Customer Supercharging in Experience-Centric Channels

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We conjecture that for online retailers, experience-centric offline store formats do not simply expand market coverage, but rather, serve to significantly amplify future positive customer behaviors, both online and offline. We term this phenomenon "supercharging" and test our thesis using data from a digital-first men's apparel retailer and a pioneer of the so-called "Zero Inventory Store" (ZIS) format—a small footprint, experience-centric retail location which carries no inventory for immediate fulfillment, but fulfils orders via e-commerce. Using a risk-set matching approach, we calibrate our estimates on customers who are "treated", i.e., have a ZIS experience, and matched with identical customers who shop online only. We find that post the ZIS experience, customers spend more, shop at a higher velocity, and are less likely to return items. The positive impact on returns is doubly virtuous as it is more pronounced for more tactile, higher-priced items, thus mitigating a key pain point of online retail. Furthermore, the ZIS shopping experience aids product discovery and brand attachment, causing sales to become more diffuse over a larger number of categories. Finally, we demonstrate that our results are robust to self-selection and potentially confounding effects of unobservable factors on the matched pairs of customers. Implications for retailing practice, including for legacy, offline-first retailers, are discussed.

Key words: Retail Operations; Marketing-Operations Interface; Omni-Channel Retailing; Experience Attributes; Quasi-Experimental Methods

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1. Introduction

The retail landscape has evolved significantly from the days in which customers only searched, shopped, and returned products within the confines of physical stores. The advent of e-commerce allowed customers to buy products online and have them fulfilled via delivery. Early research (e.g., Bakos 1997, Brynjolfsson and Smith 2000) focused on the ability of the online channel to remove frictions and deliver lower prices to consumers. More recent research (e.g., Brynjolfsson et al. 2013, Bell et al. 2014) has focused on the complementary nature, for a given retailer, of online and offline channels.

Nuances of the online-offline relationship covered in the literature include customers acquiring information online, but purchasing in stores (Gallino and Moreno 2014), online and offline sellers competing more intensely for popular products than for niche products (Forman et al. 2009), and customers experiencing products offline but completing fulfillment online (Bell et al. 2014; Wang and Goldfarb 2017; Bell et al. 2017). Online and offline sales trajectories are also affected by structural factors, including policy decisions on taxes: Anderson et al. (2010), for example, find that when a retailer establishes a tax nexus by opening a store in a state (thus requiring sales tax to be assessed on all purchases), online sales in that state fall.

Against this backdrop of academic research on online-offline interactions and customer behaviors, the business press increasingly argues that given rising costs of marketing via Google and Facebook, online-first retailers are turning to offline channels as a cost-effective way to acquire customers—see, for example, Olenski (2017). In addition, since some customers for some products simply prefer an offline shopping experience, physical presence of some sort is thought to be imperative as brands grow and scale. Indeed, the concomitant work in the literature on online-offline interaction and rising costs of acquiring customers and selling online has led to a very important, and to our knowledge unexplored aspect of the online-offline context. Specifically, how, in an omnichanel world, offline interaction with brands in an experience-centric channel drives engagement and other aspects of customer behavior. We therefore seek to answer a fundamental question: Does interaction with a brand in an experience-centric offline format alter customer behavior, and if so, how? In particular, might this interaction change the customer's trajectory for the better (from the perspective of the retailer), relative to identical customers who only experience a brand online?

The answer adds to the literature and is practically relevant too as the offline format that we study has tremendous operational efficiency—it is a small footprint, experiential, and tech-enabled "store" that carries no inventory (details to follow). As we discuss in Section 2, this format is also ubiquitous, embraced by online-first retailers, legacy retailers, and mall operators as well. Supply chain operations relative to those for a traditional store are greatly simplified, which has consequences for fulfillment, SKU-level demand forecasting, and so on.[1] Hence, demand might be generated more efficiently, relative to that generated by a store. Furthermore, if future *online demand* (over multiple

[1] The classic text Marketing Channels by Coughlan et al. (2006) identifies the two core retail functions as: (1) information provision and experiential exchange between buyers and sellers, and (2) fulfillment of product (see also Bell et al. 2014). The new kind of "store" that is the subject of our research focuses exclusively on (1), the experiential and informational component.

buying occasions) from a specific customer can be dramatically enhanced by a single offline interaction (or small number), this has implications for customer acquisition, retention, and by extension, customer value.

We have two objectives. First, to document whether the "treatment" (in a causal sense), of a customer interacting with a retailer in an experience-centric physical space changes the future trajectory of that customer. To the extent that the interaction generates positive outcomes, e.g., higher demand, we refer to customers so treated as "supercharged."[2] Using quasi-experimental data, we employ a risk-set matching approach to identify matched customers (treated and not treated) and compare their future behaviors. Our core findings hold under extensive robustness checks (see Online Appendix for details), and are not explained by potentially confounding effects of self-selection and the presence of unobservables. Second, we seek to understand the mechanism underlying supercharging by decomposing it into constituent parts. Specifically, into effects on shopping velocity, basket composition (prices paid, items, and categories bought) and return rates, and according to level of prior brand experience that has been acquired by the customer at the moment when supercharging first occurs.

We find that supercharged customers have higher average order values, greater shopping velocities (shortened inter-purchase times), and are less likely to return items in the future, whether shopping online or offline. Thus, retailers (as well as customers), benefit from customer exposure to the so-called Zero Inventory Store (ZIS). Evidence of greater affinity with the retailer is present too, as supercharged customers spend more per item while buying from a greater breadth of product categories. The beneficial change in the return rates—which fall after an offline experience—is also consistent with the notion that customers who have shopped offline acquire deeper product knowledge. This, in turn, lowers operational fulfillment costs for the retailer. This virtuous cycle also contains a positive interaction effect: while return rates drop across the board, the drop increases in the price of the items purchased, meaning that more expensive the item is, the bigger the reduction in return rates caused by ZIS experience.

The veracity of our findings is also underscored by a series of robustness checks and closer examination of the underlying mechanism. "Sooner rather than later" is an important practical insight; the benefits from supercharging are more pronounced, when customers have had less prior experience with the brand, suggesting retailers might want to explicitly encourage and incentivize customers to visit the experience-centric channel. As one might expect, supercharging effects are stronger for customers who live closer to the ZIS and therefore have lower fixed costs of shopping offline (see Bell et al. 1998). Finally, the supercharging effect is attenuated when the service experience is degraded;

[2] We thank Lawrence Lenihan, Co-founder and Co-Chairman of Resonance Companies for illuminating this idea in a lecture he delivered to the Digital Marketing and Electronic Commerce class at The Wharton School.

we demonstrate this using a proxy variable of store congestion (more congestion translates into a poorer experience) in the first ZIS visit.

In conclusion, we contribute to a growing literature on offline-online complementarity, at the level of the individual retailer and customer. We introduce the previously unidentified phenomenon of "supercharging" as both a concept and robust empirical effect. As noted above, we also unpack important practical effects on demand and returns that are consistent with supercharging as a customer learning and attachment mechanism. In so doing, we rationalize both the success of many digital-first retailers who embrace experience-centric channels as an initial foray into offline presence, and the increasing examples of legacy retailers and mall operators implementing the practice as well. Furthermore, we systematically elucidate the exact and myriad practical benefits that retailers might expect to see from this strategy.

2. Institutional Setting and Data

This section further elaborates key details of the institutional setting and its manifest importance to the overall retail ecosystem, and also explains why our chosen category, fashion apparel, and particular retail partner (a pioneer of the ZIS)[3] are especially appropriate given our research objectives. (The Online Appendix provides additional information on our retail partner.)

2.1. Institutional Setting: ZIS Offline Format and Retail Partner

A ZIS is not a "store" in the usual sense, but rather, a place where customers can try on products, experience the brand, and have purchases fulfilled via home delivery. Specifically, a small footprint store where customers have a high-service tactile experience is deployed to "divorce the purchase of a product from its distribution" (The Economist 2016). Thus, two distinguishing ZIS features are: (1) an elevated customer experience and service interaction, and (2) the absence of inventory for immediate fulfillment. In simple terms, customer engagement with the ZIS is captured by both the visiting process and the in-store experience as follows:

1. *Visiting Process.* Customers can either make an appointment or simply walk in. During the visit the customer can add items to his virtual cart and place an order while at the location, or later at his discretion. Upon leaving the ZIS, he receives an email from the person who helped him.

2. *In-Store Experience.* Not every single item (variant or SKU) is displayed; rather, the assortment is designed such that a customer can try on (say) a shirt in any size and see and touch all available fabric options (his exact combination of size and color may not be available, but he will be able to try on the right size and see the color he wants in a different size). Thus, the ZIS, relative to a regular store, carries a dramatically reduced assortment while still achieving the objective of offering customers the possibility of "experiencing" the full product line.

[3] For reasons of confidentiality, we do not name the retailer that provided our data.

To execute our research, we partnered with a digitally-native vertical brand (DNVB) which is among the pioneers of the ZIS. For our purposes it is critical that the products exhibit tactile or "non-digital" product attributes (Lal and Sarvary 1999) for which customer uncertainty is present, prior to the initial purchase. When customers experience products offline, uncertainty for both purchased (and non-purchased or trialed) products can be resolved ex ante. Conversely, when products with non-digital attributes are purchased online, full uncertainty resolution is only possible ex post (e.g., Lee and Bell 2013).

Our retail partner specializes in men's fashion apparel, a category which is a "poster child" for non-digital attributes and one plagued by the perennial problem of e-commerce, returns.[4] The retailer sells thirteen different subcategories (pants, shirts, suits, etc.), and important for our research, the extent of pre-purchase uncertainty experienced will vary by subcategory. That variation should also be correlated with price (pre-purchase, it is easier to evaluate fit aspects of socks than suits). The initial and signature product for the firm was a pair of casual pants. As the assortment expanded to include suits, dress shirts, and outerwear, more customers requested the opportunity to "try before buying." In fall 2011, the firm responded by testing a ZIS at their headquarters, with the purpose of providing a physical space for customers to try on products.

Before proceeding to the data, it is important to note that in the early days of brands born online as e-commerce operations, the received wisdom was that physical stores were potentially redundant. In fact, an early proponent of that (flawed) view was the CEO of Bonobos, who was quoted in the press as saying: "We said we would never be offline".[5] Ironically, Bonobos went on to become one of the earliest adopters and pioneers of the showroom, or ZIS, which is now part and parcel of the playbook for the current wave of DNVBs seeing success in categories as diverse as fashion apparel and accessories, to footwear, furniture, outdoor gear, luggage, and eyewear, among many other categories.[6]

2.2. Data Description and Summary Statistics

The data are from inception of the firm (October 2007) and cover all orders through October 2016, so there is no left-censoring, and the exact sequence of orders for each customer can be determined. Similarly, there is no right censoring either (e.g., for product returns) as we obtained an additional

[4] "As e-commerce captures a growing share of all retail sales, omnichannel brands that have high return rates and high return handling costs find themselves in the unenviable position of seeing their marginal economics deteriorate," (Dennis 2018).

[5] Koblin, J. "For Bonobos, a good fit in stores as well as online," *New York Times.* July 2 (2014).

[6] Among the many notable brands deploying this strategy are Allbirds (footwear), Away (luggage), Casper (bedding), Harry's (men's grooming), and Warby Parker (fashion eyewear). All five of these brands are so-called "unicorns" (valued in excess of $1 billion) and were among the first to use their head offices as de facto showrooms for customers. Harry's was acquired by Edgewell Personal Care for $1.37 billion on May 9, 2019; the other four companies are private as of that date.

three months of data beyond October 2016 (management use a three-month interval to classify whether sampling orders convert into sales). In total, the comprehensive dataset covers more than two million orders from the firm's website and ZIS' over a period of nine years since the company first opened. Individual order-level data include: unique customer identification code, item description (e.g., category and subcategory), and the price paid for each item. Returns data are at the individual customer and item level. For orders placed on or following a ZIS visit ("ZIS transactions") we know the exact ZIS location and shipping ZIP code.

By exact count, we have 2,016,554 transactions from 596,740 unique customers for orders made directly online ("Web Orders") and during a ZIS visit ("ZIS Orders"). By 2018, there were nearly 50 ZIS locations across the United States. Tables 1 and 2 in the Online Appendix provide summary statistics and key observations from these measures are:

- 23% of customers visit a ZIS at least once and 13% of orders are placed in a ZIS; customers who have visited a ZIS live about 30 miles away from one versus 96 miles for online-only customers
- ZIS orders relative to Web orders are, on average, larger in dollars ($283 vs. $177) and number of items bought (2.9 vs. 2.2), but have a lower return value as percentage of basket size (6.2 percentage points lower)
- ZIS customers (those who visit a ZIS at least once), on average, buy more subcategories (1.7 vs. 1.4) whether shopping offline or online

In summary, *orders* from the ZIS likely to be more profitable (higher value, lower return rate) and *customers* who experience a ZIS may behave differently to those who do not. Our econometric approach rigorously explores these pattens and preliminary findings.

3. Econometric Analysis

Our models and robustness checks zero in on how a ZIS experience (treatment) affects a customer's future trajectory (outcome). We start with a descriptive analysis using minimal modeling assumptions that suggests possible effects of the ZIS experience. Next, we describe the risk-based matching methodology used in our main analysis and its application to our empirical setting. Finally, we discuss several robustness checks designed to ensure that the effects we report are not an artifact of self-selection, or otherwise spurious.

In this Section, for ease of exposition and purposes of illustration, we use sales velocity as our main dependent variable of interest. In Section 4 we extend our analysis and we explore several key customer behaviors, such as the amount spent per order, velocity of shopping, basket composition in terms of prices paid, number of items and subcategories purchased per order, and, critically for e-commerce, return rates.

3.1. Descriptive Analysis

The aforementioned summary statistics (Section 2.2) provide some "model free" evidence at the *aggregate* level that ZIS customers are more valuable. However, this distinction could simply arise from innate differences between ZIS and online-only customers. Given that our data allows us to track customers over time, we can refine this analysis by adopting a *within-customer* approach. We estimate a fixed-effects panel data model (with fixed effects for each of our 596,740 customers) to more rigorously explore the amplification that customers seem to experience after they visit a ZIS for the first time. The unit of observation for this analysis is a customer-month and the model includes a variable that indicates whether the customer has previously experienced a ZIS, as well as month-year fixed effects to account for seasonality and any overall trend. The results of this analysis are presented in Table 1 (see Online Appendix for additional details) and show that, within customer, sales per month increase by $79.72 after a customer experiences the ZIS.

Table 1 Panel Data Analysis on Customers' Monthly Sales

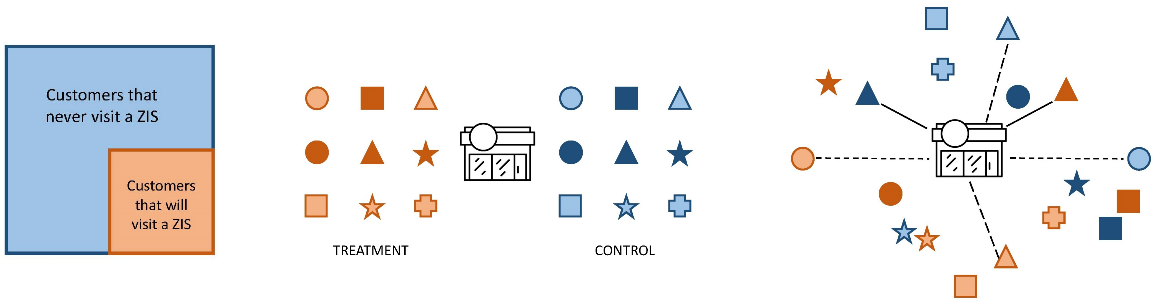
Variable	Monthly Sales
ZIS Treatment	79.72***
	(0.95)
Constant	Yes
Customer Fixed Effects	Yes
Time Fixed Effects	Month-year
Observations	5,643,894
R^2	0.37

Robust Standard Errors in parentheses
*** $p < 0.001$

These findings do not represent a causal interpretation of the effect of the exposure to the ZIS. Rather, they offer further support for a potential causal effect. It could, for example, be the case that customers have a higher propensity to gravitate to the ZIS when they are on a more intense consumption trajectory. Thus, the following subsections develop a matching approach to compare the evolution of pairs of customers (treated and control) that had very similar consumption trajectories before treatment. It is this approach that provides better support for a causal interpretation of the sales effect garnered by exposure to the experience-centric channel.

3.2. Risk-Set Matching: General Approach

Our procedure creates pairs of "identical" customers with extremely similar observable characteristics, addressing the concern that the two populations—treated and control customers—are different. Treated customers can receive the treatment, i.e., the first ZIS visit, at various times so matched pairs must be formed such that treatment and control customers are similar *before* the time of treatment. Under risk-set matching, a newly treated customer at time t is matched to one or more control customers who are not yet treated at time t, based on covariates describing customers *prior to time* t. Since we have a large number of customers who never visited the ZIS, members of this group can, at various times, serve as potential controls.



(a) Empirical Setting (b) Treatment and Control Groups (c) Including Distance to the ZIS

Figure 1 Treated and Control Customers

We match customers who receive treatment at t with customers who had the same probability of treatment at t, i.e., the same hazard rate, but who did not end up receiving treatment. This approach (Figure 1a), avoids a situation in which a control customer visits a ZIS at a later time, thus potentially biasing our comparison of outcomes for treated and control customers. Under the assumption that treatment is determined only by observed characteristics as represented by the different shapes in Figure 1b and different distances from the ZIS (Figure 1c), this resembles a situation in which customers are randomly assigned to the treatment. Of course and as noted above, unobserved characteristics may affect the probability of treatment as well. This is addressed in Section 3.4; for the moment we assume that the probability of treatment depends only on observable characteristics.

3.3. Risk-Set Matching: Application and Results

Treatment occurs at time t when customer i visits a ZIS for the first time. We match customer i at t with another customer j, chosen from among customers who never visited a ZIS during the observation period, at the time at which it best matches the treated customer. Customer characteristics as well as variables that summarize the trajectory of the customer's buying behavior, i.e., state variables that change over time, can be used in matching. We considered several variables for matching customer i before time t; in the results we report, we use the following six: total number of transactions made, time since last purchase, total dollar sales, total number of unique subcategories bought, distance from i's ZIP code to the closest ZIS at time t, and acquisition date, i.e., the time at which customer i placed their first transaction. Following Rosenbaum (2010), the same control customer could match with more than one treatment customer.

For ease of exposition, Figure 2 shows the matching chronology for two hypothetical customers. In the example, the match occurs at the second transaction of the ZIS customer, i.e., just before the first ZIS visit happens. For a treated customer i visiting a ZIS for the first time at t, we have a control customer at t' that is essentially identical to i at t and in total, we have $i = 1, 2, ..., I$ pairs of treated and control customers.

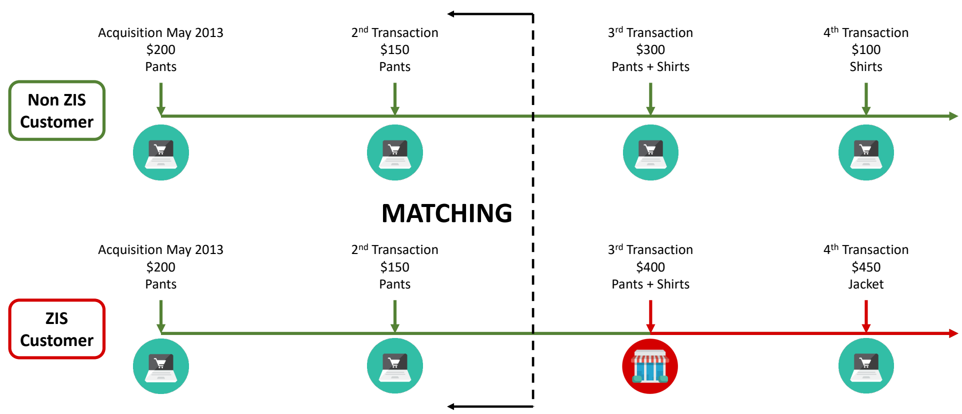


Figure 2 **Risk-Set Matching**

While our preferred method is a nearest neighbor matching using the Mahalanobis distance of the six covariates described above, with 1:1 matching between treated and control, and with a caliper of 0.3, we considered several matching approaches and the results were robust to permutations of the specific covariates, number of matches per treated unit, the distance metric, and caliper, i.e., maximum distance at which two observations are a potential match.[7] For the analysis we retain 255,792 customers: 127,896 who visited a ZIS and the best match for each of them at the time of their first visit, among the customers who did not visit a ZIS. As shown in Table 2, matching is extremely effective as the treated and control groups are virtually identical in their observable attributes that are used in the matching process.

Post matching, we compare total sales for treated versus control customers as follows:

$$Sales_{i,j} = \alpha_0 + \beta_1 ZIS\,Treatment + \beta_2 Pair_i + \epsilon_{it}, \quad (1)$$

[7] We have considered a large number of variations in the matching method, variables used, and parameters of the algorithms, and our results remain qualitatively similar. Details are available from the authors, upon request.

Table 2 Average Covariate Balance

Variable	Description	ZIS	No ZIS
Sales	Sales Prior to ZIS	71.49	71.49
		(223.08)	(223.03)
SubCat	SubCat Prior to GS	0.55	0.55
		(1.50)	(1.50)
MinDist	Min Dist to GS	24.49	24.60
		(98.04)	(98.00)
Aq.Qtr.	Acquisition Quarter	219.55	219.55
		(5.38)	(5.37)
Sequence	Order Sequence	1.46	1.46
		(1.35)	(1.35)
Recency	Months Since Last Order	1.52	1.51
		(5.65)	(5.64)

Observations per Group: 127,896
Standard errors in parentheses

where i denotes the matched pairs, j indicates whether the customer is treated or control ($j \in \{treated, control\}$), $ZIS\,Treatment = 1$ for $j = treated$ and 0 otherwise, and $Pair_i$ is a fixed effect for each matched pair. As shown in Table 3, treated customers, compared to their matched control customers, spend an average of $326.53 more over their subsequent purchase history following their first ZIS encounter ($p < 0.001$). Note that the positive coefficient on $ZIS\,Treatment$ in Table 3 is entirely consistent with what we observed from the panel data analysis in Table 1; the distinction here is that treated and control customers have been matched and the effect is estimated on total sales subsequent to ZIS treatment, rather than on customer-level monthly sales.

Table 3 Total Sales of Treated Vs. Control Customers Subsequent to the First ZIS Visit

Variable	Sales
$ZIS\,Treatment$	326.53***
	(4.57)
$Pair\,Fixed\,Effects$	Yes
$Constant$	Yes
$Observations$	255,792
R^2	0.55

Robust Standard Errors in parentheses
*** $p < 0.001$

3.4. Robustness

While we assume that observable characteristics drive the decision to visit the ZIS for the first time, it is plausible that customers who visit a ZIS self-select into doing so, and that this may depend on unobservable characteristics. If, for example, even after controlling for observables, customers who visit the ZIS are more positive towards the brand, this might create selection bias and partially explain better sales outcomes for ZIS visitors. We therefore conduct a series of robustness checks and undertake alternative analyses to rule out the possibility that our results are due to selection. The results of these checks are extremely reassuring; we summarize them below and direct the reader interested in the complete details to the more comprehensive discussion in the Online Appendix.

Matching Validation Using Rosenbaum Sensitivity Analysis. Starting with procedures advocated by Rosenbaum (2010) to assess robustness to potential self-selection issues, we test for the presence and effect of unobservables using Rosenbaum's sensitivity analysis (Rosenbaum 2010), and ask: "How large would an unmeasured covariate have to be in order to affect our conclusions?" We find that for our results to change, the hidden bias would require that for two customers who are identical in their observable covariates, the odds of receiving treatment would need to more than double for one of them. Thus, we conclude that the potential for hidden bias from unobservables is very low.[8]

Matching Cross-Validation with Socio-Demographic Variables. Using a separate dataset containing rich customer-level descriptors, we "cross-validate" our matching procedure on a subsample of our original customers. These data were collected by the firm for an entirely different purpose and made available to us for this cross-validation exercise. For subsample customers for whom we have demographic data, we can validate that the distribution of these covariates (which are not used in the matching process due to data limitations for the more comprehensive dataset of all the firm's customers) is virtually identical for treated and control groups. Thus, even though these demographic variables are *not* considered in the matching procedure using all customers, they become perfectly balanced in the treatment and control groups, post matching. This provides reassurance that any differences between the two groups, across a wide class of covariates, are minimal. Conversely, if the treated group were subject to self-selection based on variables not observed during matching, we should see covariate imbalance in the distribution of the demographic variables.

Treatment Calibration with Variation in Intensity. Here we exploit individual-level variation in the intensity of the treatment that different customers experience, in order to provide further evidence of robustness. Our hypothesis is that a (first) visit to the ZIS "supercharges" a customer by providing an intimate service experience and sensory exposure to the brand. Treated customers, however, differ in the conditions under which they visit the ZIS, and therefore in the potential intensity of the "supercharging" experience. Specifically, using data on store congestion as reflected by the number of customers served in the ZIS in that day, we have a proxy measure of the quality of the service experience on the first ZIS visit. Customers who encounter a more congested ZIS

[8] The unconditional probability of a ZIS visit is 0.23. Self-selection on unobservables would have to increase this probability to at least 0.60 in order to explain the effects we find.

should be subject to less supercharging given that they would have a (relatively) degraded service experience. As expected, we find that supercharging of sales decreases as store congestion increases.

Identification Using Timing of Store Openings Across Locations. Our focal analyses are conducted at the individual level; nevertheless, we conducted a complementary ZIP-level (geographic) analysis that uses variation in the timing of store openings to identify supercharging. ZIP codes (instead of customers), are the unit of observation and we take advantage of the fact that showrooms opened in different locations at different times. This ZIP code-level propensity score analysis reproduces patterns of results that are qualitatively very similar to the ones documented when the matching is done at the customer level.

3.5. Summary

The amplification effect, aka "supercharging" created by the ZIS is observed in different yet complementary analyses that are based on different sets of assumptions and levels of aggregation. Beginning with model-free evidence in the raw data, we are then able to detect strong effects in individual-level panel data analysis. Moving to a more causal setting, our focal matching-based analysis reproduces the key result, and the matching itself is shown to be robust under the Rosenbaum test and cross-validation using a rich set of demographic variables. Moreover, the supercharging mechanism responds as one would expect when store congestion is used as a proxy for the quality of the service experience. Finally, ZIP code-level analysis yields qualitatively identical findings, providing us with strong assurance that the overall effect and the approach used to identify it are sound.

4. Decomposing Supercharging into Constituent Behaviors

Earlier (in Section 3) we reported that treated customers, relative to their control counterparts, go on to spend, on average, \$326.53 more with the brand ($p < 0.001$). While evidence of this "sales bump" is of course important to retailers, they are also concerned with a host of other customer behaviors including shopping frequency, basket composition as reflected in prices paid and willingness to buy a broad range of items, likelihood to return products, and so on. Here, to the best of our knowledge, we provide the first elaboration as to how ZIS treatment impacts these core behaviors and in so doing offer new insights for practice and future research (discussed more fully in Section 5).

4.1. Shopping Velocity

In addition to driving more sales, retailers are also often concerned with increasing the frequency with which customers shop. Hence, we consider:

$$Frequency_{i,j} = \alpha_0 + \beta_1 ZISTreatment_j + \beta_2 Pair_i + \epsilon_{it}, \tag{2}$$

where i denotes the matched pairs, j indicates whether the customer is treated or control ($j \in \{treated, control\}$), $ZISTreatment = 1$ for $j = treated$ and 0 otherwise, and $Pair_i$ is a fixed effect for each matched pair. We define $Frequency_{i,treated}$ as the outcome for the treated customer in the i^{th} pair, and $Frequency_{i,control}$ as the outcome for the corresponding control customer. To calculate the outcome for the treated customer we count orders placed following the treated customer's first ZIS visit, i.e., transactions that happen at t or later, and we divide by the number of years between the time of the treated customer's first ZIS visit and the end of our dataset.

To see how this works, imagine a customer's first ZIS visit is on April 2, 2014 and the customer places 20 transactions between that day (included) and the end of our data (October 2, 2016, 2.5 years later). Here $Frequency_{i,treated} = 20/2.5 = 8.0$ orders / year. Under risk-set matching, t' is not necessarily identical to t. For the control customer, we consider all orders at time t' or later, and divide them by the number of years between t' and the end of our data. Table 4 (column 1) shows that the ZIS effect on shopping frequency is positive and significant ($\beta_1 = 0.61$, $p < 0.01$). The increased frequency of purchases could be due to a reduction in the uncertainty and mental costs of shopping delivered by the ZIS experience, and perhaps a concomitant increase in brand attachment.

4.2. Basket Composition: Prices Paid, Items, Categories

In simple terms, an individual order can be decomposed into prices paid, number of items bought, and number of categories represented. Estimating models analogous to equation (1) we find positive effects on the average item price ($\beta_1 = 16.35$, $p < 0.001$, Table 4 column 3) and the number of items bought ($\beta_1 = 0.61$, $p < 0.001$, Table 4 column 2). Interestingly, while "ZIS treated" customers, on average, buy more and pay higher prices per transaction, if we restrict attention to their online transactions, the number of items bought per visit goes down ($\beta_1 =$ -1.34, $p < 0.001$, Table 4 column 4), but at higher average prices ($\beta_1 = 1.59$, $p < 0.001$, Table 4 column 5). Combining findings from columns 1-5, ZIS-treated customers shop at higher velocity buying more and spending more per item overall, but with reduced online basket sizes, albeit at higher average prices.

With respect to the category-level aspect of basket composition, ZIS treated shoppers purchase a greater breadth of subcategories ($\beta_1 = 1.14$, $p < 0.001$, column 6) and their baskets are less dependent on the "signature" and first category that the firm introduced, pants ($\beta_1 =$ -0.04, $p < 0.001$, column 7). These findings imply that ZIS experience causes customers to deepen their relationship with the brand, as reflected in a willingness to diffuse their purchasing towards ancillary products, and buy more broadly across the entire product line.

4.3. Product Returns

After shopping in a ZIS, a customer's overall return rate drops 5 percentage points (Table 5, Column 1). Moreover, even for items subsequently bought online, the return rate goes down as well, in this case by 2 percentage points (Table 5, column 2). A likely explanation is that superior knowledge of

Table 4 Effect of the Experience-Centric Channel on Baskets

	(1) Order Freq.	(2) # of Items	(3) Avg. Item Price	(4) # of Items (Online)	(5) Avg. Item Price (Online)	(6) # of Cat.	(7) Share of Pants
β_1, *ZIS Treatment*	0.63***	0.61***	16.35***	-1.34***	1.59***	1.14***	-0.04***
	(0.02)	(0.01)	(0.19)	(0.01)	(0.35)	(0.02)	(0.00)
Pair Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Constant[1]	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	255,792	255,792	255,792	177,350	177,350	255,792	255,792
R^2	0.59	0.53	0.53	0.60	0.76	0.56	0.52

Estimates are obtained via OLS. Robust Standard Errors in parentheses

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

[1] Constants omitted from the Table for confidentiality reasons

taste and fit acquired from even one offline experience translates into more efficient online shopping in the future, whether the future shopping events happen offline or online.

As return rates are a critical pain point for both customers and retailers, we also consider how the impact of a ZIS experience might vary according to product value. The "cost" of an unsuitable item clearly increases in price for consumers; hence, it makes sense that customers are more likely to return items that are more expensive (β_2 = 0.0008, $p <$ 0.001, Table 5, Column 4). Of vital importance to the retailer is the negative interaction effect: the reduction in return rate due to a ZIS treatment accelerates for more expensive items (β_3 = -0.0006, $p <$ 0.001, Table 5, Column 4). Hence, a ZIS treatment not only reduces return rates for customers, but does so to an even greater extent for items that are more expensive (more on this shortly).

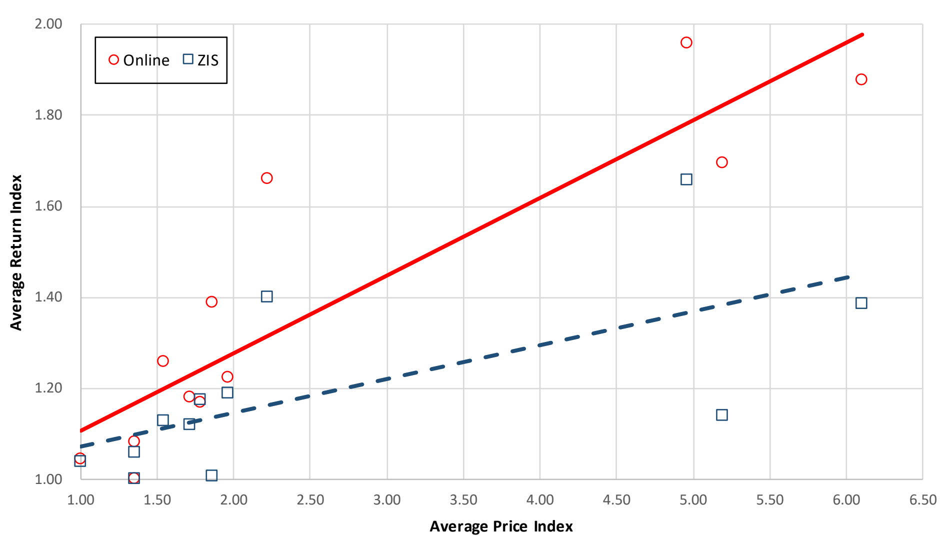
Table 5 Returns

	(1) Return %	(2) Return % Online	(3) Return %	(4) Return %
β_1, *ZIS Treatment*	-0.05***	-0.02***	-0.051***	-0.0024
	(0.00)	(0.00)	(0.001)	(0.0035)
β_2, *Avg Price*				0.0008***
				(0.0000)
β_3, *ZIS Treatment* × *Avg Price*				-0.0006***
				(0.0000)
Pair Fixed Effects	Yes	Yes	Yes	Yes
Constant	Yes	Yes	Yes	Yes
Observations	255,792	177,350	255,792	255,792
R^2	0.51	0.75	0.51	0.51

Estimates are obtained via OLS. Robust Standard Errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$
Constants omitted from the Table for confidentiality reasons

"Scissor Effect" Interaction Between Prices Paid and Reduction in Return Rate. The results in Table 5 with regard to the return rate by average price interaction are worth exploring further (and visually) as they have clear implications for the kinds of products a brand might encourage customers to buy in a ZIS. Since the retailer carries 13 separate subcategories at varying price points, this provides further opportunity to explore the connection between supercharging and returns, and, implicitly, develop more insight into the mechanism itself. In apparel, more expensive items are typically more tactile and, as noted above, the cost of "poor fit" (for individual consumers and for the retailer) is also higher as well.

Model-free evidence of this intuitive price-return rate relationship shows, as expected, a positive slope with higher return rates for more expensive items. This is true for both online-only customers (red line) and for ZIS-treated customers too (blue line) and is of course reflected in the positive coefficient on average price in Table 5 ($\beta_2 = 0.0008$, $p < 0.001$).[9] Of additional and particular interest is the "scissor-like" interaction evident in Figure 3 which is of course reflected in the negative model-based estimate of the ZIS Treatment x Average Price interaction in Table 5 (β_3 = -0.0006, $p <$ 0.001), but far more powerful when visualized. ZIS customers are not only less likely to return items across the entire price spectrum (the blue line always sits under the red), but disproportionately less likely to return items that are more expensive. Given the deleterious effect of product returns on e-commerce, the implication is clear: an experience-centric channel is an ideal setting in which to induce customers to buy and try the brand's more expensive and tactile items.



Average Return Rates (y-axis) and Average Prices (x-axis) are expressed as indices in order to preserve confidentiality

Figure 3 Average Return Rate vs. Average Price per Category

[9] For reasons of confidentiality we do not show the actual return rates in Figure 3, but simply indicate the scale.

4.4. Variation in Customer Distance to ZIS and Prior Experience

The Role of Distance to ZIS. There is considerable variation across matched pairs of treated and control customers in the distance customers must travel to visit a ZIS. The fixed cost of visiting a ZIS is lower for customers who are closer to it; hence, we hypothesize that supercharging effects will be more pronounced for customers who do not have to travel far to reach a ZIS. Conversely, for customers who are further away from a ZIS, the supercharging effect of a ZIS visit will be attenuated. Indeed, Table 6 shows that the positive effect of a ZIS on sales decreases as the minimum distance customers must travel to reach the ZIS increases (β_3 = -0.19, $p <$ 0.001). Customers who live far from a ZIS and yet *still choose* to visit it may be subject to a larger hidden bias, since factors driving their self-selection (into a ZIS visit) must be strong enough to overcome the higher costs of visiting the ZIS to begin with. The fact that the effects we obtain for those customers are smaller than for the customers who are closer to the ZIS suggests that the impact of self-selection is not strong enough to overcome the attenuation of the effects with the distance to the ZIS.

Table 6 Heterogeneity in Distance

	Sales
β_1, $ZIS\,Treatment$	331.00***
	(4.74)
β_2, $MinDist$	-0.92
	(1.54)
β_3, $ZIS\,Treatment \times MinDist$	-0.19***
	(0.04)
$Pair\,Fixed\,Effects$	Yes
$Constant$	Yes
$Observations$	255,792
R^2	0.55

Robust Standard Errors in parentheses
*** $p < 0.001$

The Effect of Prior Experience. Customers who enter the ZIS vary considerably in the extent of prior experience they have had with the brand. Some might have purchased a single item from a single visit to the website, whereas others could have purchased several items, potentially over multiple online visits. To capture this heterogeneity in prior experience we define the variable $PriorExperience_i$ as the number of items bought prior to treatment and include this variable and its interaction with $ZISTreatment_i$ into equation (1). We find that the positive impact of a ZIS visit on future sales is greater for customers who had less prior experience at the time of treatment (β_3 = -0.03, $p <$ 0.01, Table 7, Column 1)and that the reduction in return rates is also less pronounced (β_3 =0.005, p < 0.001, Table 7, Column 2). Thus, when customers have had more prior experience with the brand, the efficacy of a ZIS visit in inducing supercharging is diminished. The implication is clear: it is more beneficial for the retailer, and presumably the consumer as well, when the ZIS visit occurs before customers garner too much experience.

Table 7 Supercharging Effects as a Function of Prior Customer Experience

	Items Bought Post Supercharging (1)	Returns (2)
β_1, $ZIS\,Treatment$	0.636***	-0.051***
	(0.010)	(0.001)
β_2, $Prior\,Experience$	0.113	-0.001
	(0.010)	(0.001)
β_3, $ZIS\,Treatment \times Prior\,Experience$	-0.030**	0.005***
	(0.003)	(0.000)
$Pair\,Fixed\,Effects$	Yes	Yes
$Constant$	Yes	Yes
$Observations$	255,792	255,792
R^2	0.54	0.51

Robust Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$
PriorExperience denotes the number of products purchased before first ZIS visit

5. Conclusion

We started with a simple conjecture—that an offline and tactile experience with a brand in an experience-centric location could deepen customers' understanding of the products available for sale and alter, positively, the future trajectory of their shopping behavior. We termed this phenomenon "supercharging" and documented the attendant statistically and economically meaningful effects on key shopping behaviors: amount bought per transaction, shopping velocity, basket composition, and critically for e-commerce, return rates. Specifically, "treated" customers with ZIS experience, relative to control doppelganger customers with no offline experience:

- Spend up to 60% more on an average order
- Shop at a higher velocity, showing a 28% reduction in inter-purchase times
- Buy in 20% more product categories, buy more expensive items, and are more likely to have a "diffuse" sales distribution that is less reliant on the core and signature product that anchored the brand from inception
- Are less likely to return items overall, and disproportionately less likely to return more expensive items as well

This marked change in customer trajectory following exposure to an experience-centric channel has an important and reinforcing virtue. Customers explore more, buy more, and pay more, and yet are even less likely to return higher-priced and more tactile items. Thus, an "experience-centric" offline format designed to deliver customer service and brand interaction while leveraging online fulfillment, provides significant value creation as customers will not only generate more demand, but also do so more efficiently.

At this juncture it is important to restate explicitly, what is implicit throughout the paper. Retail business models incorporating an experience-centric offline channel, while pioneered by our data supplier and quickly adopted by numerous other digitally-native vertical brands, are new ubiquitous across retailers of all stripes. Prominent legacy retailers including IKEA, Nordstrom, Urban Outfitters, Target, Walmart and others, have adopted and tested the format.[10] One could also argue that the ZIS is a precursor of co-retailing exemplified by offline models such as Showfields, "The World's Most Interesting Store,"[11] Neighborhood Goods, and WeMRKT. Moreover, leading mall operators in the US including Simon Property Group and Macerich recently announced Brandbox and International Edit, respectively, which are collections of showrooms designed to generate mall traffic through experiential retail.[12] The substantive findings in our paper are therefore of relevance to all major classes of retail and we highlight this further in Section 5.1, via a model-based comparison of the economics of the ZIS, relative to those of a traditional store.

5.1. Implications for Digital First Retailers, Legacy Operators, and Malls

Supply chain innovation means that many goods can be delivered to customers from a distribution center with an extremely short lead time. While our findings are calibrated on data from a digitally-native retailer, the implications apply equally to legacy retailers and mall operators as well. As many stores and malls struggle and close, the ZIS offline format coupled with centralized fulfillment offers a revolutionary way forward. Indeed the combination of a small footprint experiential ZIS coupled with centralized fulfillment via e-commerce should be particularly attractive for retailers that have a large assortment, high margins, and high inventory costs.

Stores Versus Showrooms At the core of our implications for practice is the distinction between the well understood age-old format of the store and the new yet relatively unstudied ZIS. In simple terms, the traditional store seeks to accomplish two core functions, service experience and fulfillment, under one roof. In contrast, the ZIS elevates the experience function while outsourcing fulfillment entirely, to e-commerce.

[10] See, for example, Hsu, T. "Retailers Experiment With a New Philosophy: Smaller Is Better," *The New York Times* Nov. 17, 2017 and Chaudhuri, S. "IKEA Takes On Manhattan With Showroom Coming This Spring," *The Wall Street Journal* Dec. 3, 2018, and "Custom Ink's Push into Brick and Mortar includes Positions Inside Michaels, Walmart," https://www.bizjournals.com/washington/news/2019/04/05/custom-inks-push-into-brick-and-mortar-includes.html.

[11] See "'The Most Interesting Store In The World' Pops Up In New York City,' 'https://www.forbes.com/sites/jonbird1/2018/12/16/the-most-interesting-store-in-the-world-pops-up-in-new-york-city/674c7782485f

[12] See, for example, "One Part Store, One Part Retail Lab: Mall Owner Debuts "Brandbox," A New Way to Allow Retailers to Test the Waters," https://www.cnbc.com/2018/11/12/mall-owner-macerich-debuts-brandbox-a-store-that-is-part-retail-lab.html.

Not surprisingly, the economics of stores and showrooms are quite different. Table 8 compares five core facets of each and highlights how the formats differ in their ability to scale. With a store model, inventory costs increase rapidly with the number of products and stores. Because the showroom model aggregates inventory in a centralized location, it can scale in number of products and stores with a much more modest increase of inventory costs. In a store model, shipping costs are low because customers are fulfilled at the point of sale and become the bearers of shipping costs. The smaller physical size of the showroom means that real estate costs are lower and that fewer salespeople are needed to service customers.

In the decision to adopt stores or showrooms, it is essential to quantify how much demand a showroom model would lose from its inability to offer immediate fulfillment. The Online Appendix provides a detailed cost-benefit analysis, consistent with the "decision calculus" view of simulations first introduced to the management science literature by Little (1970), of the decision to invest on showrooms rather than stores. By this we mean that we calibrate a key simulation input–an estimate of the amount of demand lost when a store is converted to a showroom–by using expert judgments from 100 retail executives. Using these inputs, we are able to demonstrate that the showroom format can be optimal in a wide range of situations, taking into account reasonable values for product margins, return rates, and store operating costs (the interested reader can find the full details in the Online Appendix). This finding, coupled with the consumer insights from supercharging, reiterates why the ZIS format holds promise for digital-first brands, individual legacy retailers, and shopping mall operators alike.

Table 8 Stores vs ZIS

Factor	**Stores**	**ZIS**
Inventory costs	High	Low
Shipping costs	Low	High
Real estate	Higher	Lower
Labor costs	Higher	Lower
Demand	Higher	Lower

5.2. Implications for Research

Our paper is, to the best of our knowledge, the first to document the amplification of positive customer behavior that follows a customer visit to an experience-centric channel and what we term "supercharging". Given our findings, there are at least two promising directions for future research. First, it is important to understand the kinds of products and customers for which showrooms are efficacious, and relatedly, a likely optimal mix of stores and ZIS for retailers who might wish to deploy both. Second, while metrics to assess store performance, e.g., same-store sales over time, cross-store comparisons, etc., are widely implemented and studied, there is a dearth of counterpart metrics for the ZIS. As the ZIS becomes more ubiquitous it will be critical to assess performance both across ZIS locations, and for a given ZIS over time. This will undoubtedly require the creative development and testing of new analytics for an increasingly complex and multifaceted retail landscape.

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