeling efforts (e.g., DeHoratius and Raman, 2008; Craig et al., 2016; Kesavan et al., 2016).

Furthermore, our research takes a preliminary step to answer the call by Caro et al. (2020) to complement the empirical question about the value of physical stores with optimization-based prescriptions to determine store network plans. We develop a stylized model to study the implications of our empirical findings for the design of an omnichannel retailer's facility network. Provided the wait sensitivity of showroom demand is less than the wait sensitivity of online demand, we show that the retailer should build fewer but larger showrooms than the homogeneous wait sensitivity suggests. Admittedly, in our simple model, given that our goal is to study the design of a showroom network, we focus on consumer's choice between online and offline channels rather than the choice between different products. As a result, we assume that products are independent, although we admit that this does not capture some interdependencies between products that may exist in practice. Readers can refer to Dzyabura and Jagabathula (2017) for some initial analysis on the impacts of in-store touch-and-feel experiences on product assortment decisions in an omnichannel environment; however, they have not considered the difference in consumer wait sensitivity across channels.

Future research can also incorporate our empirical findings in analytical models to design omnichannel fulfillment algorithms (Andrews et al., 2019), the coordination of price discounts and delivery speed (Cui et al., 2019), and other important city-logistics issues (Savelsbergh and Van Woensel, 2016).

Finally, our research highlights a new aspect of physical store value. That is, physical stores, such as showrooms, significantly reduce not only product uncertainty and return costs (Bell et al., 2017; Gao and Su, 2017a; Bell et al., 2019), but also demand sensitivity to lead time. Investing in showrooms offers a return in information delivery, which can ultimately save on fulfillment costs (Gallino and Moreno, 2018). Retailers can prioritize their limited resources to expedite lead time in the non-physical channels first. Additionally, retailers should provide incentives for online customers to visit showrooms since those customers may be willing to wait longer for their products' arrival.

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Appendix

A. Subsample Analysis with Lead Time Less Than or Equal to 60 Days

We limit our sample to those orders whose lead time is less than or equal to 60 days to exclude those highly customized products, which significantly delay the lead time. We repeat our main analyses of testing the three hypotheses. The results are shown in Tables 7, 8a and 8b, and are consistent with those reported in the main paper.

Table 7: Lead Time Elasticity

Variable	Model 3 Estimated by Heckman + Control Function
ln*LEADTIME*	-0.096*** (0.006)
ONLINE	-0.103*** (0.0112)
CATALOG	-0.1686*** (0.021)
ONLINE ×ln(*LEADTIME*)	-0.030*** (0.006)
CATALOG ×ln(*LEADTIME*)	-0.033* (0.012)
Control variables	
RETURN	-0.1210*** (0.066)
FULFILLMENTMODE	-2.686* (1.161)
STOREAGE	0.003 (0.002)
ABC = B	-0.067 (0.056)
ABC = C	-0.639 (0.339)
RESIDUAL1	-3.190* (1.476)
RESIDUAL2	0.199 (0.356)
RESIDUAL3	1.934*** (0.660)
$\hat{\lambda}_{ij}$	3.154*** (0.018)
Demographic Controls	Yes
Week Effects	Yes
Product Effects	Yes
No. of observations	371,509
Adj. R^2	0.653

Notes. Cluster robust standard errors are reported in parentheses.
*$p < 0.05$, **$p < 0.01$, ***$p < 0.001$.

Table 8: Moderating Effects of Popular/Niche Products and Experience/Search Goods

(a) Moderating Effects of Popular/Niche Products

Variable	ABC
ln*LEADTIME*	-0.191***
	(0.007)
ONLINE	-0.326***
	(0.024)
CATALOG	-0.318***
	(0.016)
ONLINE ×ln*LEADTIME*	-0.034* (0.013)
CATALOG ×ln*LEADTIME*	-0.051***
	(0.010)
B	-0.091 (0.061)
C	-0.694* (0.329)
B ×ln*LEADTIME*	0.004 (0.002)
C ×ln*LEADTIME*	-0.008 (0.005)
B ×*ONLINE*	0.169** (0.049)
C ×*ONLINE*	0.227*** (0.053)
B ×*CATALOG*	0.157** (0.042)
C ×*CATALOG*	0.131*** (0.023)
B ×ln*LEADTIME* ×*ONLINE*	-0.039 (0.025)
C ×ln*LEADTIME* ×*ONLINE*	-0.062* (0.028)
B ×ln*LEADTIME* ×*CATALOG*	-0.027* (0.013)
C ×ln*LEADTIME* ×*CATALOG*	-0.023* (0.011)
Control variables	
RETURN	-0.158* (0.062)
FULFILLMENTMODE	-13.022* (1.082)
STOREAGE	-0.000 (0.003)
RESIDUAL1	-3.495* (1.355)
RESIDUAL2	-0.044 (0.459)
RESIDUAL3	2.370*** (0.545)
Demographic Controls	Yes
Week Effects	Yes
Product Effects	Yes
No. of observations	371,509
Adj. R^2	0.376

Notes. Cluster robust standard errors are reported in parentheses.
** p < 0.05, ** p < 0.01, *** p < 0.001.*

(b) Moderating Effects of Experience/Niche Goods

Variable	Experiential
ln*LEADTIME*	-0.214***
	(0.007)
ONLINE	-0.295***
	(0.025)
CATALOG	-0.356***
	(0.037)
ONLINE ×ln*LEADTIME*	-0.046* (0.018)
CATALOG ×ln*LEADTIME*	-0.037 (0.021)
EXPERIENTIAL	0.623*** (0.071)
EXPERIENTIAL ×ln*LEADTIME*	-0.023** (0.007)
EXPERIENTIAL×*ONLINE*	0.034 (0.033)
EXPERIENTIAL ×*CATALOG*	0.104*** (0.021)
EXPERIENTIAL ×ln*LEADTIME* ×*ONLINE*	-0.009 (0.021)
EXPERIENTIAL ×ln*LEADTIME* ×*CATALOG*	-0.021* (0.010)
Control variables	
RETURN	-0.032 (0.017)
FULFILLMENTMODE	-0.859***
	(0.086)
STOREAGE	-0.0013 (0.001)
RESIDUAL1	-0.781***
	(0.132)
RESIDUAL2	-0.792***
	(0.164)
RESIDUAL3	1.279*** (0.236)
Demographic Controls	Yes
Week Effects	Yes
Product Effects	Yes
No. of observations	371,509
Adj. R^2	0.368

Notes. Cluster robust standard errors are reported in parentheses.
** p < 0.05, ** p < 0.01, *** p < 0.001.*

B. Propensity Score and Covariate Balance Test

We match consumers in one channel to the consumers in another channel using *average age of household head*, *university degree*, *household size*, *home ownership*, and *residential building status* variables. Through these variables, we seek to match consumers across two channels with similar demographic characteristics and socioeconomic status.We estimate the propensity score by using a Logit regression model in which an indicator for channel selected is regressed on the observed covariates. We then obtain the propensity score from the predicted probability. The score therefore ranges between 0 to 1. We choose to use one-to-one matching with replacement because this option can often decrease bias by using consumers in one channel that look similar to consumers in another channel multiple times (Guo and Fraser, 2014). Moreover, when matching with replacement, the order in which the consumers are matched does not matter (Stuart, 2010). Our derived sample is based on the lower count of two channels. For example, the online channel has 16,176 observations, while the showroom channel has 341,878 observations. Therefore, a matching procedure carried out for the online and showroom channel will result in a derived sample of 16,176 matched observations.

To validate the effectiveness of our matching procedure, we compare the average values of each covariate, prior to matching and after matching, by conducting a *t*-test of mean difference. Table A.1 to A.3 demonstrate that our matching procedure effectively matches two groups at a time. The *t*-statistic values in the *before matching* column are all statistically significant at the 0.05 level, suggesting the means of the two groups are statistically different. However, the *t*-statistic values in the *after matching* column are all statistically insignificant, which suggests that our propensity score matching procedure manages to balance the means of the two matched groups.

Table 9: Propensity score covariate balance test (online and showroom channel)

	Before Matching			After Matching		
	Online	Showroom	*t*-statistic	Online	Showroom	*t*-statistic
Average age of household head	45.747	45.159	-29.56	45.747	45.750	0.18
University degree	0.157	0.150	-13.11	0.157	0.157	-0.07
Household size	2.331	2.386	26.61	2.331	2.330	-0.22
Home ownership	0.714	0.712	-3.24	0.714	0.714	0.05
Residential building status	0.355	0.344	-8.79	0.355	0.354	-0.80

Table 10: Propensity score covariate balance test (catalog and showroom channel)

	Before Matching			After Matching		
	Catalog	Showroom	t-statistic	Catalog	Showroom	t-statistic
Average age of household head	45.655	45.159	-34.50	45.655	45.655	0.08
University degree	0.155	0.150	-11.43	0.155	0.155	-0.19
Household size	2.352	2.386	22.77	2.352	2.351	-0.19
Home ownership	0.708	0.712	9.73	0.708	0.708	0.11
Residential building status	0.338	0.344	7.01	0.338	0.336	-0.41

Table 11: Propensity score covariate balance test (online and catalog channel)

	Before Matching			After Matching		
	Online	Catalog	t-statistic	Online	Catalog	t-statistic
Average age of household head	45.747	45.655	4.00	45.747	45.749	0.32
University degree	0.157	0.155	4.00	0.157	0.158	0.86
Household size	2.331	2.352	-8.64	2.331	2.329	-0.77
Home ownership	0.714	0.708	8.73	0.714	0.714	0.07
Residential building status	0.355	0.338	11.96	0.355	0.355	-0.80

C. Proofs

Proof of Proposition 1: The retailer's total profit function can be specified as follows:

$$
\begin{aligned}
\pi^* &= \sum_{i\in I} \pi_i^* - nc|I_s| \\
&= \sum_{i\in I} [m_i(1-\gamma)d_i - k_i\gamma d_i] + \sum_{i\in I_s} \left[2k_i\gamma \min\left(\tfrac{w_o\tau-(1-\gamma)w_s\tau+\gamma h_r}{t}, \tfrac{1}{2n}\right) nd_i - nc\right] \\
&= \begin{cases} \sum_{i\in I} [m_i(1-\gamma)d_i - k_i\gamma d_i] + n\sum_{i\in I_s} \left[2k_i\gamma \tfrac{w_o\tau-(1-\gamma)w_s\tau+\gamma h_r}{t} d_i - c\right] & \text{if } n \le \frac{t}{2[w_o\tau-(1-\gamma)w_s\tau+\gamma h_r]} \\ \sum_{i\in I} [m_i(1-\gamma)d_i - k_i\gamma d_i] + \sum_{i\in I_s} [k_i\gamma d_i - nc] & \text{otherwise} \end{cases}
\end{aligned} \tag{10}
$$

Given I_s, note that π^* is decreasing in n when $n > \frac{t}{2[w_o\tau-(1-\gamma)w_s\tau+\gamma h_r]}$, and thus the optimal number of stores $n \le \frac{t}{2[w_o\tau-(1-\gamma)w_s\tau+\gamma h_r]}$. Therefore, we simply need to solve the following optimization problem:

$$
\begin{aligned}
&\max_{n,I_s} \sum_{i\in I} [m_i(1-\gamma)d_i - k_i\gamma d_i] + n\sum_{i\in I_s} \left[2k_i\gamma \tfrac{w_o\tau-(1-\gamma)w_s\tau+\gamma h_r}{t} d_i - c\right] \\
&s.t. \quad n \le \tfrac{t}{2[w_o\tau-(1-\gamma)w_s\tau+\gamma h_r]}
\end{aligned} \tag{11}
$$

Note that the two decision variables n and I_s are separable in the objective function. Thus, it is easy to verify that $I_s^* = \left\{i \in I : 2k_i\gamma\frac{w_o\tau-(1-\gamma)w_s\tau+\gamma h_r}{t}d_i > c\right\}$. If $\sum_{i\in I_s^*}\left[2k_i\gamma\frac{w_o\tau-(1-\gamma)w_s\tau+\gamma h_r}{t}d_i - c\right] > 0$ (i.e. $I_s^* \neq \varnothing$), then π is increasing in n and thus $n^* = \frac{t}{2[w_o\tau-(1-\gamma)w_s\tau+\gamma h_r]}$. If $I_s^* = \varnothing$, then π is independent of n and thus it is optimal to set $n^* = 0$.

Proof of Proposition 2: Note that $I_s^* = \left\{i \in I : 2k_i\gamma\frac{\gamma w_o\tau+(1-\gamma)\delta\tau+\gamma h_r}{t}d_i > c\right\}$, which is increasing in δ, given w_o. Thus, $|I_s^*(\delta)| \geq |I_s^*(0)|$. Since $n^*(0) > 0$, we have $|I_s^*(0)| > 0$ and thus $I_s^*(\delta) \neq \emptyset \Rightarrow n^*(\delta) > 0$. Thus, $n^*(\delta) = \frac{t}{2[\gamma w_o\tau+(1-\gamma)\delta\tau+\gamma h_r]} < \frac{t}{2[\gamma w_o\tau+\gamma h_r]} = n^*(0)$.