Inventory Showrooms and Customer Migration in Omni-channel Retail: The Effect of Product Information

David Bell  
Marketing, The Wharton School, University of Pennsylvania, Philadelphia, PA 19104, davidb@wharton.upenn.edu

Santiago Gallino  
Tuck School of Business, Dartmouth College, Hanover, NH 03755, santiago.gallino@tuck.dartmouth.edu

Antonio Moreno  
Managerial Economics and Decision Sciences, Kellogg School of Management, Northwestern University, Evanston, IL 60208, a-morenogarcia@kellogg.northwestern.edu

Omni-channel environments where customers can shop online and offline at the same retailer are increasingly ubiquitous. Furthermore, the presence of both channels has important implications for customer demand and operational issues such as product returns. We propose that, given the opportunity, customers self-select into channels based on their need for visceral product information, i.e., the need to touch, feel, and sample physical products before purchasing. From this core idea, we develop a simple model of channel matching; it predicts that customers with a higher need for information prefer physical access to all products and that the introduction of an offline inventory display channel where none previously existed results in a more efficient match between customers and channels. Using data on display showroom introductions by WarbyParker.com, a leading US eyewear retailer, we find that: (1) the introduction of an offline channel increases demand overall and through the online channel as well, and (2) customers who migrate offline are those with the highest cost-to-serve both online and through other mechanisms such as product sampling. The second finding is evidenced by a decline in product returns through the online channel, and through a higher rate of conversion from sampling, and a reduction in repeated sampling by individual customers. The economic impact of more efficient matching made possible by the introduction of offline inventory display showrooms, is substantial.

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

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1. Introduction

Online and offline retail channels are increasingly intertwined as traditional players ramp up their Internet presence and online-first retailers open stores and showrooms or develop offline partner-
ships. This intermingling reflects the fact that while online retailing is by far the fastest growing retail sector in the United States (according to Forrester Research the market will grow from $231b in 2013 to $370b in 2017 on CAGR of 10%\(^1\)), offline retailing still anchors the sector. Both observations apply to international markets as well; 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) such that the global consumer economy is one in which omni-channel retailers and buying experiences are now the norm.

There are important firm-level motivations for omni-channel retailing. Online and offline channels differ in their ability to deliver information and product fulfillment, which are the two most critical channel functions (see, for example, Coughlan et al. 2006, p. 9-10). An omni-channel retailer can therefore respond to and cater to consumer heterogeneity in preferences for both. That is, while some customers prefer the ease of access and shopping that comes from an online experience, others prefer to physically sample the product before buying. In this paper we focus on how consumer channel migration is driven by informational differences across alternative channels, i.e., the extent to which a channel allows a customer to resolve their expectations about product fit and quality prior to a purchase decision. We also examine the implications of the differences in information provision through different channels on the operational costs to serve customers, including those related to a key fulfillment issue—product returns.

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. For example, almost 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, may introduce significant uncertainty for some consumers when presented or characterized online.

Similarly, practitioners and analysts also understand that online-first retailers face significant challenges in communicating non-digital product attribute information to customers. For example, leading industry commentator GigaOm.com refers to a 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

\(^1\)http://techcrunch.com/2013/03/13/forrester-2012-2017-ecommerce-forecast/.

comfortable about their online purchase.” A myriad of other retailers from Ayr.com and Bonobos.com to 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, and related methods to combat it.

A related and emerging academic research 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 offline store introductions for online demand (e.g., Anderson et al. 2010; Avery et al. 2011). We contribute to this growing body of knowledge by demonstrating the importance of channel-supplied information to customer migration. Furthermore, we show why migrating certain types of customers from an online to offline experience can introduce important operational and fulfillment efficiencies.

We ascertain the effects of customer migration using a propensity scoring approach on quasi-experimental data from WarbyParker.com, a leading US fashion eyewear brand (Figure 1 shows a screenshot of the website) which has been progressively introducing inventory showrooms in different locations since the firm’s inception in early 2010. The institutional setting has important features that allow us to properly isolate the effect of informational differences on customer channel migration. First, eyewear is a category with significant non-digital or “fit and feel” attributes such that direct online purchasing is difficult for some customers. Second, WarbyParker.com began as an online only retailer that also offered consumers a unique (product) sampling program nationwide called Home Try On (HTO) in which consumers could have five pairs of glasses (frames only) delivered to them free of charge for five days. Thus, we are able to identify changes in customer behavior when offline showrooms are first introduced into locations where there was already online and sampling coverage. Third, and crucially for our study, the offline locations opened (and closed) by WarbyParker.com throughout the US are display only showrooms. These display only showrooms are existing offline stores operated by other independent brands selling apparel and accessories. Customers entering these showrooms can physically inspect the entire WarbyParker.com product line and make a purchase in-store via the website, but cannot take their purchases with them. Fulfillment, conditional on a purchase, i.e., shipment to the location of the customers choosing, is identical whether the purchase is made directly at the website, at the website subsequent to an HTO experience, or at the website subsequent to product inspection in a showroom.

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4 In 2010 when WarbyParker.com entered the $22 billion US eyewear market, only 1-2% of all sales in the category occurred online.
We make two new substantive contributions to the literature on omni-channel retailing. First, we show that the introduction of a display only showroom: (1) increases overall demand in the locations around the showroom and contained in its trading area, and (2) causes some customers to migrate from one channel to another. The estimated effects are statistically and economically significant, and the overall positive demand impact alone is approximately 10%. Moreover, the positive demand impact is not solely attributable to sales through the offline channel. Direct sales through the WarbyParker.com website in these same locations increase by up to 7.0% as well. This suggests that a physical offline presence confers awareness, branding, and credibility benefits that result in incremental sales through the existing online channel. Moreover, these benefits accrue from the provision of information alone, as fulfillment from the offline display only showroom channel is identical to that through the other two channels, i.e., the online channel and the sampling program. As the same time, sales through the sampling channel decline, which suggests that some customers have migrated from the sampling program to the offline channel.

Our second contribution is to isolate and test for the mechanism driving these overall results. To do so, we develop a formal model of the match between the information delivered by each channel (online, sampling, and display showroom) and that required by customers who vary in their tolerance for resolving uncertainty before buying the product. The model predicts that customers who have the least tolerance for uncertainty, i.e., those who are the most “picky”, are more likely to migrate to the offline channel when it is available. As a consequence, the pool of customers remaining in the sampling and online channels are, on average, better matched to those channels than they were when the more picky customers were also part of these groups. This leads to higher conversion from sampling, lower rates of repeated sampling, and fewer returns from sales made in the online channel.

The empirical results are consistent with these predictions. Specifically, the conversion rate in the sampling program increases because the fall in orders through this channel (7%) exceeds the fall in sales (5%). Repeated sampling by customers declines by around 1.5% and product returns from direct sales through the website fall too, by around 1%. All of these effects are both statistically and economically significant. Since fulfillment, conditional upon purchase, is held constant in all channels (online, sampling, and display showroom), our study is, to the best of our knowledge, the first to identify and measure the critical effect of channel-delivered informational differences on customer migration in an omni-channel setting.

The remainder of the paper is organized as follows. Section 2 summarizes relevant prior research and develops our conjecture that informational differences alone will lead to customer migration in...
omni-channel settings. Section 3 describes the research setting, data, and our econometric modeling approach and quasi-experimental design. Section 4 reports the global empirical effects, highlighting a positive demand impact and customer migration when the new channel is introduced. In Section 5 we develop a formal model for the underlying mechanism and report empirical findings that are consistent with the predictions of the model. Section 6 concludes the paper.

2. Background and Prior Literature

2.1. E-Commerce Development and Omni-Channel Retailing

The consumer Internet has evolved considerably since Jeff Bezos first sold books online in 1994 and “Internet Retailing 1.0” went through boom and bust in the early 2000s. Now, most (if not all) retailers recognize the important costs and benefits conferred by online and offline channels individually and understand the need to develop, maintain and nurture an omni-channel approach.

Similarly, a large body of research emerged, initially, to understand the key reasons for firm and consumer utilization of online and offline channels and the rationale for why one channel might be preferred to the other. Many early studies (e.g., Bakos 1997; Brynjolfsson and Smith 2000; Iyer and Pazgal 2003) focused on price as a key product attribute and the ability of online retailers to reduce search frictions and deliver lower prices to end consumers. In addition, online retailers can potentially offer consumers more convenience (e.g., Balasubramanian et al. 2003) and access to increased product variety (e.g., Brynjolfsson et al. 2009; Ghose et al. 2006). In the operations management literature, Netessine and Rudi (2006) derive conditions under which retailers prefer drop-shipping to holding inventory; similarly, Randall et al. (2006) also look at fulfillment choices by online retailers and find that firms carrying high margin products and less variety are more likely to invest in holding inventory.

Furthermore, key institutional differences in online and offline channels, such as the ability to engage in directed search and access review information from other consumers affects overall metrics such as sales concentration. Brynjolfsson et al. (2011), for example, show that the online channel, relative to a catalog channel with identical products and prices has a more diffuse sales distribution, and attribute this to the ability of consumers to more readily access products in the tail of the so-called Long Tail (Anderson 2006). Other recent work has looked at structural aspects of markets that shape online-offline competition such as distance to physical stores (e.g., Forman et al. 2009), and the extent to which target customers in local markets have minority preferences and are underserved by offline providers (Choi and Bell 2011).
2.2. Consumer Uncertainty When Buying Online

When consumers make purchase decisions through certain types of channels they often lack full information; for example, “... 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.” (Anderson et al. 2009, p. 408). As noted in the Introduction, this lack of complete information about non-digital attributes for products sold online has important consequences for consumer behavior and firm profitability. It can be a deterrent to purchase and also increase operational costs through product returns should consumers experience too much of a discrepancy between what they expect from the product that is purchased online and what is actually delivered.

This matters more in some product categories than others and for some segments more than others as well; for example Andy Dunn, CEO of fashion apparel retailer Bonobos.com justifies his expansion into offline stores by noting: “There are still people who want to touch and feel (italics added) clothing before they purchase.”

In this paper, our notion of uncertainty in product fit is related to Matthews and Persico (2007) and to recent work in operations management with strategic consumers (Swinney 2011). However, our study of these issues in the context of an omni-channel retailer with different channels offering different information acquisition opportunities is, to the best of our knowledge, novel. The operations management literature has studied inventory display strategies (e.g., Yin et al. 2009) and their implications for demand (Cachon et al. 2013). However, these studies cover conventional channels where consumers can also make purchases. Thus, in these contexts there is no ability to delineate informational and fulfillment differences between channels, e.g., between an online and offline channel, and study these effects separately. Offline channels, for example, typically offer the benefit of immediate fulfillment whereas online channels offer delayed fulfillment, e.g., shipping times of 1-2 days.

Critically, in our study and analysis, the introduction of display only inventory showrooms can be seen as a shock in the product information available to some of the customers, which allows us to isolate the impact of information on the reduction of the uncertainty in product fit, holding fulfillment constant across all channel options.

Uncertainty in product fit induced by informational deficiencies is also intimately related to consumer returns. Several papers in the marketing-operations interface have studied different aspects of product returns, including the key drivers of returns (Petersen and Kumar 2009) and how a return option affects consumer utility (Anderson et al. 2009). Other authors (e.g., Guide et al. 2006, Blackburn et al. 2004) focus on how to reduce the negative impact of returns by improving the

reverse supply chain design, or through contractual provisions such as optimal fees or money-back guarantees (e.g., Davis et al. 1995, 1998, Shulman et al. 2009, Su 2009).

To the best of our knowledge, however, no previous paper has provided an empirical analysis of how return patterns evolve subsequent to the addition of a new channel. We find that it is possible to reduce the incidence of returns by better matching customers to channels; specifically, as a consequence of the defection of customers with high product fit sensitivity from channels with less information acquisition opportunities to a channel that offers greater access to visceral product information.

2.3. Customer Channel Migration

Some recent papers focus on consumer behavior dynamics in multi-channel retail settings, including customer channel migration (Ansari et al. 2008) and how the introduction of a new physical channel affects sales in the existing channels (Avery et al. 2011). We are also concerned with the dynamic effects on customer behavior as we study how the introduction of display only showrooms affects demand and returns in other channels. However, our work is substantively distinct in several important respects.

First, we focus exclusively on how sensitivity to product fit affects customer migration patterns, and we develop and test a model that shows how customers will behave when faced with channels that differ in terms of opportunities for assessing product fit.

Second, our physical channels are not stores but inventory showrooms. Inventory showrooms are physical establishments where customers can fully experience all non-digital attributes (fit, feel, touch, and style, and so on) of the complete product line. Unlike conventional offline stores however, these outlets do not allow customers the instant gratification of purchasing the product and taking it with them immediately as orders placed in a showroom are done so at the website and are fulfilled as if they were regular online orders.

Inventory showrooms are the instrument of choice used by some leading online retailers such as WarbyParker.com and Bonobos.com (who run their own inventory-only ‘guide shops’) to expand into the physical world of offline retailing. There are sound practical and theoretical reasons for adopting these types of channel as they overcome some of the limitations of the online channel to sell products with uncertain fit, yet maintain the pooling benefits of centralized fulfillment (Eppen 1979). Thus, besides studying a growing omni-channel phenomenon that is interesting in its own

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7 We use this term interchangeably with display only showrooms to mean the same thing: An offline channel where the consumer can touch, feel, and inspect the entire product line before making a purchase. In contrast to a ‘typical’ offline store however, the consumer cannot obtain immediate possession of the product—any item that is purchased is purchased in store through the website and the order filled as if it were placed directly at the website from home or any other location.
right and contributing to the recent stream of work on channel integration (see, for example, Gallino and Moreno 2012 for a study of the Buy Online, Pick up In-Store, or BOPS initiative adopted by large traditional players), we are able to hone in on the informational function of channels.

That is, the subtle but important difference between Warby Parker inventory showrooms and the more typical offline stores in terms of the fulfillment mechanism is highly relevant in our case. Inventory showrooms simply provide the opportunity for customers to better assess product fit; this allows us to isolate the value to both the customer and the firm of giving customers the ability to acquire more accurate fit information, and to separate this from other possible drivers of behavioral differences across channels, such as speed of shipment, which, for us are constant across channels.

Third, to our knowledge, all previous work that has studied the effect of the addition of physical stores has done so in settings where some physical stores already existed, and the firm was focused on geographic expansion (see, for example, Anderson et al. 2009). Conversely, we focus on a purely online-first retailer that had not established any sort of physical presence prior to the opening of the inventory showrooms.

Finally, some recent articles report on customer defection patterns in service settings: A key finding here is that customers with specific characteristics are more likely to defect as a response to particular kinds of shocks (e.g., Buell et al. 2010; Buell et al. 2011). While we focus on channel migration by some customers rather than outright defection per se, we nevertheless find a parallel result. Customers with a specific characteristic—in our case, high sensitivity to fit—are more likely to leave the “conventional” (or pre-existing) channels and move to the new one after the showrooms are introduced. This channel migration results in a better customer-channel matching and this, in turn, benefits both the customers and the firm. Demand goes up overall and the operational costs to serve customers remaining in the pre-existing channels decline.

3. Empirical Setting and Econometric Approach

3.1. Empirical Setting

We utilize observational data obtained in a quasi-experimental setting to assess the impact of channel-induced informational differences on customer behavior. WarbyParker.com, the leading online eyewear brand in the US, 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 since sold over 600,000 frames through online, sampling, and inventory only offline channels. The

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*When we refer to different channels, we refer to the medium through which customers access to product information before placing an order, i.e., we focus on the informational dimension of channels. Regardless of the channel through which information is obtained, orders are always placed through the website and centrally fulfilled in the same way regardless of how product information is acquired.*
company offers two lines of eyewear, glasses with prescription lenses and sunglasses. All frames offered by Warby Parker are exclusively designed by the company and are unavailable through traditional US retail channels such as Lens Crafters and Sunglass Hut.

As noted briefly in the Introduction, these data have three key features that make them ideal for our study. First, and most critical, eyewear is an exemplar product category for the importance of non-digital product attributes. In 2010 when WarbyParker.com was launched, only 1-2% of the $22 billion US eyewear market was transacted online. This is not surprising; as noted throughout the paper, the eyewear category is one in which many customers would like to touch, feel, and try on the product before purchasing it.

Second, while WarbyParker.com was founded as an online brand, they launched a sampling program (discussed below) immediately upon launch, leading industry observers to refer to them as the “Netflix of Eyewear”.\(^9\) This presence of this channel allows us to examine informational differences across channels in some detail, as it represents an alternative that is intermediate to full exposure to the entire product line in an inventory showroom and virtual exposure to the line through the website only.

Third, as noted previously, the inventory showrooms opened and closed by Warby Parker differed from the other two channels (online and sampling) only in regard to the amount of information available to customers pre-purchase. Thus, we isolate the behavioral impact of additional visceral product information alone, free from potential confounds due to other factors that might differ between online and offline channels.

The three channels operate as follows.

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

Customers can browse the entire product line at the website prior to deciding to make a purchase. In addition, WarbyParker.com offers customers an online tool that allows them to upload their own pictures and examine, virtually, the fit, feel and style of different frames. While this “virtual try on” tool is based on state-of-the-art technology and presents realistic images, it is not hard to imagine the limitations this tool has in closing the experiential gap, i.e., the gap 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. That is, during the observation period for our data, customers could go online and select five frames from the complete selection offered and have them shipped to their

preferred address. At the end of the five-day period these sample frames are then returned and customers decide to buy or not. As with the online channel, any purchase transaction that happens takes place at the website and the fulfillment process is identical. Following protocols established by management, an HTO order is said to “convert” if the customer receiving the HTO makes a purchase within the subsequent two month period.

In our data the conversion rate, i.e., the number of HTO deliveries that result in a purchase, is lower than 50%. Of course, customers who participate in the HTO, relative to those who go to the website only, have better product information as they have been able to physically touch, try, and test the product prior to any purchase decision. 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.

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 somewhat inadequate. Recognizing this, Warby Parker developed a third channel—the inventory showroom—to help overcome this problem and give at least some potential customers a relatively straightforward way to experience the product fully, prior to purchase.

During the period of our data, the firm opened a total of 20 showrooms in different locations across the US, where customers could visit and try on the frames. Many of the showrooms continued to operate after they first opened, but seven of them closed during the data window for our analysis. These display only showrooms are established in partnership with different local retailers that rented a portion of the retail space within their stores to the firm. In cases where a customer decided to make a purchase, transactions were placed exactly as they were for the other two channels, i.e., through the website, and orders to were fulfilled by shipment to a location designated by the customer.

3.2. Detailed Data Description

Our data cover a 37 month (158 week) period from the inception of the business in February 2010 through March 2013. (Since the data are collected from when the firm first opened, they are not left censored.) During this period we collected information on sales through the three channels, as well as orders (in the case of the sampling program) and product returns as well. We conduct most of our analyses on demand at the week-ZIP code level and focus on the channel source that originated the sale. A sale is labeled as WEB when the customer purchased the frame online without requesting an HTO or visiting a showroom. Similarly, if a customer ordered an HTO and made a purchase
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within two months of receiving the HTO, that sale is labeled an HTO sale. When customers make purchases after visiting showrooms, these transactions are labeled as SHOWROOM sales.$^{10}$

Furthermore, for each sale transaction, we observe whether the product was eventually returned; hence, we have an individual-level measure of product returns. We also obtained transaction data on the HTO program; namely, the data covering all the individual HTO orders so that we would know both how many HTO orders were placed, and how many of them translated into sales.

In addition, we obtained ZIP-code level demographic information and information on spending at offline eyewear retailers from the 2010 ESRI Demographics and Business Database, available for purchase at www.esri.org.$^{11}$ 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 matching approach in which we develop samples of locations with and without showrooms.

3.3. Econometric Approach

A naïve approach to evaluating the impact of display showrooms would look at the difference in the dependent variables of interest, i.e., demand and returns, between the period before and after the showroom opened at a particular location. This approach, unfortunately, suffers from a key flaw: Many things completely unrelated to the opening of a showroom can differ between the two (pre-showroom and post-showroom) periods. For example, seasonal factors could cause a change in sales; alternatively, a new collection of frames could have been released after the showroom opened, and so on. To deal with this challenge we utilize a difference-in-differences (DiD) approach and hold “all else constant”.

3.3.1. Difference in Differences

In order to implement a DiD approach, we must identify a portion of the population that was not affected by the intervention for which we are trying to estimate the causal effect, i.e., the opening of an inventory showroom. That is, we need to select an appropriate control group—one that shares characteristics with the group that was exposed to the treatment.

Once we identify a control group, we can measure the effect of the treatment by comparing the differences between the control group and the treatment group before and after the treatment is applied. Angrist and Pischke (2008) provide a detailed and exhaustive discussion of methods and applications in a variety of social science settings. Not surprisingly, the approach has a long and

$^{10}$In order to make possible the tracking of the SHOWROOM sales the company gave a coupon code to those customers who visited a showroom. This code was entered by the customer during the checkout process, which made it possible to link the transaction with the showroom visit.

well documented history with a variety of applications in economics and related disciplines, such as operations management (e.g., Caro and Gallien 2010, Parker et al. 2013), including multichannel retail as well (e.g., Gallino and Moreno 2012, Avery et al. 2011).

While the treatment groups are easily identified—they are simply potential customers in the trading areas of the inventory showrooms—the control groups are less immediately apparent. Specifically, the challenge is to identify a control group that can be paired with a treatment group for analysis. We propose that these two groups can be identified by considering the distance between a potential customer and a showroom location. The argument here is that 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 (as discussed shortly we also performed robustness checks with respect to this decision). Those ZIP codes falling within the 30 mile radius were assigned to the treated group while those ZIP codes outside the area of influence were assigned to the control group. As mentioned earlier, most of the showrooms stayed open during the period of analysis, while some of them opened and closed during that time. This is good for our identification strategy since it adds variation to the groups over time.

There were a total of 20 showrooms that were open at some point during our period of analysis. Figure 2 shows a map with the locations of the showrooms in the US. We focus on those ZIP codes that ordered at least 40 frames during the period of analysis. Our final panel consists of 2,256 ZIP codes, 921 of which were in the influence area of a showroom at some time during the period of analysis. Table 1 presents summary statistics for the ZIP codes on the treatment and the control group.

Our identification strategy is potentially subject to the concern that the locations where the company opened the showrooms are endogenous with demand. This is a reasonable since showrooms are not opened in random locations. Through conversations with management, we learned that although they had a clear idea about which locations (cities) were of interest to them, their decision to open a showroom in a specific ZIP code was driven by a combination of market potential and partnership opportunity at a location. This approach resulted in situations where the company might open a showroom at a less-than-ideal location and, at the same time, not open a showroom at a high-potential location.

These management decisions resulted in a showroom map that, while not random, is not completely endogenous either. Consequently, we utilize a propensity score approach to “equalize” treated and non-treated locations and to therefore mitigate potential endogeneity concerns (we discuss this in more detail in the next subsection).
3.3.2. Quasi-Experimental Design: Propensity Scores Weighting

The DiD approach is effective if the treatment and control groups follow equal trends in the pre-treatment period. This is, however, not necessarily a reasonable assumption in our case because ZIP codes that are near showrooms and ZIP codes that are far from showrooms can be very different in their characteristics, including the demographics of the local population and therefore the trading area for a showroom. For example, the median household income of the treatment group is $76,140/year, and yet the median household income of the control group is $69,457/year. Thus, to address this issue of differences in characteristics between treatment and control locations, we combine the DiD approach with a propensity score adjustment.

Imbens and Wooldridge (2009) provide a comprehensive review and discussion of the literature in program evaluation and causal inference. In particular, they evaluate the multiple methods that have been proposed to deal with endogeneity and to reduce the potential biases arising when covariates are correlated with the treatment indicator. Among the most popular and widely utilized models discussed in Imbens and Wooldridge (2009) are the propensity-score-based methods first introduced by Rosenbaum and Rubin (1983). The so-called propensity score is the probability of an individual observational unit receiving treatment, conditional on its covariates. Therefore, for subpopulations with the same propensity score, covariates will be independent of the treatment, and this eliminates the biases in the comparisons between treated and control units.

Propensity scores were first considered as a more sophisticated form of matching procedure. Propensity scores may however be used without matching by considering the scores as sampling weights. Details of this method can be found in Rosenbaum (1987), Hirano and Imbens (2001) and Hirano et al. (2003). Propensity score weighting effectively reweights treatment and control observations to make the two populations comparable in terms of their observable covariates.

Thus, we implemented an average treatment effect approach where we defined the weights as follows (following Hirano and Imbens 2001):

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

where $W = 1$ indicates a treated ZIP code and $\hat{e}(x)$ is the estimated probability of being treated. After obtaining these weights, it is possible to estimate our difference-in-differences model, including those weights in the estimation.

A detailed and extensive review of the literature on the econometrics of program evaluation, including the method we are implementing which combines regression and propensity score weighting is given in the review article by Imbens and Wooldridge (2009). Among all the methodologies they consider, the approach we take is deemed among the most attractive and recommended for
practical applications (it has, for example, been used regularly in the epidemiology literature, e.g., Bang and Robins 2005, Hernán and Robins 2006).

To implement the propensity score analysis, we considered 50 different ZIP-code-level variables from 2010 ESRI Demographics and Business Database. We focus on the demographic, socioeconomic, and business-related variables pertinent to our institutional context including population and income metrics and the proportion of households in the target age demographic (25–45 years-old). We consider market size metrics as well, including the number of offline clothing stores in the 3-digit zip code area, and the number of potential customers in related retail categories. In addition, when estimating the propensity score, these variables were further decomposed by gender.

4. Evaluating the Overall Impact of Display Showrooms on Demand and Migration

The opening of new display only showrooms has the potential to affect customers who live within the area of influence of the showroom, which we assumed to be 30 miles as discussed in Section 3. This delineation into treatment areas (ZIP codes within the trading area of a showroom) and control areas (those ZIP codes outside the trading area) allows us to run a series of quasi-experiments from which we can quantify demand and operational impact of opening a display showroom. In ZIP codes without a display only showroom 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 introduction of a display showroom adds a third channel.

We anticipate that total sales for those ZIP codes within the trading area of the showroom will almost certainly show a sales increase after the showroom is introduced, because sales through this channel were zero before the introduction of the showroom. While a positive demand effect within the treatment ZIP codes through the showroom itself is therefore to be expected, we also need to consider what happens to demand via the other two channels in these same ZIP codes. That is, whether there is any migration of customers from the two pre-existing channels to the display showroom, and if so, how that affects the sales and operational efficiency of the firm in the treated locations.

4.1. Impact on Total Sales

The effect of opening a showroom on the total sales is captured by the following regression equation:

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

We have tested alternative distances for the catchment area and found no significant differences in our results. Further details are available from the authors upon request.
where the variable $OPENSHOW_{it}$ indicates whether ZIP code $i$ is in the vicinity of one of the showrooms that is open on week $t$. Showrooms open at different points in time so the variable $OPENSHOW_{it}$ captures variation not only across different ZIP codes $i$, but also within a ZIP code over time $t$. Our specification includes fixed effects $\mu_i$ that capture any time-invariant factors related to the sales of a ZIP code, as well as time controls $W_t$ (one dummy for each time period) that capture any effects on the overall sales at a given point in time. The coefficient on $OPENSHOW_{it}$ can therefore be interpreted relative to the baseline sales of a given ZIP code and the seasonality patterns of sales on the web channel for a given week.

If $\alpha_1$ is positive and significant, this means opening a showroom is associated with an increase in overall sales for the ZIP codes in the vicinity of the showroom, compared to a situation in which a showroom is not opened.

Again, since showroom sales are by definition zero before the showroom opened, we expect a positive effect of opening a showroom on total sales, and this is what we observe. Table 3 shows the results when we include all the available ZIP codes (2,256 ZIP codes). Column 1 presents the result of the analysis without the propensity score correction and Column 2 with the propensity score correction (our preferred specification). The magnitude of the overall increase in total sales subsequent to the opening of showroom is substantial, at around 10 percent.

In Section 4.4, we report results from a robustness analysis that selects a subsample of these ZIP codes, but regardless of the specification, the results consistently show an increase in total sales after the showroom opened. The analysis in Section 4.4 highlights heterogeneity in the magnitude of the effect according to latent market potential—ZIP codes with high activity benefit more from the showroom opening than those that are less active do. This substantial increase in overall sales is unlikely to stem exclusively from new transactions that occur in the showroom only. In the next two sections we investigate the effect of a showroom in a ZIP code on sales through the other two channels (website and sampling) in ZIP codes contained in the showroom trading area.

### 4.2. Impact on the Web Channel

As before, our unit of observation is ZIP code $i$ during week $t$ but for this analysis, our dependent variable is $log(WEBSALES)_{it}$, the log of the number of units sold through the website during week $t$ to customers who live in ZIP code $i$. The specification is as follows:

$$\text{log}(WEBSALES)_{it} = \mu_i + \beta_1OPENSHOW_{it} + W_t + \epsilon_{it}$$ (2)

The variable $OPENSHOW_{it}$ indicates whether ZIP code $i$ is in the vicinity of one of the showrooms that is open on week $t$. As described before, the showrooms opened at different points in time during our period of analysis. Again, the variable $OPENSHOW_{it}$ captures variation not
only across different ZIP codes \( i \) but also within a ZIP code over time \( t \). As before, our specification includes fixed effects \( \mu_i \) that capture any time-invariant aspects related to the web sales of a ZIP code, as well as time controls \( W_t \) (one dummy for each period) that capture any effects on the overall sales at a given point in time. If the coefficient \( \beta_1 \) is positive and significant, this means that opening a showroom is associated with an increase in web sales for the ZIP codes contained within the trading area of the showroom.

Table 4 presents the results with (Column 1) and without (Column 2) the propensity score adjustment. The estimates show that opening a showroom is associated with an increase in web sales of between 3.5% (Column 2) and 7% (Column 1), confirming that the effects of opening a showroom on total sales are not confined exclusively to new sales handled by the showroom alone. The opening of the showroom in a location affects online channel sales in that location as well. Again, this finding is robust to selecting a subsample of ZIP codes or to using different models such as Poisson regression (see Section 4.4). We discuss possible explanations in more detail in Section 6 but since showroom locations are prominent on the site, it is possible that for customers who reside in the trading area of the showroom the mere presence of the showroom itself is a positive signal for the Warby Parker brand. That is, the availability of the a physical showroom confers legitimacy, which in turn, makes some customers more comfortable with buying online.

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

Again, our unit of observation is a ZIP code \( i \) during week \( t \) but our dependent variable is \( \log(HTOSALES)_{it} \), the log of the number of units sold through the HTO during week \( t \) to customers who live in ZIP code \( i \). The specification is the following:

\[
\log(HTOSALES)_{it} = \mu_i + \gamma_1 OPENSHOW_{it} + W_t + \epsilon_{it}
\]  

\( OPENSHOW_{it} \) is defined as before and the specification again includes fixed effects \( \mu_i \) as well as time controls \( W_t \). The results of this analysis are shown in Table 5 and Column 2 focuses on our preferred propensity score correction. After a showroom is opened in a location sales in the trading area from the HTO channel decrease, on average, about 5%. As shown in Section 4.4, the drop is even more pronounced in high activity zip codes.

### 4.4. Robustness

We performed multiple robustness checks to validate the direction and significance of the results described above. Tables 9 and 10 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 10 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%, and (2) increases by approximately 9% through the online channel. Furthermore, as shown in Column (3) of Table 10 sales through the HTO channel decline by almost 10%. 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.

We also tested robustness using alternative model specifications, such as a Poisson regression (see Table 11) and confirmed that the coefficients have the same sign and significance as in the log linear models. We conclude that the effects of showroom openings that we observe for total sales, web sales, and HTO sales are indeed robust. In the next section, we explore the implications of these results and the mechanism by which the showroom channel is affecting sales through the online and HTO channels.

5. Interpretation of Results: Channel Migration

Given that the overall results show an increase for total and web sales but a decrease for HTO sales we hypothesize that opening a showroom causes a channel shift by some users, resulting in a reduction of the cost to serve customers through the other channels. To do so, we start with a simple model of channel selection that makes predictions about HTO conversion rates, HTO trial repetition, and product returns through the online channel.

5.1. Consumer Sorting and Channel Cost-to-Serve

Our model considers three channels through which customers can obtain product information before placing an order: the online channel, the HTO channel, and the inventory 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 for the results in Section 4. Let \( i \) denote a customer and \( j = 1 \ldots J \) 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 $l_j$ that denotes the location in an attribute space (for simplicity, a line). 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:

$$u_{ij} = v_i - f_i(|l_i - l_j|) + \epsilon_{ij}$$  \hspace{1cm} (4)$$

Customers differ in their tolerance of 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,

$$u_{ij} = v - k_i |l_i - l_j| + \epsilon_{ij}$$  \hspace{1cm} (5)$$

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

$$U_i(\text{online}) = v - k_i E(|l_i - l_j|) - c_{i}^{\text{online}}$$  \hspace{1cm} (6)$$

where $c_{i}^{\text{online}}$ 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

$$U_i(\text{HTO}) = v - k_i E(\min_{j \in S} |l_i - l_j|) - c_{i}^{\text{HTO}}$$  \hspace{1cm} (7)$$

where $c_{i}^{\text{HTO}}$ indicates the costs of using the HTO channel for customer $i$. After receiving the HTO, the customer observes the realized value of $\min_{j \in S} |l_i - l_j|$ 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 $\epsilon_{ij}$ 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

$$U_i(SHOW) = v - k_iE(\min_j |l_i - l_j|) - c_i^{SHOW},$$

where $c_i^{SHOW}$ indicates the costs of using the showroom channel for customer $i$. After visiting the showroom, the customer learns the realized value of $\min_j |l_i - l_j|$ and places an order if the realized expected utility is positive. Again, the customer can return the product if a negative value of $\epsilon_{ij}$ 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, $U_i(SHOW) > 0$ while $U_i(ONLINE) < 0$ and $U_i(HTO) < 0$. 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 $U_i(SHOW) > U_i(ONLINE) > 0$ or $U_i(SHOW) > U_i(HTO) > 0$. 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:

$$U_i(SHOW) - U_i(online) = c_i^{online} - c_i^{SHOW} + k_i[E(|l_i - l_j|) - E(\min_j |l_i - l_j|)]$$

$$U_i(SHOW) - U_i(HTO) = c_i^{HTO} - c_i^{SHOW} + k_i[E(\min_{j \in S} |l_i - l_j|) - E(\min_j |l_i - l_j|)]$$

Since $E(|l_i - l_j|) - E(\min_j |l_i - l_j|) > 0$ and $E(\min_{j \in S} |l_i - l_j|) - E(\min_j |l_i - l_j|) > 0$, 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.

5.2. Conversion of Home Try-On Program

Earlier we showed that opening a showroom leads to a reduction in sales through the HTO channel channel in the vicinity of the showroom. According to the model, some customers who would have used the HTO program to physically examine the products in absence of a showroom, no longer use the HTO program when a showroom is opened in their vicinity.
If the channel matching hypothesis is correct, then after the pickiest customers have migrated from the HTO channel to the showroom, those who remain and are less picky, should have a higher propensity to buy. So, first, and foremost, the model predicts that the opening of a showroom reduces the number of customers in the HTO channel, which will, in turn, reduce the number of orders of the HTO program that are placed in the vicinity of the showroom.

Now since orders will fall, but the customers who remain and place orders will be less picky, then the conversion rate in the HTO channel should go up. Any change in conversion rate can of course be inferred from changes in orders and sales (converted orders). The effect of opening a showroom on the number of HTO orders placed in the vicinity of the showroom is given by

$$\log(HTOORDERS)_{it} = \mu_i + \gamma_1 OPENSHOW_{it} + W_t + \epsilon_{it}$$ (11)

where $OPENSHOW_{it}$ follows the logic described earlier and the coefficient can be interpreted in the same manner.

Table 6 shows the estimates. We expect customers to migrate from the HTO channel and indeed, the number of orders does decrease, consistent with migration. Column 2 (the preferred specification which uses the propensity score weighting) shows a decrease in orders by customers in the vicinity of the showroom of about 7.7% (the estimate in Column 1, which does not utilize the propensity score adjustment, shows a negative effect as well but it is not statistically significant).

Earlier we showed that the introduction of a showroom led HTO sales to decrease by 4.9%. Now, the fact that orders decrease more than sales do (7.7% vs. 4.9%) means that the HTO conversion rate among customers within the trading area of the showroom has increased. This is again consistent with migration as predicted by the model; "pickier" customers have selected into the full information channel, leaving those that remain in HTO channel with a higher probability of purchase, given an HTO order.

Further evidence of the effect on HTO conversion rates can be obtained from individual transaction level data. In this analysis the unit of observation is not a ZIP code week but an HTO order (which may or may not result in a purchase within the subsequent two months). We model the binary decision of purchase or non-purchase conditional upon an order using a standard logistic specification. Let $y = 1$ denote that the order placed through the home try-on program results in a purchase, and $y = 0$ otherwise. We model $p(y = 1|x) = G(x\beta)$, where

$$G(z) = \frac{\exp(z)}{1 + \exp(z)}$$ (12)

and we estimate the coefficients $\beta$ with a logit estimator. $X$ includes a constant, a dummy variable that indicates whether there is a showroom open in the vicinity of the user at the time of the
transaction \((OPEN)\), a collection of ZIP code level controls for the ZIP code where the HTO was delivered, and dummies to control for week-year pairs. A positive and significant marginal effect for the OPEN variable is evidence of higher conversion.

Table 7 shows the results and the coefficient of the \(OPEN\) variable is positive and significant. Since the model is non-linear the coefficient is not equivalent to the marginal effect; hence, we compute the average marginal effect and find that opening a showroom increases the individual-level probability of HTO conversion by 0.8%. This magnitude is statistically significant and economically significant as well, since the firm faces shipping costs for unconverted HTO orders.

5.3. Repetition of Home Try-On Program

If migration occurs such that less picky customers remain in the HTO channel after the showroom is opened, then the fraction of users in the HTO channel who will require multiple samples will decrease. In order to test this prediction, we use a dataset very similar to the one described in Section 5.2, where the unit of observation is an HTO order. Our dependent variable is an indicator of whether the HTO order leads to additional HTO attempts. Specifically, we consider that an HTO order results in repetition if user places another HTO order within two months of the first without having placed a purchase order between the HTO orders.

The model is again a logistic estimator as in Equation 12. If the repetition rate of the HTO falls after a showroom opens, then the marginal effect for the \(OPEN\) variable should be negative. Using the estimate from Column 2 of Table 7 we find that the average marginal effect is -0.015. Thus, opening a showroom in a location reduces the probability of multiple HTO orders in the showroom trading area by 1.5%. Again, this effect is statistically and economically significant.

5.4. Impact on Returns

Customers who migrate from the web channel to the showroom benefit from being able to better assess product fit prior to making a purchase. Since the pickier customers who migrate to the showroom are most likely to have previously been customers who would have been served via the web, return rates on the web channel should decrease.

Another transaction-level dataset is used to test this prediction and our outcome variable indicates whether a sale is eventually returned. We use the logit estimator (Equation 12) and Table 8 shows the estimation results. The average marginal effect for the \(OPEN\) variable is -0.0121, implying that when a showroom opens return rates for web channel sales in the showroom trading area decline by 1.2%. Again, this magnitude is statistically and economically significant (note that the firm faces shipping costs for returned items and most of the returned products are not usable because the lenses are custom made for the customer orders).
Although the point estimate in Table 8 suggests a negative effect of a showroom on returns of the HTO channel as well, the effect is not statistically significant (Column 2). This suggests that customers who decided to buy after having tried only 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. After all, even if those HTO customers physically sample only 5 frames, they end up making their purchase after trying what they are buying. This is in contrast with the web channel, where customers do not have the chance to try the product before placing their order.

In summary, we find that the overall demand results reported in Section 4 have been driven by an underlying dynamic of customer migration in response to the opportunity to obtain more complete product information prior to a purchase. Specifically, that the migration effects predicted by our consumer model presented in Section 5.1 hold in the data.

Since migration leaves a “less picky” pool of customers in the HTO and online channels, the HTO conversion rate increases, while HTO repetition rates and web sales return rates decline. This results in a reduction of the average operational costs associated with serving a customer. Of practical and theoretical interest is the fact that these changes are induced solely by a change in the amount of visceral product information available prior to purchase.

6. Conclusions

6.1. Main takeaways

In this paper, we investigate the effects of introducing additional product information into the market, in the form of an inventory only offline channel. In doing so, we provide new contributions to understanding customer behavior in omni-channel retail settings. Specifically, we find that this channel addition leads to both substantial demand and supply-side benefits for an online retailer:

- On the demand side, the introduction of inventory showrooms increases overall sales in the locations around the showroom, and causes some customers to change their preferred “touch point” and migrate from one channel to another. Since the increase in total sales cannot be fully accounted for by sales through the showroom alone and online sales within the showroom trading area increase as well, the introduction of a showroom appears to confer brand legitimacy or awareness benefits to the firm.

- On the supply-side, the migration patterns induced by the introduction of inventory showrooms have important operational consequences, mainly arising from a more efficient match between customers and channels. Inventory showrooms increase the conversion of the sample program and reduce the rate of returns in the online channel. This results in a significant reduction in the average cost-to-serve in the traditional channels.
In addition, we provide new insights into the mechanism underlying these findings. Under the assumption that customers differ in their tolerance for fit uncertainty, i.e., the discrepancy between what they know about a product before buying it and what they learn when it is delivered, and that customers can select the channel through which they acquire product information (online, sampling or showroom), we developed and tested a model to explain the observed patterns of demand. The model emphasizes the informational role of the channels; in particular, their ability to provide visceral information and to deliver either a full or more limited range of products that can be sampled. The model predicts that customers who have the least tolerance for uncertainty, i.e., those who are the most “picky”, are more likely to migrate to the offline channel when it becomes available. We demonstrate that when an inventory showroom is available, this leads to higher conversion from sampling, lower rates of repeated sampling, and fewer returns from sales made in the online channel, within the ZIP codes in the showroom trading area.

Since the fulfillment system is common and identical across channels, our results highlight the importance of the informational role of channels in achieving an efficient match between customers and customer touch points in a way that reduces operational costs.

6.2. Managerial Implications and Future Research
Our analysis has important managerial consequences. As technological advances are enabling novel business models (Girotra and Netessine 2014), the informational and fulfillment functions of channels are becoming more decoupled. Online retailers that are venturing into the physical world may emphasize one or the other function depending on the characteristics of their products. Firms such as Bonobos and Warby Parker who are selling products with high fit uncertainty are prioritizing the informational function when expanding into the physical world, and are developing a network of showrooms where customers can experience the product before placing an order. Conversely, firms like Amazon that sell goods that are more commoditized are focused on enriching the fulfillment dimension of channels, e.g., installing physical lockers where customers can pick up their products. These companies are less limited by the lack of product information, since their customers can use brick-and-mortar stores of their competitors to learn about product characteristics. As a consequence, firms like Amazon are less inclined to invest on inventory showrooms.

Compared to traditional brick and mortar retailers, online retailers often benefit from substantial cost advantages arising from centralized fulfillment and inventory management, which can yield very substantial inventory pooling benefits (Eppen 1979) and economies of scale. On the other hand, online retailers usually offer their customers fewer and less rich opportunities to sample the products. By maintaining centralized fulfillment, but in combination with a network of local

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13 See, for example, http://en.wikipedia.org/wiki/Amazon_Locker.
inventory showrooms where customers can experience the products, online retailers can compete with traditional retailers in categories where online had traditionally had a small market share.

Therefore, this combined model of centralized fulfillment and display only inventory showrooms should be particularly effective with the so-called *verticals*—retailers that control manufacturing, branding and distribution of their products, such as Bonobos or Warby Parker. In contrast, “conventional” multibrand omni-channel retailers (e.g., BestBuy) are less likely to benefit from this strategy, because the decoupling between information and fulfillment does not play in their favor—customers could then just use showrooms to obtain product information and then purchase the products elsewhere. This *showrooming* practice has hurt conventional brick-and-mortar retailers.\(^{14}\)

Interestingly, Amazon has recently started to experiment with physical inventory showrooms for their Kindle product line. This is consistent with our framework, since the Kindle product line is controlled by Amazon and not carried by many brick-and-mortar retailers (e.g., Target and Wal-mart have dropped them), which means that Amazon cannot completely rely on external showrooming opportunities for their customers.\(^{15}\)

Finally, our results also highlight that despite the growth of online channels physical location of customers continues to be as important as ever (e.g., Bell 2014). Thus, we expect that as retailers continue to develop and test their omni-channel strategies, the role of physical channels in delivering information and fulfillment will receive increasing attention from the academic and practitioner communities alike.

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**References**


Avery, Jill, Thomas Steenburgh, John Deighton, Mary Caravella. 2011. Adding bricks to clicks: Predicting the patterns of cross-channel elasticities over time. *Journal of Marketing*.


Gallino, Santiago, Antonio Moreno. 2012. Integration of online and offline channels in retail: The impact of sharing reliable inventory availability information. *Available at SSRN 2149095*.


Matthews, Steven, Nicola Persico. 2007. Information acquisition and refunds for returns .

Parker, Chris, Kamalini Ramdas, Nicos Savva. 2013. Is it enough? evidence from a natural experiment in
indias agriculture markets. Working paper.

Journal of Marketing 73 35–51.

Randall, Taylor, Serguei Netessine, Nils Rudi. 2006. An empirical examination of the decision to invest in


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

Shulman, Jeffrey D, Anne T Coughlan, R Canan Savaskan. 2009. Optimal restocking fees and information
provision in an integrated demand-supply model of product returns. Manufacturing & Service

Su, Xuanming. 2009. Consumer returns policies and supply chain performance. Manufacturing & Service

Swinney, Robert. 2011. Selling to strategic consumers when product value is uncertain: The value of matching
supply and demand. Management Science 57(10) 1737–1751.

Appendix: Tables and Figures

Table 1  Summary Statistics - Average Parameters by ZIP Code Before and After Matching

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<tr>
<th>ZIP Codes</th>
<th># of Sales</th>
<th>Web Sales</th>
<th>HTO Orders</th>
<th>Pop.</th>
<th>PCI</th>
<th>MHI</th>
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<tr>
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<td>227</td>
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<td>Control ZIP Codes</td>
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Average Weekly Parameters for all ZIP Codes

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<th>Web Sales</th>
<th>HTO Orders</th>
<th>Pop.</th>
<th>PCI</th>
<th>MHI</th>
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</thead>
<tbody>
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<td>135</td>
<td>64</td>
<td>128</td>
<td>30,820</td>
<td>37,998</td>
</tr>
</tbody>
</table>

Standard deviations in parentheses

Table 2  Variable Definitions

Evaluating the Impact of Showrooms

<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>OPENS$_{it}$</td>
<td>Dummy variable that is 1 if on week $t$ there was a Showroom open on 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>OPENS$_{it}$</td>
<td>Dummy variable that is 1 if on week $t$ there was a Showroom open on ZIP Code $i$.</td>
</tr>
<tr>
<td>Table 3</td>
<td>Impact on Total Sales.</td>
</tr>
<tr>
<td>---------</td>
<td>-----------------------</td>
</tr>
<tr>
<td>VARIABLES</td>
<td>log(SALES)</td>
</tr>
<tr>
<td>OPEN</td>
<td>0.127***</td>
</tr>
<tr>
<td>(0.00956)</td>
<td>(0.0135)</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>NO</td>
</tr>
<tr>
<td>Observations</td>
<td>358,704</td>
</tr>
<tr>
<td>R-squared</td>
<td>0.287</td>
</tr>
<tr>
<td>Number of ZIP Codes</td>
<td>2,256</td>
</tr>
<tr>
<td>Robust standard errors in parentheses</td>
<td></td>
</tr>
<tr>
<td>* p &lt; 0.05, ** p &lt; 0.01, *** p &lt; 0.001</td>
<td></td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Table 4</th>
<th>Impact on Web Sales.</th>
</tr>
</thead>
<tbody>
<tr>
<td>VARIABLES</td>
<td>log(WEBSALES)</td>
</tr>
<tr>
<td>OPEN</td>
<td>0.0696***</td>
</tr>
<tr>
<td>(0.00751)</td>
<td>(0.00878)</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>NO</td>
</tr>
<tr>
<td>Observations</td>
<td>358,704</td>
</tr>
<tr>
<td>R-squared</td>
<td>0.118</td>
</tr>
<tr>
<td>Number of ZIP Codes</td>
<td>2,256</td>
</tr>
<tr>
<td>Robust standard errors in parentheses</td>
<td></td>
</tr>
<tr>
<td>* p &lt; 0.05, ** p &lt; 0.01, *** p &lt; 0.001</td>
<td></td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Table 5</th>
<th>Impact on HTO Sales.</th>
</tr>
</thead>
<tbody>
<tr>
<td>VARIABLES</td>
<td>log(HTOSALES)</td>
</tr>
<tr>
<td>OPEN</td>
<td>-0.00678</td>
</tr>
<tr>
<td>(0.00643)</td>
<td>(0.00795)</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>NO</td>
</tr>
<tr>
<td>Observations</td>
<td>358,704</td>
</tr>
<tr>
<td>R-squared</td>
<td>0.165</td>
</tr>
<tr>
<td>Number of ZIP Codes</td>
<td>2,256</td>
</tr>
<tr>
<td>Robust standard errors in parentheses</td>
<td></td>
</tr>
<tr>
<td>* p &lt; 0.05, ** p &lt; 0.01, *** p &lt; 0.001</td>
<td></td>
</tr>
</tbody>
</table>
Figure 1  WarbyParker.com

Figure 2  Showroom Locations
Table 6  Impact on HTO Orders.

<table>
<thead>
<tr>
<th>VARIABLES</th>
<th>(1) log(HTO)</th>
<th>(2) log(HTO)</th>
</tr>
</thead>
<tbody>
<tr>
<td>OPEN</td>
<td>-0.0132</td>
<td>-0.0771***</td>
</tr>
<tr>
<td></td>
<td>(0.00932)</td>
<td>(0.0119)</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>NO</td>
<td>YES</td>
</tr>
<tr>
<td>Observations</td>
<td>358,704</td>
<td>331,992</td>
</tr>
<tr>
<td>R-squared</td>
<td>0.332</td>
<td>0.331</td>
</tr>
<tr>
<td>Number of ZIP Codes</td>
<td>2,256</td>
<td>2,088</td>
</tr>
</tbody>
</table>

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

Table 7  Impact on HTO Conversion & Multiple HTOs. Transaction-level Analysis.

<table>
<thead>
<tr>
<th>VARIABLES</th>
<th>Conversion</th>
<th>Repeat</th>
</tr>
</thead>
<tbody>
<tr>
<td>NEAR</td>
<td>-0.0192</td>
<td>-0.0397*</td>
</tr>
<tr>
<td></td>
<td>(0.0132)</td>
<td>(0.0208)</td>
</tr>
<tr>
<td>OPEN</td>
<td>0.0364**</td>
<td>-0.132***</td>
</tr>
<tr>
<td></td>
<td>(0.0162)</td>
<td>(0.0231)</td>
</tr>
<tr>
<td>Time Controls</td>
<td>Week-year</td>
<td>Week-year</td>
</tr>
<tr>
<td>Other Controls</td>
<td>Zip level info</td>
<td>Zip level info</td>
</tr>
<tr>
<td>Observations</td>
<td>219,135</td>
<td>219,100</td>
</tr>
</tbody>
</table>

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

Table 8  Impact on Returns.

<table>
<thead>
<tr>
<th>VARIABLES</th>
<th>(1) Web</th>
<th>(2) HTO</th>
<th>(3) All</th>
</tr>
</thead>
<tbody>
<tr>
<td>NEAR</td>
<td>-0.00631</td>
<td>0.0318</td>
<td>-0.00290</td>
</tr>
<tr>
<td></td>
<td>(0.0412)</td>
<td>(0.0425)</td>
<td>(0.0283)</td>
</tr>
<tr>
<td>OPEN</td>
<td>-0.110**</td>
<td>-0.0672</td>
<td>-0.0683**</td>
</tr>
<tr>
<td></td>
<td>(0.0430)</td>
<td>(0.0467)</td>
<td>(0.0290)</td>
</tr>
<tr>
<td>Time Effect</td>
<td>Month-Year</td>
<td>Month-Year</td>
<td>Month-Year</td>
</tr>
<tr>
<td>Other Controls</td>
<td>Zip level info</td>
<td>Zip level info</td>
<td>Zip level info</td>
</tr>
<tr>
<td>Observations</td>
<td>63,076</td>
<td>64,892</td>
<td>156,004</td>
</tr>
</tbody>
</table>

Robust standard errors in parentheses
* p < 0.05, ** p < 0.01, *** p < 0.001
Table 9 Robustness. Subsample Analysis.

<table>
<thead>
<tr>
<th>VARIABLES</th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
</tr>
</thead>
<tbody>
<tr>
<td>log(SALES)</td>
<td>0.210***</td>
<td>0.125***</td>
<td>-0.0527***</td>
<td>-0.0763***</td>
</tr>
<tr>
<td>log(WEBSALES)</td>
<td>(0.0174)</td>
<td>(0.0159)</td>
<td>(0.0130)</td>
<td>(0.0165)</td>
</tr>
<tr>
<td>log(HTOSALES)</td>
<td>YES</td>
<td>YES</td>
<td>YES</td>
<td>YES</td>
</tr>
<tr>
<td>log(HTOORDERS)</td>
<td>Week-year</td>
<td>Week-year</td>
<td>Week-year</td>
<td>Week-year</td>
</tr>
<tr>
<td>Observations</td>
<td>79,077</td>
<td>79,077</td>
<td>79,977</td>
<td>79,077</td>
</tr>
<tr>
<td>R-squared</td>
<td>0.498</td>
<td>0.255</td>
<td>0.332</td>
<td>0.563</td>
</tr>
<tr>
<td>Number of ZIP Codes</td>
<td>503</td>
<td>503</td>
<td>503</td>
<td>503</td>
</tr>
</tbody>
</table>

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

Table 10 Robustness. Subsample Analysis (with propensity score weighting).

<table>
<thead>
<tr>
<th>VARIABLES</th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
</tr>
</thead>
<tbody>
<tr>
<td>log(SALES)</td>
<td>0.185***</td>
<td>0.0897***</td>
<td>-0.0963***</td>
<td>-0.175***</td>
</tr>
<tr>
<td>log(WEBSALES)</td>
<td>(0.0297)</td>
<td>(0.0221)</td>
<td>(0.0183)</td>
<td>(0.0246)</td>
</tr>
<tr>
<td>log(HTOSALES)</td>
<td>YES</td>
<td>YES</td>
<td>YES</td>
<td>YES</td>
</tr>
<tr>
<td>log(HTOORDERS)</td>
<td>Week-year</td>
<td>Week-year</td>
<td>Week-year</td>
<td>Week-year</td>
</tr>
<tr>
<td>Observations</td>
<td>70,437</td>
<td>70,437</td>
<td>70,437</td>
<td>70,437</td>
</tr>
<tr>
<td>R-squared</td>
<td>0.475</td>
<td>0.228</td>
<td>0.316</td>
<td>0.563</td>
</tr>
<tr>
<td>Number of ZIP Codes</td>
<td>443</td>
<td>443</td>
<td>443</td>
<td>443</td>
</tr>
</tbody>
</table>

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

Table 11 Robustness. Poisson Regression.

<table>
<thead>
<tr>
<th>VARIABLES</th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
</tr>
</thead>
<tbody>
<tr>
<td>SALES</td>
<td>0.182***</td>
<td>0.180***</td>
<td>-0.186***</td>
<td>-0.170***</td>
</tr>
<tr>
<td>WEBSALES</td>
<td>(0.0266)</td>
<td>(0.03772)</td>
<td>(0.000)</td>
<td>(0.0139)</td>
</tr>
<tr>
<td>HTOSALES</td>
<td>YES</td>
<td>YES</td>
<td>YES</td>
<td>YES</td>
</tr>
<tr>
<td>HTOORDERS</td>
<td>Week-Year</td>
<td>Week-Year</td>
<td>Week-Year</td>
<td>Week-Year</td>
</tr>
<tr>
<td>Observations</td>
<td>358,704</td>
<td>358,704</td>
<td>358,386</td>
<td>358,227</td>
</tr>
<tr>
<td>R-squared</td>
<td>2,256</td>
<td>2,256</td>
<td>2,254</td>
<td>2,253</td>
</tr>
</tbody>
</table>

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