Offline Showrooms and Customer Migration in Omni-Channel Retail

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Omni-channel environments where customers shop online and offline at the same retailer are ubiquitous and are deployed by traditional retailers and online-first retailers alike. As such, they raise important new questions regarding their impact on demand generation and operational efficiency. We focus on the relatively understudied domain of online-first retailers and one key way that they establish an offline presence; specifically, by introducing showrooms (physical locations where customers can see and try the products) in combination with online fulfillment using centralized inventory management. We examine how a channel structure comprising offline delivery of information to customers coupled with online logistics and fulfillment of orders impacts the existing core online channel and a sampling channel.

Using quasi-experimental data on showroom openings by WarbyParker.com, the leading and iconic online-first eyewear retailer, we find that showrooms: (1) increase demand overall and in the online channel as well, (2) improve overall operational efficiency by increasing conversion in the sampling channel and by decreasing returns, (3) generate operational spillovers to the other channels by attracting customers who, on average, have a higher cost-to-serve, and (4) amplify benefits to the firm in dealing with those customers who have the most acute need for the product. Moreover, these effects strengthen with time as showrooms contribute not only to brand awareness but also to what we term channel awareness as well. Our findings are robust to numerous alternative model specifications and sample selection procedures; we conclude by elaborating the underlying customer dynamics that drive our findings and by offering implications for omni-channel growth by online-first retailers.

Key words: Omni-Channel Retailing; Showrooms; Experience Attributes; Propensity Scoring; Quasi-Experimental Methods; Retail Operations

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1. Introduction

As traditional retailers ramp up their Internet presence and online-first retailers open stores and showrooms, it is vital to understand how “omni-channel” strategies affect consumer demand and operational efficiency. Omni-channel convergence reflects the fact that while online is the fastest growing component of retail in the United States (according to Forrester Research the market will grow from $231b in 2013 to $370b in 2017 on CAGR of 10 percent\(^1\)), offline retailing still anchors the sector. Both observations also apply to international markets; China, for example, is on target to become the largest global e-commerce retail market, but offline retail there also remains strong and significant.\(^2\) Therefore, retailers of all types and in all locations increasingly interact with consumers through multiple touch points (Brynjolfsson et al. 2013, p. 23); in the global consumer economy omni-channel retailers and buying experiences are becoming the norm.

Fundamentally, retailers are attracted to omni-channel strategies because online and offline channels differ in their ability to deliver product information and execute product fulfillment, the two core channel functions (see, for example, Coughlan et al. 2006, p. 9-10). Information can be provided online or via physical access to the product, while fulfillment can be “online” (i.e., the product is shipped to the customer from a centralized location) or “offline” (i.e., the customer goes to the product). Figure 1 illustrates the 4 combinations of fulfillment and information delivery made possible the digital economy (Bell et al. 2014). In a key point of departure from existing omni-channel research (e.g., Anderson et al. 2010; Avery et al. 2012) which examines the interplay between the upper left and lower right channels, we focus on how the showroom (upper right channel) affects demand and operational efficiency for the core online channel (bottom right channel).

An omni-channel retailer (unlike a single-channel counterpart), caters to consumer heterogeneity in preferences for whether the information and fulfillment functions should be carried out online, offline, or in mixed online-offline configurations. Some customers, for example, prefer the ease of access and shopping that comes from a fully online experience, whereas others prefer to physically sample the product before buying. An important mixed configuration for online-first brands is the showroom, i.e., a zero-inventory store that combines physical access to product information with online fulfillment using centralized inventory management. When the showroom opens, it generates a shock in the product information available to customers in the showroom’s trading area. In this paper, we focus on how and why a showroom affects demand from these customers and operational efficiency in serving them. Our goal is twofold: (1) to document the market impact of

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this innovation, and (2) to elaborate on, and provide evidence for, the customer channel migration mechanism it induces. Specifically, we demonstrate that the market impacts are consistent with channel migration (from online and sampling, to offline) by customers who have the greatest need for a tactile experience.

Our paper is the first, to our knowledge, to demonstrate that retailers can realize demand and operational efficiency benefits from stores that carry no inventory, i.e., showrooms. Showrooms deliver tactile information into a market without affecting fulfillment options for customers. It is important to understand the impact of showrooms because they are significantly less operationally complex than conventional stores. Unlike stores, showrooms do not need to receive periodic inventory replenishments, nor do they require sales forecasts for each product at each individual location given that inventory is stored and managed from a centralized distribution center. Furthermore, we find that the shock in available product information arising from the introduction of showrooms delivers operational efficiency to retailers by, for example, lowering returns overall, and by further reducing returns from customers with the most complex product needs.

The discrepancy in the ability of online and offline channels to deliver certain types of product information has long been recognized as a key issue in E-commerce research and practice alike. Over 15 years ago, Lal and Sarvary (1999) drew a distinction between digital and non-digital product attributes and how information about each is communicated in online and offline channels. The former, e.g., the price of a product or length of a book, suffer no loss of information when communicated online, whereas the latter, e.g., the feel of a shirt or look of a pair of glasses, when presented or characterized online, may introduce significant uncertainty for some consumers.
Practitioners and analysts also understand that online-first retailers face significant challenges in communicating non-digital product attribute information to customers. Leading industry commentator GigaOm.com, for example, refers to the home sampling program by the fashion eyewear brand WarbyParker.com as follows: “That (home try-on) has helped Warby Parker overcome one of the biggest hurdles (italics added) for online fashion brands, getting people to feel comfortable about their online purchase.”

A myriad of other retailers from Bonobos.com and Casper.com to Wayfair.com and Zappos.com recognize that uncertainty about non-digital product attributes is a barrier to purchase for large segments of customers, and therefore employ free two-way shipping, pop-up stores, extensive customer reviews, and related methods to combat it.

A related literature in E-commerce examines relative search frictions in online and offline markets (e.g., Brynjolfsson and Smith 2000), location-based explanations for whether consumers prefer online or offline channels (e.g., Forman et al. 2009), and the implications of traditional offline store introductions for online demand (e.g., Anderson et al. 2010; Avery et al. 2012). We contribute to this literature by demonstrating, for an online-first retailer, why showrooms which inject information into a market without affecting fulfillment impact sales, conversion, and returns in the existing channels. Furthermore, we explain why customer channel migration is the underlying mechanism, and for which types of customers and buying contexts, e.g., simple versus complex products, that the effects are felt most strongly.

We ascertain the effects of showroom introductions using a propensity scoring approach on quasi-experimental data from WarbyParker.com, the leading online-first fashion eyewear brand (Figure 2 is a screenshot of the website). Since inception in February 2010, Warby Parker has progressively introduced showrooms in different locations throughout the United States. We deliberately selected this institutional setting due to three important features that allow us to properly isolate what happens when additional information alone is injected into a local market, via the introduction of a new showroom. First, eyewear has significant non-digital or “fit and feel” attributes such that many customers find it a difficult category to buy online. Second, Warby Parker began as an online-only retailer that has always offered consumers a nationwide product sampling program called “Home Try On” (HTO). Under HTO five pairs of glasses (frames only) are delivered to customers for inspection free of charge for five days. HTO is therefore an “intermediate” position between online (where all product information is only available digitally) and showrooms (where all product information is available in person). Third, Warby Parker is an innovator in the use of showrooms and by design, fulfillment from a centralized location, conditional on a purchase, is identical for all channels (online, HTO, and showroom).

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4 When WarbyParker.com entered the $22 billion US eyewear market in February 2010, only 1-2 percent of all sales in the category occurred online.
We contribute three new substantive findings.

First, showrooms increase sales within the trading area both overall and through the online channel as well. Estimated average effects of 7.4 percent and 2.9 percent, respectively, are statistically and economically significant. This implies that the showroom not only delivers sales in its own right, but also confers awareness and brand benefits that drive incremental sales in the existing online channel. We further show that the showroom is, on average, the most effective customer acquisition channel and that the brand and awareness benefits are not due to other factors, including concomitant advertising.

Second, showrooms improve operational efficiency by increasing conversion in the sampling channel and decreasing returns. Regarding conversion, sampling channel orders fall 1 percent while

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5 We subject these and all other findings to robustness checks by varying model specification, covariate selection, and data inclusion criteria and verify that our substantive findings hold in all cases. Summaries are reported throughout the paper and complete findings are available from the authors, upon request.
sampling channel sales fall by a lesser amount, 4.5 percent. This implied (and significant) conversion increase observed in the aggregate, is mirrored in individual-level data. Within the trading area of showrooms, the probability of repeated HTOs declines 1.6 percent and the probability of individual-level conversion of try-ons to sales improves by 1 percent. We elaborate later in more detail, but these findings point to the underlying customer mechanism—the showroom attracts customers with the highest haptic need—leaving those remaining in the sampling channel even though they had the option of visiting a showroom, better aligned to it. We further validate beneficial migration i.e., customers who might have ordered multiple HTOs now end up in the showroom, and alignment, i.e., the customers who choose to stay with the HTO or online channels are better suited to those channels, by documenting a significant reduction in products returns from online channel purchases made within the catchment area of a showroom. In short, because showrooms attract fit-sensitive customers with the highest cost to serve, other channels are left with a more favorable consumer mix and the firm enjoys significant demand and operational benefits (in aggregate and in the other channels) as a result.

Third, these benefits to the firm are amplified when serving customers who have the most acute need for the product. Using the diopter measure of the correctional lens as an objective proxy for intensity of product use, we show that the ability of the showroom to reduce overall return rates is heightened for these types of products. Relatedly, we find that all of the demand and operational efficiency benefits intensify with time, implying that showrooms contribute not only to brand awareness but also to what we term channel awareness as well. Specifically, showrooms have a lasting impact on customers’ ability to align to the channel best suited to them.

Finally, while our overriding goal is to document new and interesting average treatment effects on demand and operational efficiency, we appreciate that important insights can be drawn from exploring heterogeneity in effect sizes, conditional upon showroom location and other factors. In the concluding sections of the paper, we report that the aforementioned patterns hold at the individual showroom level, and comment on possible rationales for variation in effect magnitudes.

The remainder of the paper is organized as follows. Section 2 summarizes relevant prior research and develops our conjecture on customer channel migration. Section 3 describes the research setting, data, and our econometric approach and quasi-experimental design. Section 4 reports the overall demand and efficiency effects and Section 5 elaborates on the underlying customer migration mechanism. Section 6 discusses implications for practice and decision making and Section 7 concludes the paper.

6 Naturally, we verify that baseline return rates are higher, as they should be, for the more “complex” sales of high diopter lenses.

7 We thank an anonymous reviewer for suggesting these analyses.

8 A more formal model of customer decision making that is consistent with the observed effects is outlined in Appendix 2.
2. Background and Motivation

2.1. E-Commerce and Omni-Channel Retailing

The consumer Internet has evolved considerably since Jeff Bezos first sold books online in 1994 and from the “Internet Retailing 1.0” boom and bust in the early 2000s. Indeed, the evolution of the retail sector can be viewed, in simple terms, with reference again to Figure 1. Pre-Internet all retailing took place in the upper left quadrant; activities then evolved in the lower right with Amazon.com and other “pure players” leading the way. Traditional retailers (e.g., Crate & Barrel, Home Depot, Walmart, etc.) also developed a digital footprint in the lower right quadrant via their own “.com” properties.

Most recently, practitioners have come to understand that online and offline channels present different costs and benefits to customers and that an omni-channel approach embracing more than simply these two options is imperative. Interesting, the evolutionary path to quadrants 2 (upper right) and 3 (lower left) differs by retailer type. Traditional retailers with legacy real estate have innovated initiatives like BOPS that leverage offline fulfillment coupled with new ways of delivering product information online. Digital-first retailers couple existing centralized online fulfillment with new ways of delivering product information offline (this is of course our focus and we elaborate further below).

The emergent practitioner viewpoint is mirrored by developments in academic research. Early work by academics focuses on understanding why consumers and firms might prefer online to offline, or vice versa. Some initial studies (e.g., Bakos 1997; Brynjolfsson and Smith 2000; Iyer and Pazgal 2003) explained how and why online retailers can reduce search frictions for consumers and deliver lower prices. Other articles (e.g., Balasubramanian et al. 2003) showed why online sellers could be more convenient or offer more product variety (e.g., Brynjolfsson et al. 2009; Ghose et al. 2006). Operations management researchers addressed inventory management implications for firms. Netessine and Rudi (2006), for example, derive the conditions under which retailers prefer to drop-ship rather than to hold inventory. In related work, Randall et al. (2006) find that online retailers selling high margin products and offering less variety are more likely to hold inventory and Gallino et al. (2016) study the consequences of channel integration for sales dispersion and inventory management.

Structural aspects of markets including the physical distances customers must travel to offline stores (e.g., Forman et al. 2009) and the extent to which target customers have minority preferences and are underserved by offline sellers (Choi and Bell 2011) also shape online-offline preferences. Holding price, assortment, and delivery times to consumers constant, one can also observe marked

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9 The interested reader can find a comprehensive review of these and other findings in Neslin and Shankar (2009).
differences in the realized sales distribution delivered by online versus other channels. Brynjolfsson et al. (2011), for example, show that because consumers in online channels engage in direct product search and access reviews, the online channel exhibits a relatively more diffuse sales distribution, compared to a catalog channel. That is, consumers are more likely to purchase products in the tail of the so-called Long Tail (Anderson 2006). More recently, Wang and Goldfarb (2015) show that offline stores deliver a “billboard effect” that helps to drive online sales, especially in locations where the brand is relatively unknown. Shriver and Bollinger (2015) provide a structural analysis and find that newly opened offline stores can eat into online sales, in locations that within close proximity to the store.

2.2. E-Commerce and Consumer Uncertainty When Buying Online

Depending upon the channel used, consumers may lack full information prior to making a purchase. Anderson et al. 2009, p. 408, for example, note that “… fit is not fully observed by the customer prior to purchase … [in] retail settings where customers select from a catalog or Internet site without being able to fully inspect the product.” “Full inspection” is of course very important to some customers when the product has *non-digital attributes*. Therefore, customers’ inability to touch and feel products with non-digital attributes before buying through catalogs or online can:

1. act as deterrent to purchase, and
2. increase operational costs should they return products after experiencing a discrepancy between the expected and delivered product.\(^{10}\)

This uncertainty matters more in some product categories and more for some segments than others. Andy Dunn, CEO of leading online-first fashion apparel retailer Bonobos.com (see Lee and Bell 2013 for more details) justifies his expansion into offline stores by noting: “There are still people who want to *touch and feel* (italics added) clothing before they purchase.”\(^{11}\) Likewise, our conception of *fit uncertainty* is related to previous modeling work by Matthews and Persico (2007), who study the tradeoff between having customers learn about product fit ex ante, or by using the product on a trial basis, and to Swinney (2011) who looked at how strategic consumers behave when product value is uncertain. The rationale for our complementary empirical work is that showrooms are mechanisms for delivering information and reducing fit uncertainty for some customers. To the best of our knowledge, our study is the first to document the effect of quadrant 2 retail activities on demand and operational efficiency for online-first retailers.

\(^{10}\) While we focus on the offline showroom as a source of information and method for resolving uncertainty on non-digital attributes, a number of other papers study the complementary phenomenon of brick and mortar retailers providing information through the online channel. See, for example, van Nierop et al. (2011) and Pauwels et al. (2011).

In the operations management literature Yin et al. 2009 and Cachon et al. 2013 analyze inventory display strategies but do so in conventional offline channels only. Studies of this type, while valuable, are not designed to delineate informational and fulfillment differences between online and offline channels, and isolate their effects separately. For example, offline channels typically offer immediate fulfillment whereas online channels offer delayed fulfillment due to shipping times of one or more days. Critically, in our study, the introduction of showrooms is a shock to the product information available to some of the customers (but not others), and yet has no impact on fulfillment. The effect of this shock on demand not yet documented by academics (but hinted at in the Bonobos.com example above where showrooms are thought to lead to a “reduction in deterrent to purchase” for certain customers), is our first focus.

In addition, articles at the marketing-operations interface on the key drivers of returns (Petersen and Kumar 2009), the effect of return options on consumer utility (Anderson et al. 2009), reverse supply chain design (e.g., Guide et al. 2006, Blackburn et al. 2004) and contractual provisions including fees or money-back guarantees (e.g., Davis et al. 1995, 1998, Shulman et al. 2009, Su 2009) imply that an informational shock might also affect returns. Accordingly, the potential for the information shock to affect returns and operational efficiency is our second focus. We examine this directly by showing how return patterns and sampling channel efficiency evolve subsequent to a showroom introduction.

2.3. “Bricks to Clicks” and “Haus to Browse”

When a retailer adds a new channel, existing channels are naturally affected. Keeping with the themes developed thus far, the existing channel may realize more (or less) demand and / or become more (or less) operationally efficient. Hence, it helps to think of existing literature in terms of insights offered into demand effects and operational effects, and to utilize the framework in Figure 1 to illuminate what channel comparisons are made in prior studies.

Avery et al. (2012), for example, study whether, and if so why, adding new offline stores in a market helps or hurts online sales there. In industry jargon (and by title) this research focuses on “bricks to clicks”, i.e., adding quadrant 1 (offline fulfillment, offline information delivery) to quadrant 4 (online fulfillment, online information delivery). The authors find synergies—online sales increase when offline stores enter the market—initially from new customers in particular, and then in general as time progresses. In addition, catalog sales are adversely affected, confirming earlier findings (e.g., Pauwels et al. 2011).12

Our work is substantively distinct from these and related studies in three important ways. First and foremost, we focus on what happens when Quadrant 2 (online fulfillment, offline information

12 A number of other studies focus on the reverse problem, i.e., what happens when quadrant 4 is added to quadrant 1. For an excellent review of key findings and conceptual summary see Avery et al. (2012).
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delivery) is added to Quadrant 4 (online fulfillment, online information delivery). Showrooms, the instrument of choice used by leading online-first retailers like WarbyParker.com and Bonobos.com, among others, are not stores as they hold no inventory. In showrooms, consumers can touch, feel, and inspect products, prior to any purchase that is fulfilled online. We are therefore able to focus directly on the connection between customers’ need for tactile product information prior to purchase and channel preferences, because the impact of Quadrant 2 on Quadrant 4 occurs only via information delivery.¹³

Second, there are sound theoretical reasons for showrooms, yet, to our knowledge, no supporting empirical studies. Showrooms overcome limitations of the online channel in selling products with uncertain fit, yet maintain the pooling benefits of centralized fulfillment (Eppen 1979). As noted earlier, showrooms, which require neither replenishment nor demand forecasting, are far less operationally complex than stores. If showrooms unlock incremental sales and operational benefits then practitioners may want to give serious consideration to this type of cost-efficient offline channel. Consequently, managerial implications arising from our work are different from, yet complementary to, those from the existing literature. In the spirit of Gallino and Moreno 2014 who show how Buy Online, Pick up In-Store (or BOPS) initiatives help offline-first retailers, we show another nuance to the informational function of channels, by demonstrating how showrooms help online-first retailers.

Third, and similar to prior omni-channel studies in marketing, we report findings on the demand impact of channel innovation. In addition, however, we add new results relating to operational efficiency—an area largely overlooked in the extant literature. If, for example, information shocks via showrooms induce customer migration and alter channel alignment (we elaborate on these terms subsequently) this may impact operational efficiency. Specifically, whether customers become more or less likely to return products or convert to purchase from sampling. Recent research in operations management shows that customers with specific characteristics are more likely to defect in response to shocks in service levels and migrate to the competitor that best serves them (e.g., Buell et al. 2010; Buell et al. 2011). We investigate the conceptually parallel phenomenon of whether customers with a specific characteristic—high sensitivity to fit—are more likely to leave pre-existing online and sampling channels and move to showrooms. And if so, whether this is operationally efficient for the retailer.

In summary, we focus directly and precisely on the core channel function of information, and how and why the information delivery mechanism affects operational efficiency as well as realized demand. As such, the point of comparison is very much whether customers obtain information via

¹³ Studies that measure the impact of Quadrant 1 on 4 (and vice versa) do not seek to isolate informational or fulfillment effects separately as information delivery and logistics methods are both different in the two channels.
“browse” (online) or via “haus” (offline), and what this means not only for digital-first retailers but also any retailer considering the “zero inventory store”, aka showroom, as part of their omni-channel strategy.

3. Institutional Setting, Data, and Econometric Approach

3.1. Institutional Setting

WarbyParker.com, the iconic and leading online eyewear brand, supplied sales and returns data which we augmented with additional data derived from the US Census and other sources. Founded in February 2010, the firm has sold over 1,000,000 frames through online, sampling, and offline channels. The company sells glasses with prescription lenses and sunglasses and all frames offered by Warby Parker are exclusively designed by them and unavailable through traditional offline retail channels (Lens Crafters, Sunglass Hut, etc.). During the period of our data all eyewear sold for 95 dollars (including prescription lenses).

These data have three features that make them ideal for our research. First, and most critical, eyewear is an exemplar product category for the importance of non-digital product attributes in the purchase process. When WarbyParker.com launched in 2010, only 1-2 percent of the $22 billion US eyewear market was transacted online. This is not surprising as eyewear is a category in which many customers would like to touch, feel, and try on the product before purchasing it. Second, while WarbyParker.com was founded online, the company offered a sampling program (discussed below) immediately upon launch, leading industry observers to refer to them as the “Netflix of Eyewear”. In terms of visceral product information, the sampling channel is “intermediate” between full exposure to the entire product line in a showroom, and virtual exposure online, which allows us to examine the information function in detail. Third, the showrooms differ from the other two channels (online and sampling) only in regard to the amount of information available to customers pre-purchase. Since all three channels use identical online fulfillment we can isolate the impact of information alone, free from potential confounds related to differences in fulfillment. The three channels, with additional description are:

i. Web Channel (with “Virtual Try-On” Option)

Customers can browse the entire product line at the website prior to purchasing. In addition, they can upload their own pictures and examine, virtually, the fit, feel and style of different frames. This “virtual try on” tool is based on state-of-the-art technology and presents realistic images, yet it is not hard to imagine the limitations it has in closing the experiential gap, i.e., the gap

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14 The channel is the medium through which customers access to product information before placing an order, as orders are always placed through the website and centrally fulfilled in the same way.

between what customers might learn about products from the virtual process and what they might experience when the product is delivered.

ii. Sampling Channel (“Home Try-On” Program)

Customers who participate in the Home Try-On (HTO) program receive five frames free of charge, for five days. Specifically, customers go online and select five frames from the complete selection offered and have them delivered. When the five days are up, customers return the frames and decide to buy or not. Purchases are made on the web and fulfillment is identical to that for the web channel. We follow protocols established by management, where an HTO order is said to “convert” if the customer receiving the HTO makes a purchase within the subsequent two months. In our data the conversion rate (fraction of HTO orders that lead to a purchase) is lower than 50 percent. Customers who participate in the HTO, relative to those who go to the site only, have better product information as they have been able to physically touch, try, and test the product prior to any purchase.

iii. Showroom Channel

For customers who want to touch, feel, try, and experience the entire product line physically prior to making a purchase decision, the preceding two channels are inadequate. Recognizing this, Warby Parker developed a third channel, the showroom, to help overcome this problem. During the period of our data, the firm opened a total of 20 showrooms in 15 different locations across the US (13 were in continuous operation, 7 closed). Showrooms are established in partnership with different local retailers who devote a portion of their retail space to displaying the Warby Parker product line. In cases where customers purchased, transactions were placed exactly as they were for the other two channels, i.e., through the website and were fulfilled online.

3.2. Detailed Data Description

We utilize data on: (1) sales through the three channels, (2) HTO orders (requests made by customers to receive samples using the aforementioned program, which may or may not result in a purchase) and, (3) product returns. The data cover a 37 month (158 week) period from the opening of the business in February 2010 through March 2013, and include all transactions. Since sales data are collected from inception they are not left censored. To mitigate right censoring we considered returns and conversions that cover a period that expands until May 2013, i.e., a further two months (as noted earlier the firm uses a two-month window to determine “conversions”). Most of our analyses are at the week-ZIP code level and focus on the channel source that originated the

16 Although HTO is free to the customers, and helpful for closing the experiential gap, it is not free for Warby Parker and has a significant impact on gross margins.
sale. WEB sales are online purchases, HTO sales are purchases made within two months of when the customer received the HTO order (sample), and SHOWROOM sales occurred offline.\textsuperscript{17}

For each sale, through each channel, we know the ZIP code to which it was shipped. In addition, we obtained ZIP-code level data on household demographics and spending at offline eyewear retailers from the 2010 ESRI Demographics and Business Database.\textsuperscript{18} These data contain ZIP code level variables typically available from the US Census (e.g., population size, area, household income, etc.) as well as others that are germane to the offline retail environment. We use these data to construct ZIP code level control variables and also develop the propensity score matching approach in which we develop samples of locations with and without showrooms.

Some individual-level data were also made available to us. Specifically, we know: (1) whether the order was a first order for a particular customer or a repeat order, (2) if the transaction included a prescription, (3) the details of the lenses in the order (prescription strength), (4) whether the product was eventually returned, and (5) when an individual placed an HTO order and if it resulted in a sale.

3.3. Econometric Approach

We use a Difference-in-Differences (DiD) approach with propensity score adjustment. Conversely, a naïve approach would simply look at the difference in dependent variables of interest, e.g., demand and returns, between the period before and after the showroom opened at a particular location. Unfortunately, factors completely unrelated to the opening of a showroom can differ between the two (pre-showroom and post-showroom) periods, hence the need to utilize a DiD approach and hold “all else constant”.

3.3.1. Standard Difference-in-Differences (DiD)

Angrist and Pischke (2008) provide an exhaustive discussion of social science applications of DiD; moreover, there are several recent applications in marketing and operations management (e.g., Caro and Gallien 2010, Parker et al. 2014), including multichannel retail as well (e.g., Gallino and Moreno 2014, Avery et al. 2012). To implement the DiD method in our research, we must identify a portion of the population unaffected by the intervention, i.e., the opening of a showroom. To do this, we select a control group that shares characteristics with the group that was exposed to the treatment and the effect of the treatment is ascertained by comparing the differences between the control group and the treatment group, before and after the treatment is applied.

\textsuperscript{17} To track SHOWROOM sales the company implemented the following system. After a customer decided to buy while in the showroom, they were given a 5 dollar coupon code which the salesperson entered at the end of the checkout process, making it possible to link the transaction with the showroom visit.

\textsuperscript{18} These are available for purchase at www.esri.org, http://www.esri.com/data/esridata/demographic-overview for details.
We delineate the two groups by considering the distance between a potential customer and a showroom location. Only those customers contained within a reasonable trading area around the showroom are potentially influenced by its presence; hence, those within the trading area in the treatment group and those without are in the control group. Following criteria set forth by the firm, we defined the area of influence of a showroom as a 30 mile radius from the location of the showroom. ZIP codes within the 30-mile radius are in the treated group and those outside are in the control group. The empirical distribution of showroom sales shows that 82 percent come from ZIP codes within a 15 mile radius of a showroom and 87 percent come from within a 30 mile radius.

A total of 20 showrooms were open at some point during our period of analysis. 13 were in continuous operation and 7 opened and closed. This helps identification since it adds variation to the control and treatment groups over time. For the results that follow, we focus on those ZIP codes that saw orders of at least 40 frames during the period of analysis. Our final panel consists of 1,972 ZIP codes, 823 of which were in the influence area of a showroom at some time during the period of analysis. For ease of exposition, Table 1 presents summary statistics for illustrative variables used in the analysis.

A potential concern with our identification strategy is that the locations where the company opened the showrooms are endogenous with demand. Indeed, one would not expect showrooms to be opened in “random” locations. Management informed us that while they had a clear idea about cities of interest, their decision to open a showroom in a specific ZIP code was driven by a combination of market potential and partnership opportunity. These decisions by management resulted in a showroom map that, while not random, is not completely endogenous either. As discussed next, we therefore utilize a propensity score model to “equalize” treated and non-treated locations.

### 3.3.2. Quasi-Experimental Design: Propensity Scores Weighting

DiD is an effective approach when the treatment and control groups follow equal trends in the pre-treatment period. In our case, this assumption may not hold as ZIP codes near showrooms and ZIP codes far from showrooms are potentially very different in their characteristics. The median household income of the treatment group, for example, is $75,798/year whereas the corresponding number for the control group is much less ($68,693/year).

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19 We varied this distance and conducted extensive robustness checks, all of which are documented later in the paper and available from the authors upon request.

20 As we did with the 30-mile radius showroom trading area, we again check the robustness of the results to this decision. We find that all results hold allowing the sales value per ZIP code to range from 1 to 150 and report the results throughout the text. Complete results are also available from the authors, upon request.

21 Summary statistics for all variables in the master list are available from the authors, upon request.
Table 1  Summary Statistics - Mean (Standard Deviation) by ZIP Code

<table>
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<th>Unit</th>
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<td></td>
<td>(410)</td>
<td>(96)</td>
<td>(281)</td>
<td></td>
</tr>
<tr>
<td>HTO Orders (Units)</td>
<td>Orders</td>
<td>241</td>
<td>198</td>
<td>216</td>
</tr>
<tr>
<td></td>
<td>(278)</td>
<td>(190)</td>
<td>(232)</td>
<td></td>
</tr>
<tr>
<td>Population</td>
<td>Count.</td>
<td>33,973</td>
<td>31,673</td>
<td>32,633</td>
</tr>
<tr>
<td></td>
<td>(20,746)</td>
<td>(16,115)</td>
<td>(18,227)</td>
<td></td>
</tr>
<tr>
<td>Households</td>
<td>Count.</td>
<td>13,083</td>
<td>12,531</td>
<td>12,762</td>
</tr>
<tr>
<td></td>
<td>(7,559)</td>
<td>(5,604)</td>
<td>(6,498)</td>
<td></td>
</tr>
<tr>
<td>Diversity Index</td>
<td>Index</td>
<td>57</td>
<td>51</td>
<td>54</td>
</tr>
<tr>
<td></td>
<td>(21)</td>
<td>(19)</td>
<td>(20)</td>
<td></td>
</tr>
<tr>
<td>Median Household Income</td>
<td>Dollars</td>
<td>75,798</td>
<td>68,693</td>
<td>71,658</td>
</tr>
<tr>
<td></td>
<td>(33,346)</td>
<td>(29,382)</td>
<td>(31,294)</td>
<td></td>
</tr>
<tr>
<td>Per Capita Income</td>
<td>Dollars</td>
<td>40,979</td>
<td>36,738</td>
<td>38,508</td>
</tr>
<tr>
<td></td>
<td>(19,709)</td>
<td>(14,331)</td>
<td>(16,916)</td>
<td></td>
</tr>
<tr>
<td>Eyeglasses &amp; Contact Mkt.</td>
<td>Index</td>
<td>106</td>
<td>95</td>
<td>100</td>
</tr>
<tr>
<td></td>
<td>(50)</td>
<td>(42)</td>
<td>(46)</td>
<td></td>
</tr>
<tr>
<td>ZIP Codes</td>
<td>Count.</td>
<td>823</td>
<td>1,149</td>
<td>1,972</td>
</tr>
</tbody>
</table>

A propensity score adjustment is one effective way to counter imbalances in values of the characteristics for treatment and control locations. Propensity score-based methods first introduced by Rosenbaum and Rubin (1983) are among the most popular and widely used social science models for dealing with endogeneity (see Imbens and Wooldridge 2009 for a comprehensive review and discussion). Since potential biases arise when covariates are correlated with the treatment indicator, the so-called propensity score is the probability that an individual observational unit receives the treatment, conditional on its observed covariates. Therefore, for subpopulations of observations with the same propensity score, covariates will be independent of the treatment. This eliminates the biases in the comparisons between treated and control units.

Propensity scores can be used by considering the scores as sampling weights (see Rosenbaum 1987, Hirano and Imbens 2001, Hirano et al. 2003 and Gensler et al. 2012), as propensity score weighting re-weights treatment and control observations to make the two populations comparable in terms of their observable covariates. Following Hirano and Imbens (2001) we defined the weights as follows:

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

where $W = 1$ indicates a treated ZIP code and $\hat{e}(x)$ is the estimated probability of being treated. After obtaining these weights, we estimate our DiD model, including those weights in the estimation. Among all methods considered in the comprehensive review by Imbens and Wooldridge (2009), the approach we take is deemed especially attractive for practical applications (e.g., Bang and Robins 2005, Hernán and Robins 2006). We do our matching at the most granular geographic
level available to us: the ZIP code. To compute the weights, we utilize almost 50 different ZIP-code-level variables from 2010 ESRI Demographics and Business Database including demographic, socioeconomic, and business-related variables pertinent to our institutional context.  

### 3.3.3. Validation of Propensity Score Weighting Approach

Propensity score weighting can be implemented in a variety of ways, according to the choice of link function, number of variables used in estimation, and so on. First, in order to ensure that our approach works as it should, we consider logit and probit link functions estimated on both “large” (47) and “small” (22) sets of variables and confirm that our substantive findings are robust to these alternative computations of the weights.

Second, we check to make sure that our weights actually balance the treatment and control groups properly. To do this, we follow Guo and Fraser (2009) and simply compare estimates from a set of weighted and unweighted regressions. Specifically, in these regressions, the dependent variable is a particular covariate, e.g., “Total ZIP code population”, and the independent variable is the treatment indicator, i.e., whether a showroom opened or not in a ZIP code. When we use the logit link function and all 47 variables, the estimate for this covariate from the unweighted regression is highly statistically significant ($\beta = 10,911, p<.001$), whereas the estimate from the weighted regression is not ($\beta = 6,036, n.s.$). That is, showrooms are more likely to be placed in ZIP codes with more people, and any reliable analysis will need to account for this fact. Similarly, we find that the unweighted regressions imply that showrooms are, for example, more likely in ZIP codes with higher per capita income, larger eyewear market size and retail market potential, and younger populations. The weighted regressions eliminate all these significant differences, again providing evidence that our propensity score method properly balances the data.

### 4. The Overall Impact of Showrooms on Demand and Migration

The opening of a showroom can affect customers who live within the trading area, which we assumed to be 30 miles (see Section 3). In ZIP codes where customers cannot access a showroom (control ZIP codes) there are two channels through which customers can obtain product information: the WEB channel and the HTO channel. For ZIP codes in the treatment group, the SHOWROOM channel is added as a third option. Total sales in ZIP codes in the treatment group, i.e., those

---

22 Specific measures include ZIP-code level population and income metrics, the proportion of households in the target age demographic (25–45 years-old), market size metrics such as the number of offline eyewear stores in the 3-digit zip code area, and so on. A full list of these variables along with descriptive statistics is available from the authors, upon request.

23 All regression results for all four permutations: logit and probit link functions, large and small variable sets, are available from the authors, upon request.
within the trading area of a showroom, are expected to increase once it opens simply because sales through the showroom channel were zero before it opened. In addition to this positive demand effect in treatment ZIP codes through the showroom itself, we also measure the impact on demand via the other two channels as well. Specifically, whether customers migrate from the two pre-existing channels to the showroom, and if so, how that affects sales and operational efficiency. Table 2 summarizes the variables used in these analyses.

<table>
<thead>
<tr>
<th>Variable Name</th>
<th>Definition</th>
</tr>
</thead>
<tbody>
<tr>
<td>TOTALSALES$_{it}$</td>
<td>Total frames sold (in units) at ZIP Code $i$ on week $t$.</td>
</tr>
<tr>
<td>WEBSALES$_{it}$</td>
<td>Total frames sold (in units) through the WEB at ZIP Code $i$ on week $t$.</td>
</tr>
<tr>
<td>HTOSALES$_{it}$</td>
<td>Total frames sold (in units) through the HTO program at ZIP Code $i$ on week $t$.</td>
</tr>
<tr>
<td>OPEN$_{it}$</td>
<td>Dummy variable that is 1 if on week $t$ there was a Showroom open in ZIP Code $i$.</td>
</tr>
</tbody>
</table>

### Conversion of Home Try-On Program

<table>
<thead>
<tr>
<th>Variable Name</th>
<th>Definition</th>
</tr>
</thead>
<tbody>
<tr>
<td>HTOORDERS$_{it}$</td>
<td>Total HTO orders through the HTO program at ZIP Code $i$ on week $t$.</td>
</tr>
<tr>
<td>OPEN$_{it}$</td>
<td>Dummy variable that is 1 if on week $t$ there was a Showroom open in ZIP Code $i$.</td>
</tr>
</tbody>
</table>

#### 4.1. Impact on Total Sales

The following regression equation captures the effect of the showroom opening on total demand:

$$ \log(TOTALSALES)_{it} = \mu_i + \alpha_1 OPEN_{it} + W_t + \epsilon_{it} $$ (1)

where $OPEN_{it} = 1$ indicates that ZIP code $i$ is in the vicinity of a showroom that is open on week $t$, and 0 otherwise. Showrooms open at different points in time so $OPEN_{it}$ captures variation not only across different ZIP codes but also within a ZIP code over time. Fixed effects $\mu_i$ capture any time-invariant factors, and $W_t$ (one dummy for each time period) capture the trend in overall sales over time. The coefficient on $OPEN_{it}$, $\alpha_1$, is interpreted relative to baseline sales for a given ZIP code and the seasonality patterns for a given week. If $\alpha_1$ is positive and significant, then opening a showroom delivers an increase in overall sales for ZIP codes in the vicinity of the showroom, compared to matched ZIP codes where a showroom is not accessible.

Showroom sales are by definition zero before a showroom opens, so we expect $\alpha_1 > 0$. Table 3 shows the results with (Column 2) and without (Column 1) the propensity score adjustment (our preferred specification).\(^{24}\) The effect of a showroom opening on total demand is substantial and

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\(^{24}\) For ease of exposition we report only the propensity-score adjusted results for the remainder of the paper. The unadjusted regression results deliver the same substantive conclusion and all are available from the authors, upon request. Moreover, this first finding and all those reported subsequently are robust to functional form changes as well (linear and Poisson regression models produce the same substantive conclusion).
economically meaningful, at about 7.5 percent ($\alpha_1 = 0.074, p < 0.001$). An effect of this magnitude is probably not solely due to new sales through the *showroom only*, but to a combination of effects through all three channels. Moreover, the effect(s) could arise from increases in brand awareness rather than provision of visceral information per se, and there could be heterogeneity in the effect according to latent market potential and so on. As such, we explore these nuances shortly.

<table>
<thead>
<tr>
<th>Variables</th>
<th>(1)</th>
<th>(2)</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>OPEN</strong></td>
<td>0.105***</td>
<td>0.074***</td>
</tr>
<tr>
<td></td>
<td>(0.009)</td>
<td>(0.021)</td>
</tr>
<tr>
<td><strong>Fixed Effects</strong></td>
<td>YES</td>
<td>YES</td>
</tr>
<tr>
<td><strong>Time Controls</strong></td>
<td>Week-year</td>
<td>Week-year</td>
</tr>
<tr>
<td><strong>Prop. Score Weighting</strong></td>
<td>NO</td>
<td>YES</td>
</tr>
<tr>
<td><strong>Observations</strong></td>
<td>313,570</td>
<td>313,570</td>
</tr>
<tr>
<td><strong>R-squared</strong></td>
<td>0.297</td>
<td>0.285</td>
</tr>
<tr>
<td><strong>Number of ZIP Codes</strong></td>
<td>1,972</td>
<td>1,972</td>
</tr>
</tbody>
</table>

Robust standard errors in parentheses

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

### 4.2. Impact on the Web Channel

The regression specification is unchanged except that the dependent variable is now $\log(WEBSALES)_{it}$:

$$\log(WEBSALES)_{it} = \mu_i + \beta_1 OPEN_{it} + W_t + \epsilon_{it}$$ (2)

If $\beta_1$ is positive and significant, then opening a showroom delivers an increase in web sales for ZIP codes in the vicinity of the showroom, compared to matched ZIP codes where a showroom is not accessible. Table 4 shows the results. Opening a showroom is associated with an increase in web sales of 2.9 percent ($\beta_1 = 0.029, p < 0.001$), which confirms the total increase in sales observed in Table 3 was not solely attributable to sales in the showrooms alone. The web sales increase could be due to customers browsing in the showroom and buying online. Alternatively, a customer visiting WarbyParker.com could attribute more legitimacy to the brand simply because it has a local physical presence, and therefore be more inclined to buy online.

---

25 The percentage increase can be calculated as $(e^{\alpha_1} - 1) \times 100$. 

Table 4  Impact on Web Sales.

<table>
<thead>
<tr>
<th>VARIABLES</th>
<th>log(WEBSALES)</th>
</tr>
</thead>
<tbody>
<tr>
<td>OPEN</td>
<td>0.029***</td>
</tr>
<tr>
<td></td>
<td>(0.007)</td>
</tr>
<tr>
<td>Fixed Effects</td>
<td>YES</td>
</tr>
<tr>
<td>Time Controls</td>
<td>Week-year</td>
</tr>
<tr>
<td>Prop. Score Weighting</td>
<td>YES</td>
</tr>
<tr>
<td>Observations</td>
<td>313,570</td>
</tr>
<tr>
<td>R-squared</td>
<td>0.145</td>
</tr>
<tr>
<td>Number of ZIP Codes</td>
<td>1,972</td>
</tr>
</tbody>
</table>

Robust standard errors in parentheses

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

4.3. Impact on the Sampling Channel (Home Try-On)

The regression specification is unchanged except that the dependent variable is now $\log(HTOSALES)_{it}$:

$$
\log(HTOSALES)_{it} = \mu_i + \gamma_1 \text{OPEN}_{it} + W_t + \epsilon_{it}
$$

(3)

If $\gamma_1$ is positive and significant, then opening a showroom delivers an increase in home try on sales for ZIP codes in the vicinity of the showroom, compared to matched ZIP codes where a showroom is not accessible. Table 5 (Column 1) shows the results. Opening a showroom, however, is associated with a decrease in home try on sales of 4.5 percent ($\gamma_1 = -0.045, p < 0.001$). As we show later in the robustness section, the drop in sales through this channel is even more pronounced in “high activity” ZIP codes, i.e., those where the base level of total sales is high.

Of course the effectiveness of the sampling program depends not only on total sales through this channel but also on the number of orders that went out in the first place, and therefore the implicit rate of conversion from “samplers” to customers. Hence, we estimate:

$$
\log(HTOORDERS)_{it} = \mu_i + \delta_1 \text{OPEN}_{it} + W_t + \epsilon_{it}
$$

(4)

Table 5 (Column 2) shows the results. Opening a showroom is also associated with a decrease in home try on orders ($\delta_1 = -0.100, p < 0.001$). Notice, however, that the decrease in orders exceeds that of sales, which implies that the conversion rate of the sampling program improves in locations where showrooms are opened. Taken together, these results suggest that a statistically significant number of customers migrate from the sampling program to the showroom, after the latter is opened, and that those who remain in the sampling program after a showroom opens are more likely to generate successful conversions.
Table 5  Impact on HTO Sales and Orders.

<table>
<thead>
<tr>
<th>VARIABLES</th>
<th>(1) log(HTOSALES)</th>
<th>(2) log(HTOORDERS)</th>
</tr>
</thead>
<tbody>
<tr>
<td>OPEN</td>
<td>-0.045***</td>
<td>-0.100***</td>
</tr>
<tr>
<td></td>
<td>(0.008)</td>
<td>(0.015)</td>
</tr>
<tr>
<td>Fixed Effects</td>
<td>YES</td>
<td>YES</td>
</tr>
<tr>
<td>Time Controls</td>
<td>Week-year</td>
<td>Week-year</td>
</tr>
<tr>
<td>Prop. Score Weighting</td>
<td>YES</td>
<td>YES</td>
</tr>
<tr>
<td>Observations</td>
<td>313,570</td>
<td>313,570</td>
</tr>
<tr>
<td>R-squared</td>
<td>0.173</td>
<td>0.431</td>
</tr>
<tr>
<td>Number of ZIP Codes</td>
<td>1,972</td>
<td>1,972</td>
</tr>
</tbody>
</table>

Robust standard errors in parentheses

* p < 0.05, ** p < 0.01, *** p < 0.001

4.4. Alternative Explanation and Robustness

The findings discussed so far can be explained by customer heterogeneity in the need for information. When the showroom channel becomes available, it attracts some customers that would not buy if this information was not available and it also may attract those customers with the highest need for touch and feel, who may have used another channel in absence of the showroom, and now gravitate to the showroom. An alternative conjecture could be that intense (and unobserved to us) advertising activity occurs at the time when a showroom opens, driving more sales to this channel. While our conversations with management suggest this is not the case, we can also use the data to demonstrate the same point. If such advertising occurred, the largest impact would be felt when the showroom first opened. To confirm that this did not happen we rerun all four regressions (Total Sales, Web Sales, HTO Sales and HTO Orders) excluding data from periods when showrooms first opened. We find results almost identical, in sign and magnitude, to those presented thus far.

Besides this analysis, we performed multiple robustness checks (described in Appendix 1) to validate the direction and significance of our findings. We find no substantial differences when we consider different data selection criteria such as alternative minimum sales thresholds to select the ZIP codes that we consider (see Tables 11, 12 and 13). We also checked alternative model specifications, including a simpler linear model (without logs) and a Poisson regression and confirmed that the coefficients have the same sign and significance as in the log-linear models. In addition, we validated our results using different approaches to propensity scoring (large and small sets of predictor variables, logit and probit link functions). We have also estimated the models using a

---

26 It is harder to argue, however, that intense advertising would improve the conversion rate of the sampling channel.

27 Although we favor the propensity score methods described in the paper, we have conducted additional analysis using synthetic controls (Abadie et al. 2011). We find qualitatively similar results (the results are available from the authors).
variety of lagged variables with no significant changes in our results. Taking all of these analyses into account, we conclude that the reported effects of showroom openings on total sales, web sales, and HTO sales and orders are indeed robust.

5. The Migration Mechanism

So far, we have shown that opening a showroom: (1) increases overall demand, (2) increases demand through the web channel, (3) decreases demand through the sampling channel, and (4) increases the sampling channel conversion rate. In this section we provide insight into the underlying consumer behavior. We conjecture, and provide evidence, that a showroom causes: (1) an influx of new customers, (2) a channel shift by customers with the highest need for a tactile shopping experience, and (3) a reduction in the operational cost to serve customers, both at the aggregate level and also for the transactions from the two original channels.

5.1. Showrooms and Customer Acquisition

We estimate the effect of a showroom on new customer acquisition via:

\[ \log(\text{FIRSTSALES})_{it} = \mu_i + \theta_1 \text{OPEN}_{it} + W_t + \epsilon_{it} \]  

(5)

Where the variable FIRSTSALES corresponds to the total number of orders placed exclusively by customers that haven’t purchased from the company before. Table 6 shows that after a showroom opens the number of first time purchases within the trading area of the showroom increases substantially, by about 7.3 percent.

<table>
<thead>
<tr>
<th>VARIABLES</th>
<th>(1) log(FIRSTORDERS)</th>
</tr>
</thead>
<tbody>
<tr>
<td>OPEN</td>
<td>0.073***</td>
</tr>
<tr>
<td></td>
<td>(0.019)</td>
</tr>
<tr>
<td>Fixed Effects</td>
<td>YES</td>
</tr>
<tr>
<td>Time Controls</td>
<td>Week-year</td>
</tr>
<tr>
<td>Prop. Score Weighting</td>
<td>YES</td>
</tr>
<tr>
<td>Observations</td>
<td>313,570</td>
</tr>
<tr>
<td>R-squared</td>
<td>0.239</td>
</tr>
<tr>
<td>Number of ZIP Codes</td>
<td>1,972</td>
</tr>
</tbody>
</table>

Robust standard errors in parentheses
\* p < 0.05, ** p < 0.01, *** p < 0.001

The raw data show that showrooms not only increase first-time purchases overall, but also alter the mix of first-time and repeat purchases coming through the other channels. In locations without
showrooms the fractions of new customers per channel are 82 percent and 75 percent, for HTO and web, respectively. In locations with showrooms, the fractions of new customers decline in both of the original channels. Specifically, from 82 percent to 78 percent in the HTO channel and from 75 percent to 67 percent in the web channel. At the same time, the fraction customers in a showroom itself that are first time customers is about 83 percent. Hence, the showroom seems to be especially effective at attracting customers who are new to the brand.  

5.2. Showrooms and Migration and Alignment

Customer heterogeneity is the sine qua non of marketing. Customers in the eyewear market will therefore differ in the extent to which they need to “sample” the non-digital attributes of eyewear, including fit, feel, style, and perhaps even social approval. With only two channels to chose from, those with a greater need for tactile experiences will, on average, favor the sampling channel over the web channel. Among those preferring the sampling channel, some will find it largely sufficient for their needs. Others, however, while finding it preferable to the web channel, still consider it less than ideal. To gain insight into the mechanism, we focus on this latter group, who are rather “poorly matched” to the sampling channel.

These somewhat reluctant users of the sampling program may find five frames alone insufficient to resolve their pre-purchases uncertainty, and, absent a showroom, might order more than one home try on. Therefore, when the showroom opens, it becomes attractive to this segment of customers, which results in two demand effects in the sampling channel. First, those finding the single sample insufficient, will migrate to the showroom, thereby reducing the incidence of multiple home try-ons per customer. At the same time, those remaining in the sampling channel even though they have the option of going to showroom are indicating a weak preference for HTO. In short, high touch customers migrate from the HTO channel to the showroom; those that remain in HTO are better aligned to it. We utilize individual-level choice data to uncover evidence of these two effects. Recall that earlier Table 5 showed that a showroom opening is associated with an HTO sales decline of 4.5 percent and an HTO order decline of 10 percent. This implies an implicit improvement in conversion (sales per order) and we now test this directly. Specifically, instead of modeling aggregate demand at the ZIP code and weekly level, we model individual-level conversion.  

28 Some companies are experimenting with itinerant pop up showrooms that try to capitalize on these customer acquisition effects. For example, after our period of analysis for this paper Warby Parker launched an initiative by which a school bus was retrofitted and converted into an itinerant showroom that would tour different cities in the United States.

29 Recall from Section 3.1 that an HTO order to a specific customer “converts” when a sale occurs within the next two months.
We model the customer-level decision of purchase or non-purchase conditional upon an order, as a logistic specification. Let $y = 1$ when an HTO result in a purchase and $y = 0$ otherwise, then $p(y = 1|x) = G(x\beta)$, where

$$G(x\beta) = \frac{exp(x\beta)}{1 + exp(x\beta)} \quad (6)$$

$X$ includes a constant, ZIP and person-level control variables, and fixed effects for time. Of substantive interest are the variables $OPEN_{ijt} = 1$ when there is a showroom open in the vicinity of customer $j$ at the time of the sale, 0 otherwise, and $FIRST_{ijt} = 1$ if this is the first purchase made by customer $j$, 0 otherwise. In this individual-level model, the endogeneity issue is less of a concern as in this study it pertains more to management choices of where to put a showroom (which will be codetermined with expected performance), rather than directly to individual choices of which ZIP codes to live in. Adding a rich set of ZIP code level control variables (the same variables considered in the propensity-score based models reported in Section 4) accounts for systematic differences driven by this choice.

We can use a similar specification to model whether a customer is placing multiple HTOs. Table 7 shows the estimates and evidence for the two effects ($y = \{\text{multipleHTOs, conversion}\}$). Column 1 reports a significant negative impact of showrooms on the probability of multiple HTOs ($\beta_1 = -0.142, p < 0.001$). After taking derivatives and combining the estimate with the data we obtain an average marginal effect of -1.6 percent (since the model is non-linear the coefficient is not equivalent to the marginal effect). After a showroom opens, individual customers within the trading area who participate in the sampling channel are less likely to order multiple home try-ons. Column 2 reports a significant positive impact of showrooms on the probability that an HTO order leads to a sale ($\beta_1 = 0.036, p < 0.05$). The implied marginal effect is just under under 1 percent.

In summary, because showrooms attract customers who are more sensitive to fit (and therefore are the most costly to serve), the sampling channel is left with a more favorable consumer mix after a showroom is introduced, which is manifested through an increase in the conversion rate of the HTO and a reduction in the likelihood of multiple HTOs. In other words, the introduction of the showroom channel generates operational efficiency spillover effects in the HTO channel.

5.3. Showrooms and Operational Efficiency

There is another channel through which showrooms affect operational efficiency. It is operationally efficient to sell to customers who are satisfied with the product and do not return it. Reducing returns is a key objective for any retailer and online sales are especially vulnerable as about a third of all Internet transactions are returned by shoppers.\(^{30}\) Put simply, returns are a major source of

Table 7 Impact of Showrooms on Multiple HTOs & Conversion

<table>
<thead>
<tr>
<th>VARIABLES</th>
<th>P(Multiple HTOs)</th>
<th>P(Conversion)</th>
</tr>
</thead>
<tbody>
<tr>
<td>OPEN</td>
<td>-0.142*** (0.021)</td>
<td>0.036* (0.015)</td>
</tr>
<tr>
<td>FIRST</td>
<td>-0.036** (0.013)</td>
<td>-0.184*** (0.010)</td>
</tr>
<tr>
<td>Time Controls</td>
<td>Week-year</td>
<td>Week-year</td>
</tr>
<tr>
<td>Other Controls</td>
<td>ZIP Info</td>
<td>ZIP Info</td>
</tr>
<tr>
<td>Observations</td>
<td>252,086</td>
<td>252,086</td>
</tr>
</tbody>
</table>

Robust standard errors in parentheses

∗ p < 0.05, ∗∗ p < 0.01, ∗∗∗ p < 0.001

operational complexity and margin erosion (e.g., from unnecessary shipping and wasted materials since lenses have to be discarded).

Since for each purchase we observe whether it is returned or not, we can study the effects of returns at the individual transaction level. Our model has the same structure as the one described by Equation 6, but we consider the indicators of return (for datasets including web, HTO and all sales) as the dependent variable. It stands to reason that customers buying through the showroom have greater exposure to the product prior to purchase and therefore should be less likely to return it. Indeed, the average total marginal effect of showrooms on returns (Table 8, Column 3) is -0.011, meaning that once a showroom opens returns fall by 1.1 percent. More nuanced, and indicative of the mechanism, are the separate effects on returns on sales made through the HTO and web channels. The effect of showrooms on returns on sales made through the HTO channel is negatively signed, but not significant (Table 8, Column 2). This suggests that customers who remained in the HTO channel (even though they had access to a showroom) and decided to buy after having tried five frames do not experience a significantly higher fit uncertainty than those customers who had physical access to the entire product line before making their purchases. These customers were not only “comfortable enough” with the HTO channel as a means to reduce pre-purchase uncertainty, but also had the opportunity to try before buying.

This is in contrast with the web channel, where customers do not have the chance to try the product before placing their order. Those who migrate from the web channel to the showroom benefit from being able to better assess product fit prior to making a purchase. Those who remain in the web channel are, on average, less sensitive to fit, and we expect this to result in a decrease in return rates on the web channel, which is indeed what we find (Table 8, Column 1). This is

31 The model includes the same rich set of ZIP code level information as controls.
another instance of the operational efficiency spillovers (in this case, to the web channel) arising from the introduction of the showroom.

Table 8  Impact of Showrooms on Operational Efficiency - Returns

<table>
<thead>
<tr>
<th>VARIABLES</th>
<th>(1) Web</th>
<th>(2) HTO</th>
<th>(3) All</th>
</tr>
</thead>
<tbody>
<tr>
<td>OPEN</td>
<td>-0.098*</td>
<td>-0.080</td>
<td>-0.074**</td>
</tr>
<tr>
<td></td>
<td>(0.042)</td>
<td>(0.044)</td>
<td>(0.029)</td>
</tr>
<tr>
<td>FIRST</td>
<td>-0.283***</td>
<td>-0.450***</td>
<td>-0.371***</td>
</tr>
<tr>
<td></td>
<td>(0.023)</td>
<td>(0.028)</td>
<td>(0.016)</td>
</tr>
</tbody>
</table>

Time Controls: Week-year  Week-year  Week-year
Other Controls: ZIP info  ZIP info  ZIP info
Observations: 76,074  74,427  191,567

Robust standard errors in parentheses
* p < 0.05,  ** p < 0.01,  *** p < 0.001

In summary, the overall results reported in Section 4 are driven by the underlying dynamics of customer migration to showrooms by those who value the opportunity to obtain more complete product information prior to a purchase, coupled with a better fit between what the sampling channel facilitates and those who choose to remain in it.

5.4. Showrooms and Intensity of Use

Customers differ not only in their need for fit and feel information prior to purchase, but also in the intensity with which they use the product. With eyewear, some customers will use the product for reading only, whereas others may use it continuously throughout the day. This opens another avenue through which we can gather evidence that it is the information provision aspect of the showroom channel that is driving our results. Specifically, a showroom with the attendant service and ability of customers to fully experience the product prior to purchase, will be more valuable to these “high intensity” users.

To operationalize “intensity of use” we utilize an objective measure of product complexity that is fundamental to eyewear. Individual prescriptions are characterized by diopeters\(^{32}\) and an individual requiring a measurement of 6 or greater has more “challenged” eyesight and is likely to use the product more frequently than a wearer of a lower measured lens. We anticipate that customers needing these kinds of products, will, on average, show higher returns. In fact, evidence of this indicates that separating products by diopter rating is, in fact, a useful way to proxy complexity and

\(^{32}\) A diopter is a unit of measurement of the optical power of a prescription lens in eyewear. Technically, it is equal to the reciprocal of the focal length measured in meters.
intensity of use. More critically for our conjecture, if showrooms are indeed making fit information more accessible, their ability to reduce return rates documented above, should be amplified for these customers.

We estimate a set of models that have the same structure as the one described in Section 5.3, but with additional variables: an indicator of whether the prescription is *COMPLEX* which denotes high diopter lenses and its interaction with *OPEN*, as well as the interaction between *FIRST* and *OPEN*. As anticipated, eyewear with high diopter prescriptions are more likely to be returned, regardless of the channel through which they were purchased. Columns (1) - (3) of Table 9 show positive and statistically significant coefficients for the variable *COMPLEX* which denotes high diopter lenses. These coefficients translate into marginal effects of 15.6 percent, and 13.9 percent for Web and Total returns, respectively. Consistent with our information conjecture are the negative interaction effects (which also translate into negative marginal effects). Consider returns through the web channel. While opening a showroom reduces the *overall return rate* about about 1 percent (Table 8) the effect of the showroom on returns for complex products is far greater, at 3.6 percent (Table 9).

### Table 9 Impact of Showrooms on Operational Efficiency - Returns (Complexity)

<table>
<thead>
<tr>
<th>VARIABLES</th>
<th>(1) Web</th>
<th>(2) HTO</th>
<th>(3) All</th>
</tr>
</thead>
<tbody>
<tr>
<td>OPEN</td>
<td>-0.106**</td>
<td>-0.095</td>
<td>-0.083**</td>
</tr>
<tr>
<td></td>
<td>(0.052)</td>
<td>(0.062)</td>
<td>(0.036)</td>
</tr>
<tr>
<td>COMPLEX</td>
<td>0.504***</td>
<td>0.271***</td>
<td>0.387***</td>
</tr>
<tr>
<td></td>
<td>(0.044)</td>
<td>(0.047)</td>
<td>(0.031)</td>
</tr>
<tr>
<td>OPEN*COMPLEX</td>
<td>-0.180***</td>
<td>0.024</td>
<td>-0.091**</td>
</tr>
<tr>
<td></td>
<td>(0.068)</td>
<td>(0.083)</td>
<td>(0.045)</td>
</tr>
<tr>
<td>FIRST</td>
<td>-0.304***</td>
<td>-0.446***</td>
<td>-0.376***</td>
</tr>
<tr>
<td></td>
<td>(0.032)</td>
<td>(0.034)</td>
<td>(0.023)</td>
</tr>
<tr>
<td>FIRST*OPEN</td>
<td>0.046</td>
<td>0.015</td>
<td>0.024</td>
</tr>
<tr>
<td></td>
<td>(0.046)</td>
<td>(0.058)</td>
<td>(0.032)</td>
</tr>
<tr>
<td>Showroom</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>0.072***</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.022)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Web</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>0.192***</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.017)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Time Controls</td>
<td>Week-year</td>
<td>Week-year</td>
<td>Week-year</td>
</tr>
<tr>
<td>Other Controls</td>
<td>ZIP info</td>
<td>ZIP info</td>
<td>ZIP info</td>
</tr>
<tr>
<td>Observations</td>
<td>76,074</td>
<td>74,427</td>
<td>191,567</td>
</tr>
</tbody>
</table>

Robust standard errors in parentheses
* p < 0.05, ** p < 0.01, *** p < 0.001
5.5. Showrooms And “Channel Awareness”

We demonstrated that showrooms are effective for acquiring customers and building brand awareness. In addition, the longer a showroom is present in a market, the more opportunity there is for customers to become aware of the channel that is most appropriate for their needs. We uncover evidence for what we term channel awareness by estimating:

\[
\log(DV)_{it} = \mu_i + \gamma_1 OPEN[0 - 3]_{it} + \gamma_2 OPEN[3 - 6]_{it} + \\
\gamma_3 OPEN[6 - More]_{it} + W_t + \epsilon_{it}
\]  

(7)

where \((DV)_{it}\) is, in turn, Total Sales, Web Sales, HTO Sales, and HTO Orders.

\(OPEN[0 - 3]\) indicates that the showroom is in the first three months of operation, \(OPEN[3 - 6]\) the period between 3 and 6, and \(OPEN[6 - More]\) captures the effects after the showroom has been open for more than 6 months. Table 10 gives the results. Note that for each outcome variable, the effect of the showroom is not only directionally consistent over time but also that the magnitude of the effect increases (read down the rows). Specifically, overall demand benefits (Column 1) and awareness and legitimacy benefits (Column 2) get stronger with time. Similarly, HTO sales and orders decline at an increasing rate, and the implicit conversion rate of the HTO channel (sales to orders) therefore increases accordingly (Columns 3 and 4).

<table>
<thead>
<tr>
<th>VARIABLES</th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
</tr>
</thead>
<tbody>
<tr>
<td>First 3 month</td>
<td>0.031</td>
<td>0.001</td>
<td>-0.029**</td>
<td>-0.061***</td>
</tr>
<tr>
<td></td>
<td>(0.019)</td>
<td>(0.009)</td>
<td>(0.011)</td>
<td>(0.015)</td>
</tr>
<tr>
<td>3 to 6 month</td>
<td>0.072***</td>
<td>0.029**</td>
<td>-0.035***</td>
<td>-0.075***</td>
</tr>
<tr>
<td></td>
<td>(0.019)</td>
<td>(0.009)</td>
<td>(0.009)</td>
<td>(0.015)</td>
</tr>
<tr>
<td>More than 6 month</td>
<td>0.109**</td>
<td>0.050***</td>
<td>-0.063***</td>
<td>-0.144***</td>
</tr>
<tr>
<td></td>
<td>(0.035)</td>
<td>(0.009)</td>
<td>(0.010)</td>
<td>(0.021)</td>
</tr>
<tr>
<td>Fixed Effects</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Time controls</td>
<td>Week-year</td>
<td>Week-year</td>
<td>Week-year</td>
<td>Week-year</td>
</tr>
<tr>
<td>Prop. Score Weight</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Observations</td>
<td>313,570</td>
<td>313,570</td>
<td>313,570</td>
<td>313,570</td>
</tr>
<tr>
<td>R-squared</td>
<td>0.286</td>
<td>0.280</td>
<td>0.173</td>
<td>0.431</td>
</tr>
<tr>
<td>Number of ZIP Codes</td>
<td>1,972</td>
<td>1,972</td>
<td>1,972</td>
<td>1,972</td>
</tr>
</tbody>
</table>

Robust standard errors in parentheses
* \(p < 0.05\), ** \(p < 0.01\), *** \(p < 0.001\)
6. Implications

In the Introduction we noted that numerous “online-first” retailers are opening offline showrooms. We conjectured that this strategy alters the amount of information available to customers in specific locations, and our goals were to: (1) determine the impact on demand and operational efficiency, and (2) elaborate the migration mechanism underlying the observed effects. We now discuss some practical aspects that can affect the decision of whether and where to open a showroom.

6.1. Showrooms and Retailer Types

What type of online-first retailers are more likely to benefit from opening showrooms? Our framework described in Figure 1 shows that when venturing into the offline world, online-first firms can prioritize the information or the fulfillment dimension. Firms like Bonobos and Warby Parker selling products of their own brand with high fit uncertainty tend to prioritize the informational function in the offline world. Conversely, firms like Amazon that sell goods that are more commoditized are focused on enriching the fulfillment dimension of channels. These companies are less limited by a lack of product information offline, since their customers can use competitors’ brick-and-mortar stores to learn about product characteristics.

Showrooms offer online-first retailers substantial cost advantages compared to conventional stores, since they allow them to maintain centralized fulfillment and inventory management, which can yield very substantial inventory pooling benefits (Eppen 1979) and economies of scale. This is particularly relevant when offering high variety to the market, which is the case for firms like Warby Parker. A potential downside for customers is the fact that they cannot take possession of the product immediately, since it is shipped from a centralized location. Consequently, a showroom strategy is less well suited to categories where immediate gratification is very important.

6.2. The Economics of Showrooms

An important implication of our research is that the decision to open a showroom needs to account for the nuanced interaction between this new channel and the mix of customers who will continue through the online channel (and in our application, the sampling channel as well). More practically, the firm needs to compute the demand indifference point for opening a showroom. In our application domain, we ask: How many additional frames does Warby Parker need to sell in order to justify opening a showroom in a specific location?

We first estimate the likely operating costs of a showroom using data from Storefront (https://www.thestorefront.com). These data lead us to focus on realistic cost levels given the

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33 Amazon, for example, is installing physical lockers where customers can pick up their products, see http://en.wikipedia.org/wiki/Amazon_Locker.

34 Storefront is ideal since it provides cost information for renting retail spaces within existing stores of different sizes and locations throughout the United States. Thus, it exactly mirrors the “Warby Parker Showroom.”
current locations of Warby Parker showrooms. The costs that we consider are $3,000, $4,000, $5,000 and $6,000 dollars per month. Second, our empirical analysis supplies the following changes in sales and sampling program orders, subsequent to the opening of a showroom: Total Sales (7.4 percent increase), Web Sales (2.9 percent increase), HTO Sales (4.5 percent decrease), HTO Orders (10 percent decrease). Third, the cost of shipping HTO orders can vary over time and locations so we consider a cost range between 5 and 40 percent of the selling price ($95 dollars).

Next, we build a model to compare income, net of the showroom and HTO costs, before and after a showroom is opened and display the results in Figure 3. These indifference curves illustrate that for particular operating cost (say $4,000 dollars a month) and HTO cost (say 15 percent), the firm would be indifferent between opening a showroom or not if volume was at least 500 frames per month.

![Figure 3 Sensitivity Analysis](image)

6.3. Heterogeneity of the Effects

Our primary goal is to measure and document the average treatment effects of showrooms on demand and operational efficiency as no prior study has considered them. That notwithstanding, we have implemented some individual showroom-level analysis to document heterogeneity and to provide a range of plausible values for the observed effects. To do this, we replicate our main analysis, but consider each showroom one at a time. This means that we run as many difference-in-difference (DiD) analyses per effect, as there are showroom locations in our data (15 different

35 The software code is available from the authors, upon request.
cities). For robustness, we consider three different approaches: (1) Base case, no matching, (2) Propensity-score weighting method using for each showroom the weights as calculated from the main analysis, and (3) Propensity-score weighting method, using idiosyncratic weights where for each showroom we recalculate weights individually. We obtain qualitatively similar results for each approach and for consistency we report the results obtained under method (2). We find that 11 of the 15 sales lift coefficients are statistically greater than zero (the remaining 4 are zero), and that they range from zero to 25%, i.e., overall sales in a location improve by up to 25% after the introduction of a showroom. Individual showroom location estimates replicate the directional patterns of the aggregate analysis, i.e., an increase in total sales, a decrease in HTO sales, and a larger decrease in HTO orders. Figure 4 plots the declines in HTO orders against sales lift and the black dot represents the average effect.

![Figure 4 Effect Heterogeneity by Showroom Location](image)

We also explored whether geographic characteristics help to explain heterogeneity in the effects. For example, we hypothesized more intense effects in areas where: (1) prior to opening showroom the incidence of the HTO was larger (since this reveals a larger need for information), and (2) there is a larger fraction of customers with complex needs, i.e., those who have higher utility for the information provided in the showroom. Unfortunately, we are very constrained as we have only 15 different showroom locations and consequently only 15 data points. Nevertheless, we find, as conjectured, positive correlations between sales lift in a location and (1) the prior incidence of HTO, and (2) the fraction of customers with complex needs.
With these results in hand, we revisit the question asked in Section 6.3: How many additional frames does Warby Parker need to sell in order to justify opening a showroom in a specific location? This time, however, we seek to better understand the implications of the heterogeneity across showrooms. To do this, we assume a fixed cost for operating the showroom ($5,000 per month) and a fixed cost of fulfilling a HTO (20% of the sale price of a frame). These numbers are representative of the situation faced by Warby Parker. Next, we compare the income, net of the showroom and HTO costs, before and after a showroom is open, for different plausible values of the heterogenous effects on sales and HTO. Figure 5 highlights the resulting indifference curves. These curves illustrate, for particular total sales lift in the area of influence of a showroom (say 16 percent), and HTO order reduction (say 12 percent), the market size that would make the firm indifferent between opening a showroom or not. Our analysis suggests, for example, that at these values (16% sales lift, 12% HTO order decline), the market size that makes the firm indifferent is 500 frames per month.

![Figure 5 Sensitivity Analysis to Considering Effects Heterogeneity](image)

7. Conclusions

To the best of our knowledge, this paper is the first to isolate the information function of channels in the important context of online-first retailers adding showrooms. Using a variety of models and approaches, we verify that showrooms deliver substantial demand (marketing) and supply-side (operational) benefits. Specifically:
• **Demand Generation.** Showrooms increase sales within their catchment area, both overall, and through the web channel as well. Showrooms are especially important to customer acquisition as they garner a higher proportion of first time buyers than the other channels do. These findings underscore awareness benefits from the showroom (we also verify that these effects cannot be accounted for by an initial boost due to coincident advertising). The showroom induces beneficial customer migration and channel matching benefits for the firm and these effects amplify, rather than dissipate, over time.

• **Operational Efficiency.** Customers with the highest need for a tactile experience migrate to the showroom, leaving those who remain in other channels to be better matched to them. The important operational consequences are reductions in the probability that items are returned and that multiple samples are ordered, which results in a significant reduction in the average cost-to-serve. These operational benefits are amplified when dealing with customers who have the most acute need for the product, illustrating important product-channel interaction effects.

Our substantive conclusions were subject to an exhaustive set of robustness checks in which we varied data selection criteria, model functional form, and the set of predictors. In all cases the substantive findings were unchanged, leading us to conclude that the ability of showrooms to drive incremental demand and generate operational efficiencies is a vital and robust phenomenon within the emerging omni-channel landscape, and one that holds considerable promise for retailers so inclined to leverage it.

**Acknowledgments**

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*Bell, Gallino and Moreno: Offline Showrooms and Customer Migration in Omni-Channel Retail*


Appendix 1: Robustness Checks

We performed multiple robustness checks to validate the direction and significance of the results. In our main results we restricted the sample to those ZIP codes that sold at least 40 frames during the period of analysis. Focusing on those ZIP codes helps us avoid a large number of observations with zero sales and helps estimate the impact of the showroom implementation where is most relevant. However, this approach could rise a concern regarding potential selection bias. Table 11 shows the result for the analysis of total sales when we consider ZIP codes that sold 1, 5, 20 and 40 frames during the period of analysis. As it can be seen on the table our results are not driven by a particular number of sales by ZIP codes in the analysis.

Tables 12 and 13 restrict the attention to a subsample of the ZIP codes with more activity (at least 150 sales in the period of analysis). The qualitative insights continue to hold, and the effects in measured in these “denser” ZIP codes, i.e., those with higher levels of sales, are even more pronounced.

Consider the estimates in Table 13 which are based on ZIP codes with sales of at least 150 units and are obtained under the propensity score adjustment. After an inventory showroom opens in a ZIP code, demand in the trading area of the showroom: (1) increases overall by about 18.5 percent, and (2) increases by approximately 9 percent through the online channel. Furthermore, as shown in Column (3) of Table 13 sales through the HTO channel decline by almost 10 percent. With the HTO channel however, sales are not the only important metric. In order to understand the efficacy of this channel we must also consider the number of HTO orders that were delivered to customers and the conversion rate from deliveries to sales. We focus on this issue in some detail in Section 5 below.

In our analysis we also tested robustness using alternative model specifications, such as considering a simpler linear model (without logs) or a Poisson regression and confirmed that the coefficients have the same sign and significance as in the log linear models. In addition to the different model specification we validated our results considering different PS approaches. We include different sets of variables to generate the PS and we estimate the PS with both a logit and a probit approach. We conclude that the effects of showroom openings that we observe for total sales, web sales, and HTO sales are indeed robust.

<table>
<thead>
<tr>
<th>Table 11</th>
<th>Robustness Analysis Considering ZIP Codes with Different Total Sales</th>
</tr>
</thead>
<tbody>
<tr>
<td>Sales per ZIP Code</td>
<td>1</td>
</tr>
<tr>
<td></td>
<td>log(SALES)</td>
</tr>
<tr>
<td>OPEN</td>
<td>0.094***</td>
</tr>
<tr>
<td>Fixed Effects</td>
<td>YES</td>
</tr>
<tr>
<td>Time Controls</td>
<td>Week-year</td>
</tr>
<tr>
<td>Observations</td>
<td>1,168,000</td>
</tr>
<tr>
<td>Number of ZIP Codes</td>
<td>11,601</td>
</tr>
<tr>
<td>R-squared</td>
<td>0.142</td>
</tr>
</tbody>
</table>

Robust standard errors in parentheses

* p < 0.05, ** p < 0.01, *** p < 0.001
Table 12 Robustness. Subsample Analysis.

<table>
<thead>
<tr>
<th>VARIABLES</th>
<th>(1) log(SALES)</th>
<th>(2) log(WEBSALES)</th>
<th>(3) log-HTOSALES</th>
<th>(4) log-HTOORDERS</th>
</tr>
</thead>
<tbody>
<tr>
<td>OPEN</td>
<td>0.159***</td>
<td>0.076***</td>
<td>-0.059***</td>
<td>-0.095***</td>
</tr>
<tr>
<td></td>
<td>(0.017)</td>
<td>(0.014)</td>
<td>(0.010)</td>
<td>(0.017)</td>
</tr>
<tr>
<td>Fixed Effects</td>
<td>YES</td>
<td>YES</td>
<td>YES</td>
<td>YES</td>
</tr>
<tr>
<td>Time Controls</td>
<td>Week-year</td>
<td>Week-year</td>
<td>Week-year</td>
<td>Week-year</td>
</tr>
<tr>
<td>Prop. Score Weight</td>
<td>No</td>
<td>No</td>
<td>No</td>
<td>No</td>
</tr>
<tr>
<td>Observations</td>
<td>71,560</td>
<td>71,560</td>
<td>71,560</td>
<td>71,560</td>
</tr>
<tr>
<td>R-squared</td>
<td>0.546</td>
<td>0.298</td>
<td>0.374</td>
<td>0.611</td>
</tr>
<tr>
<td>Number of ZIP Codes</td>
<td>411</td>
<td>411</td>
<td>411</td>
<td>411</td>
</tr>
</tbody>
</table>

Robust standard errors in parentheses
* p<0.05, ** p<0.01, *** p<0.001

Table 13 Robustness. Subsample Analysis (with propensity score weighting).

<table>
<thead>
<tr>
<th>VARIABLES</th>
<th>(1) log(SALES)</th>
<th>(2) log(WEBSALES)</th>
<th>(3) log-HTOSALES</th>
<th>(4) log-HTOORDERS</th>
</tr>
</thead>
<tbody>
<tr>
<td>OPEN</td>
<td>0.185***</td>
<td>0.111***</td>
<td>-0.094***</td>
<td>-0.186***</td>
</tr>
<tr>
<td></td>
<td>(0.063)</td>
<td>(0.019)</td>
<td>(0.015)</td>
<td>(0.024)</td>
</tr>
<tr>
<td>Fixed Effects</td>
<td>YES</td>
<td>YES</td>
<td>YES</td>
<td>YES</td>
</tr>
<tr>
<td>Time controls</td>
<td>Week-year</td>
<td>Week-year</td>
<td>Week-year</td>
<td>Week-year</td>
</tr>
<tr>
<td>Prop. Score Weight</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Observations</td>
<td>71,560</td>
<td>71,560</td>
<td>71,560</td>
<td>71,560</td>
</tr>
<tr>
<td>R-squared</td>
<td>0.494</td>
<td>0.386</td>
<td>0.346</td>
<td>0.584</td>
</tr>
<tr>
<td>Number of ZIP Codes</td>
<td>411</td>
<td>411</td>
<td>411</td>
<td>411</td>
</tr>
</tbody>
</table>

Robust standard errors in parentheses
* p<0.05, ** p<0.01, *** p<0.001

Appendix 2: A Model of Channel Choice

Our model considers three channels through which customers can obtain product information before placing an order: the online channel, the HTO channel, and the offline showroom. Each channel has different costs and benefits for the consumers and potential consumers decline to make a purchase if the costs exceed the benefits of doing so. Before a showroom is opened, customers have two options. They can simply examine product information online, or they can participate in the HTO program and sample the product (and purchase or not). Prices are identical and fulfillment is as well as there is no charge for shipping in either case. After the showroom opens, customers have a third option, again with identical prices, purchase processes, and free shipping.

The following stylized model of channel choice leads to testable hypotheses along the lines of the results presented in Sections 4 and 5. Let $i$ denote a customer and $j = 1,...,J$ denote the different products offered by the company. A product is defined as a vector of attributes and for simplicity, we assume a product can be summarized with a scalar value $l_{ij}$ that denotes the location in an attribute space (for simplicity, a line) as perceived by customer $i$. The customer may have prior beliefs on this value but the actual value is learned only after the customer either: buys the product, receives and tries products through the sampling program, or visits an inventory showroom and inspects products in person. A customer $i$ has a preferred location $l_i$ or ideal product. Customer $i$ gets utility $u_{ij}$ from product $j$ which is expressed as the utility from buying the
“ideal” product minus a value that depends on the distance from the actual product to the ideal product, plus a random error:

$$u_{ij} = v_i - f_i(|l_i - l_{ij}|) + \epsilon_{ij}$$  \hspace{1cm} (8)

Customers differ in their tolerance for bad fit: every customer has a “pickiness” parameter $k_i$ and $f_i(x)$ is increasing in $k_i$ — the pickier the customer, the higher the loss in utility from being far from the ideal product location. For simplicity, we assume $v_i = v$ and $f_i(x) = k_i x$. Therefore,

$$u_{ij} = v - k_i |l_i - l_{ij}| + \epsilon_{ij}$$  \hspace{1cm} (9)

A customer who expects a positive utility makes a purchase; however, if the realized utility is negative, the customer returns the product. The utility of not buying is normalized to 0, $U(\emptyset) = 0$. Since each channel offers different opportunities to experience the product there are channel-specific and differential impacts on the expected utility. These differences are captured shortly.

If the customer decides to buy online, there is no sampling opportunity before placing an order so the expected utility of placing an order is

$$U_i(\text{online}) = v - k_i \text{disc}^{\text{online}}_i - c^{\text{online}}_i$$  \hspace{1cm} (10)

where $\text{disc}^{\text{online}}_i$ is the expected distance between the ideal location of customer $i$ and the location of the product bought using the online channel, and $c^{\text{online}}_i$ indicates the costs of using the online channel for customer $i$. All else equal, the higher the “pickiness” parameter $k_i$, the more likely the customer will be to return the product, since $k_i$ is multiplying the realized distance to the ideal product that reduces the experienced utility.

If the customer orders an HTO, he receives a subset $S$ (five products, in our setting) of the $J$ products. The customer then considers purchasing the product of the $S$ that provides the highest utility. The expected utility of placing an HTO request will be

$$U_i(\text{HTO}) = v - k_i \text{disc}^{\text{HTO}}_i - c^{\text{HTO}}_i,$$  \hspace{1cm} (11)

where $\text{disc}^{\text{HTO}}_i$ is the expected distance between the ideal location of customer $i$ and the location of the product bought using the HTO channel (with $\text{disc}^{\text{HTO}}_i \leq \text{disc}^{\text{online}}_i$, since the customer can choose the best fitting among five frames selected online), and $c^{\text{HTO}}_i$ indicates the costs of using the HTO channel for customer $i$. After receiving the HTO, the customer observes the realized value of the distance and makes a purchase if the realized expected utility is positive. This probability decreases with $k_i$. The customer can return the product if a negative value of the utility is realized.

Note that the probability of making a purchase increases in the number of products in the sample (since the expectation of the minimum decreases in the sample size) and will decrease with the “pickiness” of the customer (since $k_i$ amplifies the difference between the actual location of the product and the ideal one). If, after receiving the sample, the customer realizes the realized expected utility is negative, that individual will not make a purchase. In this case, the customer may place another order to sample $S$ new products, i.e., a repetition.
Customers who go to the physical showroom can evaluate the entire set of products \( J \). The customer will then consider purchasing the product of the \( J \) that provides the highest utility. The expected utility of visiting a showroom will be

\[
U_i(\text{SHOW}) = v - k_i \text{disc}^\text{SHOW}_i - c^\text{SHOW}_i,
\]  

where \( \text{disc}^\text{SHOW}_i \) is the expected distance between the ideal location of customer \( i \) and the location of the product bought using the showroom channel (with \( \text{disc}^\text{SHOW}_i \leq \text{disc}^\text{HTO}_i \leq \text{disc}^\text{online}_i \), since the customer can choose the best fitting among all existing frames), and \( c^\text{SHOW}_i \) indicates the costs of using the showroom channel for customer \( i \). After visiting the showroom, the customer learns the realized value of the distance and places an order if the realized expected utility is positive. Again, the customer can return the product if a negative value of the utility is realized.

With this information in hand we can ascertain the effect of opening a showroom. First, there is a direct effect. For some customers, \( U_i(\text{SHOW}) > 0 \) while \( U_i(\text{ONLINE}) < 0 \) and \( U_i(\text{HTO}) < 0 \). That is, some customers who buy in the showroom would not buy in the other channels. This channel extension effect contributes to the increase in total sales that we identified in Section 4.

Besides new customers, the showroom channel migrates customers who otherwise would use the online channel or the HTO channel. This happens if \( U_i(\text{SHOW}) > U_i(\text{ONLINE}) > 0 \) or \( U_i(\text{SHOW}) > U_i(\text{HTO}) > 0 \). More specifically, we can check which customers are more likely to shift towards the showroom channel and the consequences of this shift. To do that, we look at the difference in expected utility between using a showroom and using one of the other channels:

\[
U_i(\text{SHOW}) - U_i(\text{online}) = c^\text{online}_i - c^\text{SHOW}_i + k_i[\text{disc}^\text{online}_i - \text{disc}^\text{SHOW}_i]\]

\[
U_i(\text{SHOW}) - U_i(\text{HTO}) = c^\text{HTO}_i - c^\text{SHOW}_i + k_i[\text{disc}^\text{HTO}_i - \text{disc}^\text{SHOW}_i]\]

Since \( \text{disc}^\text{online}_i - \text{disc}^\text{SHOW}_i > 0 \) and \( \text{disc}^\text{HTO}_i - \text{disc}^\text{SHOW}_i > 0 \), i.e., the greater expected fit is achieved in the showroom, where customers can evaluate all the products, the difference in utility is increasing in \( k_i \). In other words, the “pickier” the customer, the more likely the customer is to migrate to the inventory showroom channel. Migration of these “pickier” customers, as a group, changes the mix of customers remaining in the other two original channels, i.e., the online channel and the HTO channel. This leads to the following predictions:

- After an inventory showroom is opened, the conversion rate of the HTO program within the trading area of the showroom will increase. As noted above, the probability that an HTO customer ends up making a purchase decreases with \( k_i \). Therefore, if customers with higher \( k_i \) are more likely to migrate from the HTO channel to the showroom, the HTO channel will be left with a mix with “less picky” customers, which will result in higher probability of purchase through this channel.

- After an inventory showroom is opened, the number of repeated HTO orders within the trading area of the showroom will decrease. An HTO customer may place a repeated HTO order if the realized expected utility of keeping an item from the first HTO is negative. (Recall that the HTO program
delivers only 5 frames to the customer.) The higher the \( k_i \), the higher the probability that this is the case. As above, if customers with higher \( k_i \) are more likely to migrate from the HTO channel to the inventory showroom, the HTO channel will be left with a mix of “less picky” customers, which will result in lower probability of HTO repetition.

- After an inventory showroom is opened, the rate of returns in the online channel within the trading area of the showroom will **decrease**. As noted above, in the online channel, the probability of product returns increases with \( k_i \). If customers with higher \( k_i \) are more likely to migrate, the online channel will have a mix with “less picky” customers, which will result in a lower probability of returns in the online channel. Furthermore, there will be customers who now buy in the showroom who would not have otherwise bought at all. Because these customers were able to fully resolve their pre-purchase uncertainty through physical exposure to the entire product line, they will have a lower rate of return than customers who buy directly online. This leads to a **decrease** in the total return rates as well.

If the three predictions from the model hold true in the data, the introduction of inventory showrooms will have led to a decrease in the operational cost to serve customers in the trading areas of the showrooms. Furthermore, as the showrooms provide full display of products only, the effect is driven by informational differences across the three channels which serve to cause pickier customers to migrate offline (in order to reduce their own shopping costs). These pickier customers, who are more expensive to serve through the online or HTO channels are attracted to the showroom channel, where the marginal costs of a sale are very low.