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Inter-Retailer Channel Competition: Empirical Analyses of Store Entry Effects on Online Purchases

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This study empirically examines the effect of offline store entry on a competing online retailer in the footwear industry and investigates how this effect depends on the relative product assortment and price between the offline store and the online retailer. Using transaction data from a large online footwear retailer and offline store entry data from 19 major shoe retail chains and 3 department store chains, we quantify the entry effect of offline stores. Categorizing offline stores by assortment and price, we find that the entry of regular-price narrow-assortment stores generates a complementary effect that increases online purchases, while the entry of discount wide-assortment stores leads to a substitution effect that reduces online purchases. The store entry of other types has no significant effect on online purchases. We further find that the complementary effect is mainly driven by the mechanism of unsatisfied product exploration due to a narrow assortment in stores, rather than the mechanism of product uncertainty reduction due to overlapping products with lower prices online. Therefore, the complementary effect not only increases the online purchases of store-brand products but also creates spillovers to other brands. Moreover, the substitution effect driven by the reduced transportation cost is mitigated primarily by consumers' proximity to pre-existing stores.

Key words: store entry; channel competition; complementary effect; substitution effect; store type
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1. Introduction

In the age of e-commerce, several online giants, such as Amazon and Alibaba, present daunting challenges for brick-and-mortar retailers. In the United States, the online share of total retail revenue for apparel and accessories was 36.7% as of May 2020 (Statista 2020). Despite steadily encroaching competition from online retailers, brick-and-mortar stores still offer a shopping experience that is not digitally replicable. Instant gratification and the ability to physically confirm the quality and fit of products are the top reasons for in-store shopping, especially for fashion products (MarketingCharts 2017). While many department stores have reduced their physical presence, the number of stores for mid-tier women's apparel, fast fashion, and discount and luxury goods has greatly increased in recent years (Coresight Research 2019).

Opening new stores, as a key strategy for chain retailers to cope with changing market trends, has important implications for their performance (Srinivasan et al. 2013). Both analytical and empirical work find that offline stores provide demand enhancement effects for their online counterparts because of information spillover (Levin et al. 2003, Kwon and Lennon 2009, Wang and Goldfard 2017) , new customer acquisition (Avery et al. 2012, Bell et al. 2018, Nault and Rahman 2019) and operational integration (e.g., purchase online and pickup/return in store) (Bell et al. 2018, Gallino and Moreno 2014, Gao and Su 2017, Kumar et al. 2019, Melis et al. 2015, Song et al. 2020).

In the inter-retailer setting, store openings create a strategic interaction between the chain retailer and the competing online retailer via consumer search (Jiang and Anupindi 2010). Most empirical evidence points to the demand substitution effect for the online retailer as the new store reduces transportation costs and thus lowers offline search costs for nearby consumers (Brynjolfsson et al. 2009, Forman et al. 2009). Recent developments in the theoretical literature also suggest the possibility of complementary effects because of consumer showrooming (Balakrishnan et al. 2014, Jing 2018, Kuksov and Liao 2018, Mehra et al. 2018), in which consumers examine products in stores but purchase online for lower prices (Zimmerman 2012).

Compared to the effect on the same retailer's online channel, the store opening effect on a competing online retailer is complicated by the relative price and assortment of the two retailers. When retailers compete in experience products with fit uncertainty, both prices and assortments affect consumers' optimal search behavior and their channel choices (Sun and Gilbert 2019). While most online retailers offer a wide assortment and mixed prices, offline stores are more varied. In terms of assortment, while single-brand stores (or manufacturers' stores) (e.g., Nike and Nine West) sell products of the manufacturer's brand only, multi-brand stores (or downstream retailers' stores) (e.g., Payless ShoeSource and Footlocker) sell products of various brands. Moreover, department stores (e.g., Macy's and Kohl's) carry many brands and categories. Regarding pricing, although regular-price stores offer promotions or discounts occasionally, they sell most products at the suggested full prices, whereas discount stores sell most products at marked-down prices.

Given the different types of offline stores, their opening effects can be different. The literature on retail competition has shown that competition across retail formats (e.g., mass merchandisers vs. grocery stores) can be fundamentally different from competition within a single format (Fox et al. 2004, Lim et al. 2020). Kalnins (2004) finds that encroachment varies across the business formats of franchised and company-owned branded chains. Sun and Gilbert (2019) suggest that a retailer's pricing strategy should differ substantially depending on the assortment of the retailer's rival. However, Forman et al. (2009) find no empirical evidence for the difference between the entry effect of discount bookstores and that of large bookstores in online book purchases.

Therefore, we address two research questions in this study: How does the store opening effect on the purchases at a competing online retailer depend on the store type as categorized by price and assortment? How can this effect be explained by consumers' search behavior? To answer these questions, we collected data from the footwear industry in the United States on the offline entries of six store types: regular single-brand, discount single-brand, regular multi-brand, discount multi-brand, regular department stores, and discount department stores. We find that regular single-brand store openings increase purchases at the competing online retailer, while the openings of discount multi-brand and discount department stores decrease online purchases; the opening effects of other store types are insignificant. The complementary entry effect can be driven by product uncertainty reduction which increases the online purchases of overlapping products at lower prices, or unsatisfied product exploration, which increases online purchases because consumers cannot find best-fit products in stores. Our results suggest that unsatisfied product exploration in stores is the primary force and results in increased online purchases of both store brand and non-store brand items. We also confirm that the substitution effect occurs via transportation cost reduction and increases with consumers' distance to the pre-existing stores.

The remainder of the study is organized as follows. We review the theoretical background and develop research hypotheses in Section 2. Section 3 describes our research context and datasets. The empirical methodology and results are detailed in Section 4. Section 5 conducts robustness checks. Finally, Section 6 concludes the study.

2. Hypotheses

Consumers search for both price and fit information from multiple retailers competing on price and assortment. The Internet reduces consumer search costs for the digital attributes of a product (e.g., price and dimension) but not for nondigital attributes (e.g., how well it fits) (Cachon et al. 2008). On the one hand, store openings can generate a complementary effect on online purchases by providing fit information on overlapping products (Gao and Su 2017). For many products, including apparel and furniture, consumers need to physically experience the product to assess its valuation (Sun and Gilbert 2019). High search costs of fit information may deter online purchases (Bhatnagar et al. 2000, Emrich et al. 2015, Kollmann et al. 2012). Store openings reduce the search costs of fit information by allowing nearby consumers to physically examine overlapping products and increase the probability of online purchases (Bell et al. 2018, Kumar et al. 2019). With resolved product uncertainty and given the low search cost for price information with the Internet, strategic consumers would purchase from the retailer with a lower price (Balakrishnan et al. 2014, Goolsbee 2001). Such consumer behavior will lead to increased online purchases of store products at relatively lower prices. When the new offline store offers regular prices, the online retailer will have a more prominent price advantage. Therefore, compared to the entry of discount stores, the entry of regular-price stores is more likely to result in a complementary effect on online purchases.

In addition to the mechanism of product uncertainty reduction, store openings may lead to a complementary effect on online purchases by capturing the unsatisfied demand in stores. Lower search costs for fit information when a new store opens have a market expansion effect that dampens competition because both retailers gain access to a broader pool of potential customers when consumers search more (Cachon et al. 2008). Although store openings attract consumers' store visits, not all of them can find their preferred products in stores, especially when the store assortment is limited (Pozzi 2012, Wan et al. 2012). Consumers who are unable to find their preferred products in stores can continue to search and make purchases online (Jiang and Anupindi 2010), as the online market usually provides a much wider product assortment than the offline market (Avery et al. 2012, Brynjolfsson et al. 2009, Brynjolfsson et al. 2003, Choi and Bell 2011, Zentner et al. 2013). According to Gallino and Moreno (2018), providing virtual fit information increases online purchases of not only products with virtual fit information available but also those without virtual try-on. Similarly, upon store openings, the fit information of store products may increase consumers' awareness and knowledge of the store brands, leading to increased online purchases of store brands. Furthermore, such experiential information can also spill over to non-store products online by helping consumers better parse their choice sets, especially when they are not satisfied with how the store products fit. From this perspective, a broad assortment at a new store reduces the number of "no-purchase in store" customers by increasing consumers' likelihood of finding the best-matched product (Alan et al. 2019, Berger et al. 2007, Cachon and Kok 2007, Hoch et al. 1999, Lancaster 1990, Mehra et al. 2018) and reducing consumers' value of continuing a search (Cachon et al. 2005, Sun and Gilbert 2019). The perception of assortment can be increased via product or brand variety (Kahn and Wansink 2004). In sum, compared to the entry of wide-assortment stores, the entry of narrow-assortment stores is more likely to result in a complementary effect on online purchases.

On the other hand, store openings can generate a substitution effect on online purchases when purchases that would otherwise be made online are made offline. A longer travel distance to an offline store reduces the likelihood of shopping at the store (Lim et al. 2020) and increases the likelihood of shopping online (Berry et al. 2002, Chintagunta et al. 2012, Emrich et al. 2015, Forman et al. 2009, Verhoef et al. 2007). An offline store entry can reduce the transportation cost for consumers who live far from pre-existing offline stores, shifting consumers' preferences in favor of the offline store (Brynjolfsson et al. 2009). Accordingly, the reduced transportation costs for consumers located near the new offline store would lead to a substitution effect on their online purchases. Contrary to the complementary entry effect, the price and assortment of the opening store will have the opposite impacts on the substitution entry effect. Consumers are more likely to find their best-fitting products in an opening store that offers a wide assortment and make final purchases in an opening store that offers lower prices than the online retailer. As such, the entry of discount wide-assortment stores is most likely to result in a substitution effect on online purchases.

Therefore, we propose the following hypotheses:

HYPOTHESIS 1. *The entry of a regular narrow-assortment store increases purchases at a competing online retailer, resulting in a complementary effect*

HYPOTHESIS 2. *The entry of a discount wide-assortment store decreases purchases at a competing online retailer, resulting in a substitution effect*

3. Research Context and Data

3.1. Empirical Setting

We combine datasets from multiple sources to assess the offline store entry effect on a competing online retailer. First, we collected data on consumer purchases at a large US online retailer that primarily sells footwear. This online retailer carries more than 40,000 unique footwear items. In 2013, it generated over $2 billion in revenue,[1] accounting for approximately 25% of the revenue of all online footwear retailers (Hurley 2016). During our study period, the online retailer sold products exclusively online. Our data contain purchase transactions of footwear products from January 30 to August 14, 2013. Each record contains the purchase date and time, the zip code location of the customer, and information on the purchased product, including ID, name, brand, original price, and purchase price. Because consumer identity is anonymous, we aggregate the transaction-level data by zip code. Henceforth, we use "location" to refer to a zip code area. To ensure a sufficient number of observed purchases in each period, we aggregate the transactions by week. As a result, each observation in our data is a particular location-week. Our complete data of online transactions span 28 weeks and contain 32,424 US zip codes that had at least one transaction during the 28 weeks.

Second, we acquired data on offline store entries in 2013 in the United States by all footwear retailers from a proprietary database. The database provides the address and the general timeframe, but not the exact date, for offline store entries. We selected all footwear retail chains with more than five store entries in 2013.[2] Through corporate press releases, social media channels, and local newspaper articles, we cross-referenced and identified the opening dates for all new stores that opened during the period of January 1 to September 2, 2013. The observation period of store entries spans a total of 34 weeks, including 4 weeks prior to and 2 weeks after the observation period of online transactions. A total of 19 footwear chain retailers and their respective store entries are included

(Table 1). These stores and their brands are all well recognized by consumers. Designer Shoe Warehouse (DSW) and Foot Locker were considered the first and second leading footwear retailers in the United States in 2015 based on sales per store (Statista 2015). We also included store entries by major department store chains, including Macy's, Dillard's, Kohl's, JCPenney, Belk, Nordstrom, Neiman Marcus, Lord & Taylor, and Saks Fifth Avenue. From January 1 to September 1, 2013, only Macy's, Kohl's, and Nordstrom Rack had new store openings.[3] The total sales of the 22 chain retailers together can capture most of the market share in offline footwear sales. The price and assortment levels of these retailers are characterized in Table 2.

We also collected additional data on location characteristics for 34,320 US zip codes from multiple sources. First, from the 2010 census data by the US Census Bureau, we obtained zip code demographic and economic information, including population, household, economic standing, gender, race, age, and local businesses. To control for economic growth, we utilized yearly entry and exit rates of establishments and the yearly job creation and destruction rate from 2010 to 2012 from business dynamics statistics by the Census Bureau. The 3-year average rates are used to control for local business changes. Also from the Census Bureau, for population growth, we collected data on the yearly population growth ratio from 2010 to 2012 and calculated the 3-year average rate. Second, from the US Bureau of Economic Analysis, we collected data on regional price parities by metropolitan statistical area and nonmetropolitan area for the year 2010, which can be used to gauge for the price sensitivity of local consumers. Third, to capture consumer purchasing patterns, we collected data on the existing stores of our sample department store chains, including Macy's, Kohl's, Nordstrom, and Nordstrom Rack, from the official websites of these retailers. We then calculated the nearby (i.e., within 30 miles) stores of these retailers for each location. In addition, because online shopping is facilitated by Internet access, we utilize data on Internet access and services for each location provided by Federal Communications Commission Form 477 dated December 31, 2012. Finally, data on the geographic information of zip codes and their distances were collected from zip-codes.com.

Table 2 Product Assortment and Price of Offline Store Openings

Price / Assortment	Regular	Discount
Narrow	Regular single-brand (RS) store	Discount single-brand (DS) store
Wide	Regular multi-brand (RM) store Regular department (RD) store	Discount multi-brand (DM) store Discount department (DD) store

Table 1 Offline Store Entries

(1) Store type	(2) Retailer	(3) # Entries	(4) # Regular-price store entries	(5) # Discount store entries
Single-brand store	Aerosoles	4	2	2
	Aldo	14	10	4
	Clarks	17	15	2
	Converse	4	1	3
	New Balance	11	4	7
	Skechers	10	2	8
	Steve Madden	7	5	2
	Vans	10	9	1
	Stride Rite	4	2	2
	Flip Flop	12	12	0
Multi-brand store	DSW	9	0	9
	Famous Footwear	25	0	25
	Finish Line	13	4	9
	Fleet Feet	6	6	0
	Foot Locker	5	5	0
	Payless Shoe Source	3	0	3
	Rack Room Shoes	4	0	4
	Shoe Carnival	23	0	23
	Shoe Dept. Encore	14	0	14
Department store	Kohl's	9	0	9
	Macy's	4	4	0
	Nordstrom Rack	8	0	8
Total	22	216	81	135

3.2. Data Description

During our 28-week sample period, the online retailer sold a total of 4.85 million footwear items[4] from approximately 650 brands. Based on purchase prices, the computed total revenue was $384 million, and the average weekly revenue per location was $423. Among all the brands carried by the online retailer, New Balance, Clarks, Converse, and Vans ranked among the top 10 most popular brands in terms of sales volume during our study period. The items sold for all nine brands of the single-brand stores account for approximately 14% of the total sales volume. Table 3 presents the weekly summary statistics.

During our data period, there were 81 single-brand, 114 multi-brand, and 21 department store entries. Figure 1 shows a map of the United States indicating the locations of the 216 store entries, which are geographically concentrated on the east side and in the states of Illinois, California, Florida, Georgia, Texas, Pennsylvania, New York, Missouri, and Arizona. Figure 2 shows the staggered timings of the 216 store entries. For each store entry, we define its influence area to include the locations within a 30-mile radius. As a robustness check, we change this influence area to be within a 15-mile radius in Section 5.3.

Table 3 Summary Statistics of Online Purchases by Location-Week

	Observations	Mean	Std. Dev.	Min	Max
Number of items purchased	960,960	4.99	14.3	0	1188
Full-price items	960,960	3.50	10.4	0	1014
Off-price items	960,960	1.48	4.44	0	223
Revenue	960,960	394.8	1171.1	0	90,708
Revenue from full-price items	960,960	285.4	869.8	0	79,237
Revenue from off-price items	960,960	109.4	345.7	0	19,498
Average discount rate	423,525	0.073	0.078	0	0.7
Average purchase price	423,525	78.1	29.7	6.95	1173
Average original price	423,525	84.9	34.0	6.95	1173

The numbers of locations affected by store entries of different types are reported in Table 4.

4. Empirical Methodology

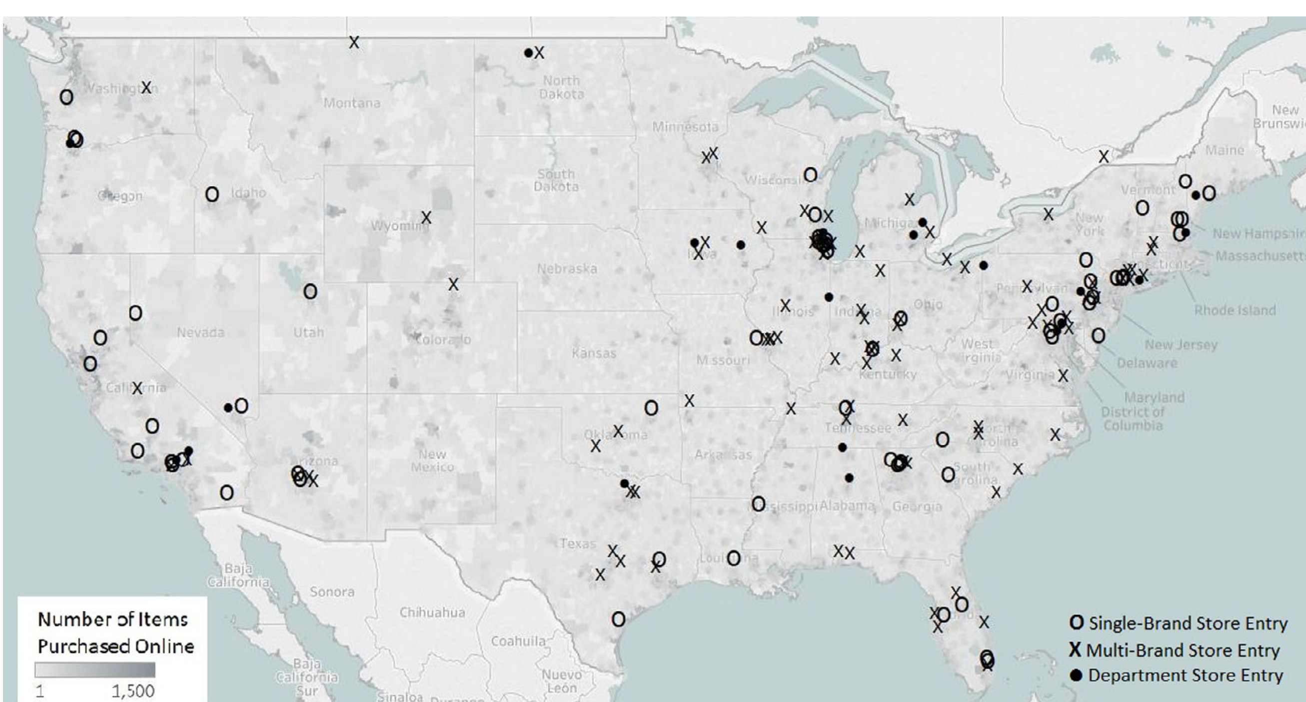
4.1. Propensity Score Matching

We employ a generalized difference-in-differences (DID) approach for multiple time periods (Bertrand et al. 2004) combined with propensity score matching (PSM) to examine the effects of offline store entries on online purchases. The DID approach identifies the store entry effect by comparing the treated locations, the zip codes affected by store entries, in the pre- and post-treatment periods with the untreated locations, those not affected by store entries. Because the factors that are common to both groups would be "differenced out" (Card and Krueger 1994), DID requires that the treated and untreated locations follow parallel time trends. However, this condition is unlikely to hold given their significant differences in all location characteristics shown in Columns (1)–(3) of Table 5.

Therefore, PSM is used to correct for potential selection bias due to the observable differences between the treated and untreated locations. The goal is to construct a sample of untreated locations that are similar to the treated locations. Because different types of stores potentially have different strategic

Figure 2 Timings of Offline Store Entries

Figure 1 Locations of Offline Store Entries [Color figure can be viewed at wileyonlinelibrary.com]



Map based on Longitude and Latitude. Color shows number of items purchased online by zip code.

Table 4 Distribution of Locations Affected by Offline Store Entries

	# Locations	% Locations
Unaffected	20,776	60.5%
Affected	13,544	39.5%
Affected by regular-price single-brand store entries	7168	20.9%
Affected by discount single-brand store entries	2690	7.8%
Affected by regular-price multi-brand store entries	4238	12.4%
Affected by discount multi-brand store entries	8336	24.3%
Affected by regular-price department store entries	539	1.6%
Affected by discount department store entries	2783	8.1%
Affected by one type of store entry only	6630	19.3%
Affected by multiple types of store entry	6914	20.2%
Total	34,320	100%

considerations for locations (Huang et al. 2019, Pancras et al. 2012), we pair each treated location with an untreated location with a similar probability of experiencing the same type of store entry. Specifically, we identify a comparable untreated location by separately calculating the propensity score for each of the six entry types. In conducting separate PSM procedures for the six entry types, we use one-to-one matching with replacement under a caliper size of two standard deviations of the propensity score differences (Aral et al. 2009). As shown in Columns (4)–(6) of Table 5, after matching, the treated and control locations are well balanced with all the standardized differences of location characteristics reduced to below 0.2 in absolute values (Rosenbaum and Rubin 1985). For each entry type, the treated locations and control locations are also well balanced in terms of the observable location characteristics after matching (Table A.1 in Appendix A).

4.2. DID Approach

After constructing the matched locations for each type of store entry, we build the panel dataset at the location (i)-week (t) level using the matched locations. The key variables are defined as in Table 6. The outcome variable of interest is $Items_{it}$, the number of items purchased from the online retailer. As the distribution of $Items_{it}$ across locations is highly skewed, we use its log-transformation, $\ln(Items_{it})$.[5]

In addition to the balance check of the location characteristics between the treated and control

Table 5 Comparison of Treated and Control Locations Before and After PSM

	Before matching			After matching		
	Treatment Mean (1)	Control Mean (2)	Standardized Difference (3)	Treatment Mean (4)	Control Mean (5)	Standardized Difference (6)
CBSA type metro[1]	0.93	0.64	0.733	0.94	0.94	0.018
CBSA price parities	96.17	92.08	0.724	97.14	98.65	−0.112
CBSA estabs entry rate[2]	18.17	16.96	0.396	18.48	19.48	−0.098
CBSA estabs exit rate	17.29	16.69	0.302	17.51	17.81	−0.140
CBSA job creation rate[2]	13.22	12.62	0.343	13.35	13.77	−0.097
CBSA job destruction rate[2]	11.61	11.37	0.193	11.72	11.78	0.139
County population growth rate[2]	0.80	0.05	0.812	0.83	0.77	0.061
County internet subscribers[3]	4.20	3.54	0.971	4.22	4.24	−0.046
Population[4]	12.49	6.89	0.393	13.54	15.68	−0.132
Households[4]	4.66	2.65	0.381	5.04	5.71	−0.114
Average house value[4]	191	148	0.235	204	213	−0.042
Average house income[4]	48.77	51.06	−0.071	52.54	57.46	−0.119
Female population[4]	6.38	3.48	0.397	6.91	7.93	−0.123
Median age	27.51	41.41	−0.956	29.01	31.15	−0.129
Male median age	26.82	40.59	−0.963	28.28	30.38	−0.130
Female median age	28.10	42.21	−0.951	29.61	31.80	−0.130
Retail businesses	329	156	0.412	356	378	−0.046
Retail employees[4]	5.40	2.23	0.383	5.77	6.45	−0.072
Kohl's stores[5]	10.91	1.57	1.492	10.15	9.93	0.035
Macy's stores[5]	7.85	0.74	1.166	6.91	6.90	0.003
Nordstrom Rack stores[5]	2.48	0.18	1.006	2.15	1.82	0.154
Nordstrom regular stores[5]	1.83	0.15	0.898	1.57	1.59	−0.012
Shoe stores[5]	464	45	0.970	362	336	0.081
Min distance to shoe stores[5]	3.15	11.58	−1.178	3.12	3.51	−0.085
#Unique zip codes	13,544	20,776		11,045	4,356	

Note: 1. Equals 1 if the CBSA is a metropolitan area and 0 otherwise. 2. Averaged from year 2010 to 2012. 3. Fixed-line. Internet subscribers per 1000 households. 4. In thousands. 5. In miles for distance to shoe stores within a 30-mile radius.

Table 6 Key Variables and Definitions

Variable	Definition
For matched location i in week t	
$StoreEntry_{it}$	Entry indicator for a new store entry
$DiscountSingleEntry_{it}$	Entry indicator for a new discount single-brand (DS) store
$RegularSingleEntry_{it}$	Entry indicator for a new regular-price single-brand (RS) store
$DiscountMultiEntry_{it}$	Entry indicator for a new discount multi-brand (DM) store
$RegularMultiEntry_{it}$	Entry indicator for a new regular-price multi-brand (RM) store
$DiscountDeptEntry_{it}$	Entry indicator for a new discount department (DD) store
$RegularDeptEntry_{it}$	Entry indicator for a new regular-price department (RD) store
$Items_{it}$	Total pairs of shoes purchased from the online retailer
$MinDistance_i$	Minimum distance to nearby pre-existing shoe stores if any shoe stores existed within 30 miles; 30 miles otherwise
$StoreDistance_i$	Distance to a nearby opening shoe store if any shoe stores within 30 miles opened during the study period; 30 miles otherwise
For single-brand store entry matched location i in week t	
$SameBrandItems_{it}$	Pairs of shoes purchased of the same brand as the opening single-brand store
$CrossBrandItems_{it}$	Pairs of shoes purchased of different brands from the opening single-brand store
$SameBrandOffPriceItems_{it}$	Pairs of shoes of the same brand as the opening single-brand and purchased at discounted prices
$SameBrandFullPriceItems_{it}$	Pairs of shoes of the same brand as the opening single-brand and purchased at regular prices

locations, we also check whether they follow parallel time trends prior to the treatment, as required by the DID approach. Specifically, we plot the average online purchases of the treated locations and the matched control locations over time for each entry type (see Figure 3). In our context, because the store entries occurred at different time points, the treatment starting times are staggered. The treated locations remain treated after a nearby store entry; thus, more treated locations are progressively treated over time. Instead of using the actual opening week, we plot online purchases over the relative opening week. Specifically, for a treated location, the relative week is the chronological distance between an observation period and its treatment starting time (i.e., when the new offline store first opened near that location); for a control location, the relative week takes the same value as its matched treated location for the same observation period. As shown in Figure 3, the online purchases of the treated and control locations closely follow parallel time trends in the pre-treatment periods for all types of store entry. We further test the parallel time trend assumption using relative time models as a robustness check in Section 5.2.

Following the generalized DID approach for multiple time periods, our empirical model is specified as follows:

$$\ln(Itmes_{it}) = \alpha + \beta StoreEntry_{it} + \mu_i + w_t + \varepsilon_{it}. \quad (1)$$

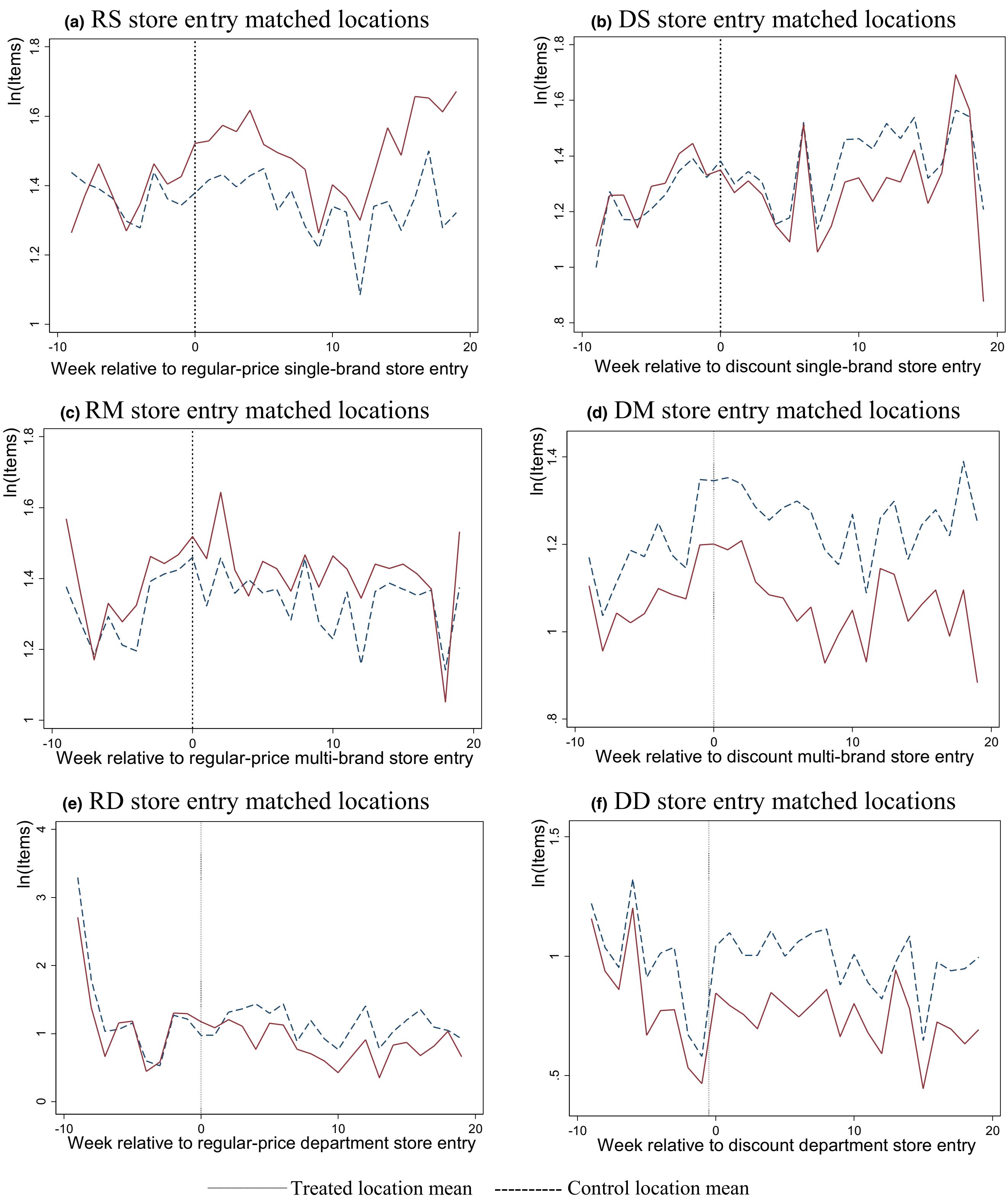
where the dependent variable (DV), $\ln(Itmes_{it})$, is log-transformed online purchases from location i in week t. $StoreEntry_{it}$ is the treatment indicator that equals 1 for treated locations after the store entry and 0 otherwise. The coefficient β thus captures how online purchases change after an offline store entry. Finally, α is an intercept, μ_i is a location-fixed effect, w_t is a time-specific effect, and ε_{it} is a mean-zero random error term. We apply model (1) based on the matched locations for each entry type. In these estimations, for brevity, we use $StoreEntry_{it}$ to refer to a type-specific store entry. As we use panel data on locations for multiple periods before and after the treatment, the error terms may be subject to autocorrelation over time. Therefore, we cluster the standard errors of coefficients by location in all of our estimations (Bertrand et al. 2004).[6]

4.3. Main Results

We present the estimation results of the matched locations in Table 7. Columns (1)--(6) present the results based on the matched locations for regular-price single-brand store entries (RS matched), discount single-brand store entries (DS matched), regular-price multi-brand store entries (RM matched), discount multi-brand store entries (DM matched), regular-price department store entries (RD matched), and discount department store entries (DD matched), respectively. The coefficients of $StoreEntry_{it}$ thus reflect the entry effects of corresponding entry types. According to Column (1), the entry effect of regular-price single-brand stores on online purchases is positive and statistically significant, supporting H1. Column (2) shows that discount single-brand stores also have similar entry effects. According to Columns (3) and (5), regular-price multi-brand and department store entries have no significant effect on online purchases. Finally, Columns (4) and (6) show that the entry effects of both discount multi-brand and discount department stores are negative and statistically significant, supporting H2.

Based on these results, we find a dominant complementary effect for both regular-price and discount single-brand store entries, leading to increased online purchases by 2.7% and 2.8%, respectively. The effect of a discount single-brand store entry is only marginally significant. In contrast, a dominant substitution effect is observed for the discount multi-brand and

Figure 3 Average Online Purchases of the Matched Locations over Relative Weeks [Color figure can be viewed at wileyonlinelibrary.com]



department store entries, which reduce online purchases by 3.4% and 3.0%, respectively. This finding confirms that the store entry effect depends on the relative assortment and price levels of the offline store and the online retailer. Moreover, our results seem to suggest that the complementary effect is driven by the narrow assortment of the offline store regardless of its price level, while the substitution effect is driven

Table 7 Estimation of Entry Effects by Store Type

DV: $\ln(Items_{it})$	RS Matched (1)	DS Matched (2)	RM matched (3)	DM matched (4)	RD matched (5)	DD matched (6)
$StoreEntry_{it}$	0.027*	0.028+	−0.010	−0.034***	−0.024	−0.030*
	(0.012)	(0.016)	(0.018)	(0.011)	(0.053)	(0.014)
Time fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Location fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	127,042	32,951	66,964	183,784	9349	39,407
Zip codes	6267	1781	3375	8508	503	1736
Adjusted R^2	0.853	0.880	0.879	0.839	0.827	0.847

Standard errors in parentheses are clustered by location. Observations after multiple types of openings are excluded for locations with multiple entry types. $^+p < 0.1$, $^*p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$.

jointly by the wide assortment and low price of the offline store. Quantitatively, compared to the cannibalization effect of a store opening on nearby outlets of the same retailer ranging from −5.14% to −17.5% (Pancras et al. 2012), the store opening effect on a competing online retailer is much smaller, ranging from −3.4% to 2.8%.

4.4. Additional Analyses of the Complementary Effect

As we hypothesized in Section 2, the complementary effect of single-brand store entries can be driven by either unsatisfied product exploration or product uncertainty reduction. We examine whether both mechanisms are at play. The mechanism of unsatisfied product exploration is based on consumers' search for the best-fitting product (Mehra et al. 2018). It increases online purchases because the online retailer provides a wider assortment than the offline retailer, leading to increased purchases of both store and non-store brand products. However, the mechanism of product uncertainty reduction is driven by consumers' showrooming behavior (Lal and Sarvary 1999, Zimmerman 2012). It increases online purchases because of lower online prices for store products, resulting in increased online purchases of store products only. Therefore, for single-brand stores, we differentiate the online purchases of the treated locations into *SameBrandItems* and *CrossBrandItems* according to the brand of the new offline store. Correspondingly, the store brand for a control location is the store brand of the treated location to which it is matched. We further differentiate store-brand purchases (*SameBrandItems*) into full-price purchases (*SameBrandFullPriceItems*) and off-price purchases (*SameBrandOffPriceItems*). Then, we estimate the entry effects of single-brand stores on *CrossBrandItems*, *SameBrandItems*, *SameBrandFullPriceItems*, and *SameBrandOffPriceItems*.[7]

Table 8 presents the results for the regular-price single-brand store entries based on RS-matched locations. Columns (1) and (2) show that both cross-brand and same-brand purchases increase significantly following a regular-price single-brand store entry. According to Columns (3) and (4), the increase in same-brand purchases online is due to the increased same-brand items purchased at full price but not those purchased at off prices. These results jointly suggest that the complementary entry effect of regular-price single-brand stores is primarily driven by unsatisfied product exploration in stores and that the product uncertainty reduction mechanism is insignificant. This finding implies that the positive spillover effect for online retailers when a regular-price single-brand store opens is mainly because the store is unable to offer best-fitting products for consumers due to a narrow assortment. Different from Balakrishnan et al. (2014), we find that consumer showrooming behavior is not a significant concern for offline retailers.

Table 9 presents the results for the discount single-brand store entries based on DS matched locations. Column (1) shows that only cross-brand purchases increase following a discount single-brand store entry. According to Columns (3) and (4), same-brand items purchased at full price increase, but this increase is statistically insignificant, whereas same-brand items purchased at off prices decrease significantly, resulting in an insignificant change in overall same-brand purchases in Column (2). As such, the complementary effect of discount single-brand store entry is driven by increased cross-brand purchases. Therefore, this complementary effect can only be attributed to the mechanism of unsatisfied product exploration in stores, consistent with the results for regular-price single-brand store entries. Moreover, our results suggest a strong substitution effect for same-brand purchases at off prices because of the lower price offered by the discount single-brand store.

4.5. Additional Analyses of the Substitution Effect

We further examine the mechanism underlying the substitution effect when a discount multi-brand or a

Table 8 Entry Effects of RS Stores on Same- and Cross-Brand Purchases Online

	RS matched locations Treated locations			
DV:	ln(*CrossBrand Items*) (1)	ln(*SameBrand Items*) (2)	ln(*SameBrand FullPriceItems*) (3)	ln(*SameBrand OffPriceItems*) (4)
$RegularSingleEntry_{it}$	0.027 (0.012)*	0.013 (0.004)**	0.015 (0.003)***	–0.001 (0.003)
Time fixed effects	Yes	Yes	Yes	Yes
Location fixed effects	Yes	Yes	Yes	Yes
Observations	127,042	127,042	127,042	127,042
Zip codes	6,267	6,267	6,267	6,267
Adjusted R^2	0.855	0.358	0.300	0.182

Note: For the treated locations, we measure the same-brand items according to the shoe brand of the newly opened single-brand store. For instance, when Clarks opens, it is calculated as the number of Clarks items purchased at the online retailer. For the matched control locations, we measure same-brand items according to the shoe brand of the matching treated locations. Observations after multiple types of openings are excluded for locations with multiple entry types. Standard errors in parentheses are clustered by location. $^+p < 0.1$, $^*p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$.

Table 9 Entry Effects of DS Stores on Same- and Cross-Brand Purchases Online

	DS matched locations Treated locations			
DV:	ln(*CrossBrand Items*) (1)	ln(*SameBrand Items*) (2)	ln(*SameBrand FullPriceItems*) (3)	ln(*SameBrand OffPriceItems*) (4)
$DiscountSingleEntry_{it}$	0.026 (0.016)$^+$	–0.005 (0.010)	0.005 (0.009)	–0.017 (0.006)**
Time fixed effects	Yes	Yes	Yes	Yes
Location fixed effects	Yes	Yes	Yes	Yes
Observations	32,951	32,951	32,951	32,951
Zip codes	1781	1781	1781	1781
Adjusted R^2	0.879	0.498	0.429	0.269

For the treated locations, we measure same-brand items according to the shoe brand of the newly opened single-brand store. For instance, when Clarks opens, it is calculated as the number of Clarks items purchased at the online retailer. For the matched control locations, we measure same-brand items according to the shoe brand of the matching treated locations. Observations after multiple types of openings are excluded for locations with multiple entry types. Standard errors in parentheses are clustered by location. $^+p < 0.1$, $^*p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$.

discount department store opens. Offline store entries reduce nearby consumers' transportation cost for offline shopping and thus can capture consumers who would otherwise purchase online due to high transportation costs. The change in transportation costs is affected by consumers' proximity to the new offline store and their proximity to pre-existing stores. Forman et al. (2009) find that consumers nearer to newly opened offline stores have a greater decrease in their online purchases in the context of book retailing. The role of proximity to pre-existing stores has yet to be tested empirically. Therefore, we re-estimate the entry effect of discount multi-brand and department stores with the interactions between the store entry indicators and the two distance measures using the DM matched locations and the DD matched locations, respectively, in Table 10.

In Table 10, $StoreDistance_i$ is the distance consumers in location i must travel to the new footwear store that opened in the study period, and $MinDistance_i$ is the minimum travel distance to the nearest footwear store prior to the new store entry.[8] According to Column (1), we find that *StoreDistance* moderates the negative entry effect of discount multi-brand stores positively. That is, the greater the travel distance to the new store, the smaller the reduction in online purchases. This finding is consistent with Forman et al. (2009). The substitution effect of discount department stores, however, is not significantly moderated by *StoreDistance*, as shown in Column (2), suggesting that consumers are less sensitive to travel distance when department stores open compared to when multi-brand stores open. Columns (3) and (4) show that *MinDistance* moderates the entry effects of both discount multi-brand stores and discount department stores. Specifically, online purchases decrease more for consumers who were farther from pre-existing offline stores following the entry of discount wide-assortment stores. Compared to discount multi-brand store entry, discount department store entry is more sensitive to proximity to pre-existing stores. When both interaction terms are included in Columns (5) and (6), distance to pre-existing stores still moderates the substitution effect significantly, whereas distance

Table 10 Interaction between Substitution Entry Effects and Distance to Offline Stores[9]

DV:ln($Items_{it}$)	DM matched (1)	DD matched (2)	DM matched (3)	DD matched (4)	DM matched (5)	DD matched (6)
$StoreEntry_{it}$	−0.023*	−0.056*	−0.021*	0.003	−0.005	−0.003
	(0.010)	(0.028)	(0.009)	(0.018)	(0.010)	(0.025)
$StoreEntry_{it}$	0.0007+	−0.002			0.0013	−0.0004
$*StoreDistance_{it}$	(0.0004)	(0.002)			(0.0014)	(0.0013)
$StoreEntry_{it}$			−0.003***	−0.009***	−0.003***	−0.009***
$*MinDistance_i$			(0.0007)	(0.018)	(0.001)	(0.002)
Time fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Location fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	183,784	39,407	183,784	39,407	183,784	39,407
Zip codes	8,508	1,736	8,508	1,736	8,508	1,736
Adjusted R^2	0.839	0.851	0.839	0.851	0.839	0.851

Note: Observations after multiple types of openings are excluded for locations with multiple entry types. Standard errors are clustered by location and presented in parentheses. $^+p < 0.1$, $^*p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$.

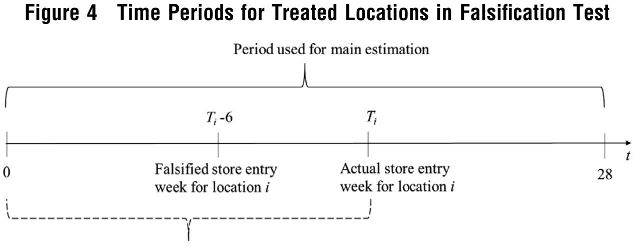
to new stores no longer has a significant moderating effect. Our findings suggest that the substitution entry effect driven by reduced transportation costs is more sensitive to the distance to pre-existing stores than the distance to the new store.

5. Robustness Checks

5.1. Falsification Test

It is possible that the entry effects of the treated locations are due to differences in the pre-treatment time trends between the treated and the control locations instead of the store openings offline. Following Jung et al. (2019), we first adopt a falsification test to re-estimate the entry effects of different types of stores using the matched locations and placebo treatment weeks for each respective type. Specifically, for the treated locations of each type, we now shift $StoreEntry_{it}$, the binary indicator of store opening, 6 weeks earlier. For example, for location i with actual regular single-brand store entry in week T_i, $RegularSingleEntry_{it}$ will equal 1 for week t if $T_i - 6 \leq t < T_i$ and 0 if $t < T_i - 6$, as shown in Figure 4. For treated locations with $T_i \leq 6$, $RegularSingleEntry_{it}$ will equal 1 for all weeks before T_i. For the control locations, the treatment indicators and the period used remain the same as in the main estimations. Then, we re-estimate the store entry effects of each store type on the matched locations for that type. The results in Table 11 show no significant

Figure 4 Time Periods for Treated Locations in Falsification Test



entry effects for the falsification tests for all types of store entries. As an alternative to 6 weeks earlier, we also checked the results with placebo entry weeks 7 and 8 weeks earlier, and the results remained qualitatively consistent.

5.2. Relative Time Models

To further rule out the difference in pre-treatment time trends between the treated and the control locations, we specify a relative time model:

$$\ln(Items)_{it} = \alpha + \sum_{j=T-4}^{T+4} \beta_j (Treated_i * \varphi_{ijt}) + \mu_i + w_t + \varepsilon_{it}, \tag{2}$$

where $Treated_i$ is a binary indicator that equals 1 for treated locations and 0 for control locations and φ_{ijt} are relative time dummies indicating the chronological distance between an observation period and the treatment starting time for treated locations, or the matched counterparts for control locations. Furthermore, μ_i and w_t are location and time fixed effects, respectively, and ε_{it} is the error term. We set the relative time periods to range from minus 4 to 4, representing the periods 4 months before and 4 months after store entry. To avoid the dummy variable trap, we choose 1 month before as the baseline and omit the dummy variable for that period (Burtch et al., 2018, Jung et al. 2019).

We estimate the relative time model for the matched locations for each entry type and present the results in Table 12. Except for the matched locations for regular-price multi-brand store entry, the relative pre-treatment time dummies (i.e., T-4, T-3, and T-2) are all insignificant. According to Column (1), comparing the treated locations with a regular-price single-brand store entry with their matched control locations, the results show no significant difference in their pre-treatment trends but significantly more

Table 11 Falsification Test of Store Entry Effects with Placebo Entry Weeks

DV:ln($Items_{it}$)	RS matched (1)	DS matched (2)	RM matched (3)	DM matched (4)	RD matched (5)	DD matched (6)
$StoreEntry_{it}$	−0.013	−0.002	0.018	−0.010	0.010	0.012
	(0.021)	(0.014)	(0.014)	(0.011)	(0.041)	(0.033)
Time fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Location fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	99,318	38,782	58,980	151,237	9439	25,661
Zip codes	6251	1869	3064	8538	503	1736
Adjusted R^2	0.844	0.891	0.883	0.845	0.838	0.852

Note: Standard errors are clustered by location and presented in parentheses. $^+p < 0.1$, $^*p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$.

Table 12 Relative Time Model Estimation

Dependent variable: ln($Items_{it}$)	RS matched (1)	DS matched (2)	RM matched (3)	DM matched (4)	RD matched (5)	DD matched (6)
T-4m	−0.017	−0.022	-0.034^+	0.001	0.053	−0.022
	(0.018)	(0.015)	(0.017)	(0.012)	(0.058)	(0.020)
T-3m	0.019	−0.026	-0.023^+	−0.004	−0.003	−0.025
	(0.012)	(0.023)	(0.012)	(0.012)	(0.048)	(0.020)
T-2m	0.003	−0.040	−0.002	−0.025	0.042	−0.011
	(0.009)	(0.027)	(0.018)	(0.017)	(0.065)	(0.013)
T-1m	Omitted	Omitted	Omitted	Omitted	Omitted	Omitted
T + 0m	0.027^{**}	−0.009	-0.022^*	-0.038^+	0.036	-0.020^+
	(0.010)	(0.016)	(0.010)	(0.019)	(0.043)	(0.011)
T + 1m	0.015^+	0.009	-0.033^*	-0.050^*	0.000	-0.020^+
	(0.009)	(0.029)	(0.015)	(0.022)	(0.057)	(0.012)
T + 2m	0.002	−0.030	−0.027	−0.033	−0.047	-0.016^+
	(0.010)	(0.028)	(0.018)	(0.024)	(0.060)	(0.009)
T + 3m	0.035^{**}	-0.037^+	−0.017	−0.039	-0.115^+	0.006
	(0.011)	(0.019)	(0.011)	(0.028)	(0.059)	(0.015)
T + 4m	0.032^*	−0.034	-0.038^{***}	-0.053^+	−0.054	−0.004
	(0.014)	(0.042)	(0.009)	(0.029)	(0.041)	(0.008)
Time fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Location fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	127,042	32,951	66,964	183,784	9,349	48,608
Zip codes	6,267	1,781	3,375	8,508	503	1,736
Adjusted R^2	0.853	0.216	0.879	0.206	0.827	0.851

Note: Standard errors in parentheses are clustered by location. $^+p < 0.1$, $^*p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$.

online purchases from the treated locations after the store entry. Column (4) compares the treated locations with a discount multi-brand store entry with their matched control locations, indicating no significant difference in their pre-treatment trends but significantly fewer online purchases from the treated locations after the store entry. For discount department store entry, a similar result is shown in Column (6). Although the treated locations tend to have (statistically insignificant) lower pre-treatment online purchases than their matched counterparts, the store entry seems to increase this difference, making the online purchases of the treated locations even lower, especially in the first few weeks after the store entry, according to Figure 3f. Hypotheses H1 and H2 thus remain supported.

5.3. Alternative Specifications

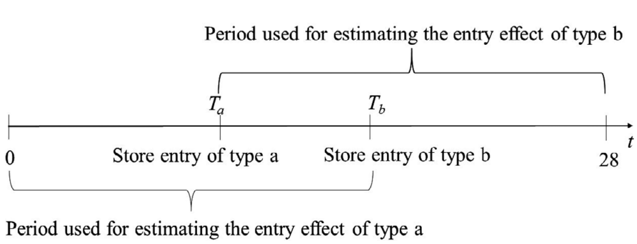
In addition to the pre-treatment time trends, the treated and control locations may differ in unobservable characteristics that may confound both the store openings and the online demand. To address this concern, we estimate the entry effects on the treated locations only. Instead of matching treatment locations to similar locations without store openings, this alternative specification uses the treatment locations that are not yet treated as controls for the already-treated locations. Because the store openings are staggered, the locations that are treated later are compared against the treated locations with earlier store entries. For each entry type, since all the locations are eventually treated and experience store entry of the same type, they represent a more homogeneous group compared to the matched locations. The results are shown in Table B1 (Appendix B).

Alternative to the travel distance of 30 miles, we change the influence area of a store entry to be within a radius of 15 miles. Without reconducting PSM, we exclude the treated locations that are more than 15 miles from the opening stores and their matched control locations. The results are presented in Table B2 (Appendix B). Moreover, instead of using the already-matched locations, we reconduct PSM for this alternative travel distance of 15 miles, estimate the entry effects on the rematched locations, and obtain similar results, as shown in Table B3 (Appendix B).

A potential endogeneity concern is the timings of the store openings across the treatment locations. To address this concern, we use an alternative instrumental variable (IV) estimation where the number of store openings of the same type in the other treatment locations for location *i* in week *t* and the lagged store opening indicator of the type from week *t-1* are used as IVs for $StoreEntry_{it}$. The number of simultaneous store openings of the same type elsewhere, reflecting the general time trend of store openings, is likely to be correlated with the store opening timings of the focal location. For example, many chain retailers such as Shoe Carnival and DSW tend to set the same date for the grand openings of multiple stores of different locations. Moreover, the number of store openings elsewhere is, by nature, unlikely to be correlated with the online purchases of the focal location in other ways. Thus, they are valid IVs for store opening indicators. The IV estimation results are presented in Table B4 (Appendix B).

In the main analyses, for locations with multiple entry types, to control for the influence of the other types, only the observations before the second types of entry are included in the estimations. Instead, we can split the observation period of these locations into different time intervals for the different entry types so that given an interval for an entry type, there are no other types of store entry. For example, as shown in Figure 5, for locations with two entry types, two different time periods are used to estimate the effects of the two entry types. Alternatively, we can simply exclude such locations as well as their matched control locations in the estimations. Similar results are obtained under both ways of dealing with locations with multiple entry types, as shown in Table B5 and B6 (Appendix B).

Figure 5 Alternative Time Periods for Locations with Multiple Types of Store Entry



Finally, although all the standard errors are clustered by location in all estimations, they may still be underestimated. According to Bertrand et al. (2004), applying the DID estimation to the time series data of many periods may result in inconsistent standard errors even after clustering. The suggested solution is to collapse the time series into a "pre" and "post" period. Following Bertrand et al. (2004), we first time-demean $\ln(Items_{it})$ based on all locations and divide the time-demeaned $\ln(Items_{it})$ of the treated locations into two groups: the weeks before and after the store entry. Using the averaged $\ln(Items_{it})$ for the before and after periods, the panel with many periods is converted into two periods only. Then, the entry effects are estimated on the two-period panel for the treated locations with location fixed effects (Table B7 in Appendix B). Moreover, the standard errors clustered by location only capture the unspecified correlation between observations on the same location over time. There may also exist correlations between observations of different locations at the same time. Following Petersen (2009), we double cluster the standard errors by both location and time simultaneously (Table B8 in Appendix B).

Under these robustness checks, although the entry effect of discount single-brand stores is insignificant, the entry effects of regular-price single-brand stores, discount multi-brand stores, and discount department stores remain consistent with our main results, supporting Hypotheses H1 and H2.

6. Discussion and Conclusions

By integrating opposing theories on substitution and complementary cross-channel effects, our study examines how the impact of an offline store opening on a competing online retailer depends on their relative product assortment and price in the footwear industry. Using a rich dataset of offline store openings from many chain retailers and online transactions from a major pure-online retailer, we find that the entry of regular narrow-assortment (i.e., single-brand) stores leads to a complementary effect on the online retailer, whereas the entry of discount wide-assortment (i.e., multi-brand and department) stores generates a substitution effect on the online retailer. The complementary effect, leading to increased online purchases of both store-brand and non-store-brand items, is mainly driven by unsatisfied in-store product exploration. The substitution effect depends on the proximity to pre-existing stores. Proximity to the new store moderates the substitution entry effect of discount multi-brand stores but not that of discount department stores.

6.1. Theoretical Contributions

Our study makes several important contributions to the literature. First, although store characteristics have been found to be important influencers of consumers' store choices offline (Lim et al. 2020, Mortimer and Clarke 2011), how they affect consumers' tradeoff between online and offline retailers remains largely unknown. To the best of our knowledge, our study is the first to examine the role of the relative assortment and price between online and offline retailers in consumers' channel choices. Our findings extend the current understanding of both channel substitution (e.g., Forman et al. 2009, Glaeser et al. 2019, Pancras et al. 2012) and complementarity (e.g., Avery et al. 2012, Bell et al. 2018, Nault and Rahman 2019) by demonstrating the contingent effects of store openings. In the offline setting, Kalnins (2004) attributes varying entry effects across store types to their different strategic locations, while Fox et al. (2004) attribute them to consumers' multiformat shopping behavior. By controlling for the location strategies of different store types, our results support and enrich the findings of Fox et al. (2004) on retailer competition across retail formats as well as extend their results from the offline setting to the online-offline context. Specifically, we find that offline discount wide-assortment retailers, because of similar assortment and lower prices, are close substitutes for the online retailer. In contrast, offline single-brand retailers, because of their narrower assortment, are complementary to the online retailer in generating stimulated but unmet consumer demand.

Second, our study contributes to the literature on retailer competition under consumer search. Although retailers prefer retailer-driven search in many scenarios (Jiang and Anupindi 2010), consumer-driven search is often unavoidable. Our findings suggest that consumers frequently search among competing online and offline retailers for products that match their preferences at a reasonable price. Cachon et al. (2008), based on theoretical models, show that an easier search creates both a competition-intensifying effect and a market expansion effect among offline retailers as retailers adjust their prices and assortment according to demand. Our findings complement their work with empirical evidence for retailers with preset prices and assortments. When the search cost decreases for a retailer with both a wide assortment and lower prices, the competition-intensifying effect dominates for other retailers. However, when the search cost decreases only for a regular-price narrow-assortment retailer, the market expansion effect is observed on other retailers with a wide assortment. That is, with consumer search under fit uncertainty, discounting is essential in capturing the stimulated consumer demand when a wide-assortment retailer competes with another wide-assortment retailer but not when it competes with a narrow-assortment retailer (Sun and Gilbert 2019).

Third, the literature on how offline channels increase the information level of online products has focused on the information role of physical showrooms for overlapping products, often because of the same-retailer setting (Balakrishnan et al. 2014, Balasubramanian 1998, Bell et al. 2018, Gao and Su 2017). Our study in the inter-retailer setting advances this stream of literature by highlighting the information spillover to non-store brand products that are unavailable in stores. As a form of pseudo-showrooming (Gu and Tayi 2017), store products encourage consumers' search for and learning about online products even when physical stores do not completely resolve uncertainty about these products. This occurs when consumers leverage how the store products fit to help parse their wider choice sets online, similar to the information spillover from virtual fitting tools to products without virtual try-ons (Gallino and Moreno 2018). This information spillover creates a more complicated interaction across competing brands. In contrast to showrooming behavior, pseudo-showrooming cannot be prevented by lowering prices without increasing assortment, as demonstrated by the increased cross-brand purchases when a discount single-brand store opens.

Finally, our work contributes to the literature on proximity to a physical store in offline-online retail competition. According to Fox et al. (2004), household grocery spending at nearby regular-price stores decreases as travel time increases, but household spending at discount stores nearby is not sensitive to travel costs. Our results add to their insights into the different roles of travel costs across retail formats. In particular, our findings show that the proximity to the new store moderates the substitution entry effect of discount multi-brand stores but not that of discount department stores. This suggests that consumer purchases at discount department stores are less sensitive to travel costs than those at discount multi-brand stores. In contrast, consumer purchases at discount department stores are more sensitive to travel costs prior to store entry than those at discount multi-brand stores.

6.2. Managerial Implications

Our study offers several valuable insights for online retailers. First, online retailers need to differentiate offline store entries by assortment and price to gauge their competitive edge in the nearby locations. Discount wide-assortment stores will be the main competitors to online retailers, whereas other store types are unlikely to substitute for online retailers. Narrow-assortment stores, on the contrary, stimulate more online purchases. In sum, online retailers can leverage location-based recommendations and pricing to capture consumer demand in response to dynamic changes in different geographic regions. To compete against mostly local discount wide-assortment stores, online retailers can offer price matches or selective discounts for overlapping products. Facing mostly narrow-assortment stores offline, online retailers are better off making recommendations from a variety of brands and products than offering discounts.

Second, the implications also depend on the type of the online retailer. According to our findings, the complementary entry effect on online purchases is driven by the assortment advantage of the online retailer, while the substitution effect is caused by the price advantage of the offline retailer with a similar assortment. Our results are based on an online retailer with a wide assortment and mostly regular-price products. Therefore, we expect the complementary effect of a single-brand store entry to be reduced for an online retailer with a narrow assortment. Similarly, we expect the substitution effect of a discount wide-assortment store entry to be reduced for an online retailer with mostly discounted products. Moreover, some online retailers, such as Bonobos and Warby Parker, have invested in offline showrooms to provide fit information, which has been shown to increase online demand and reduce fulfillment costs (Bell et al. 2018, Gao and Su 2017). This strategy is applicable for online retailers that carry exclusive products but may not be necessary for online retailers that carry overlapping products with offline retailers, as offline stores can essentially serve as physical showrooms for online retailers. It would be more effective for such online retailers to expand their assortment and maintain competitive pricing.

For brick-and-mortar retailers, which have been battling online competitors since the dawn of e-commerce, it is important to differentiate sales lost to consumer showrooming from those lost to pseudo-showrooming. The former is driven by price competition, whereas the latter may reflect other issues such as product misfit. While both the literature and practices have focused on defending against the former with price match policy (Mehra et al. 2018), we find that the latter is the main reason for no-purchase-in-store customers to search and buy online. Offline retailers can turn consumer-driven search into retailer-driven search by assisting unsatisfied consumers in searching for and exploring products at other store locations or online under a revenue sharing scheme (Jiang and Anupindi 2010). The retailer's online channel with a wider assortment can be recommended and promoted to consumers to defend against other competing online retailers.

For brand manufacturers, our study suggests that their omni-channel strategy should consider various online and offline downstream distributors and offers guidance for strategies in offline store investments and downstream product distribution. The omni-channel strategy for a retailer that only focuses on integrating the retailer's online and offline stores is no longer sufficient because the purchases of the brand at the downstream distributors would affect and be affected by those at the manufacturer-owned channels. Offline store location and investments thus need to address the issue of sales attribution caused by potential channel interactions. Supplier encroachment, the competition between the independent retailer and the manufacturer-owned store (Li et al. 2016), is not a serious issue for online retailers with a much wider assortment. In contrast, online retailers can benefit from the manufacturer-owned store, and such benefits do not always go to the manufacturer's brand. To reduce the demand spillover to other brands online, the manufacturer needs to carefully select the product mix in its own store to satisfy local preferences and to build strong brand loyalty and product awareness (Tsay and Agrawal 2004).

6.3. Limitations

Our study bears several limitations. First, because our dataset was aggregated at the zip code level, we were unable to fully observe how consumer heterogeneity would affect our results. Future research with individual consumer-level data can explore differences across consumer segments (e.g., existing vs. new customers, heavy vs. occasional shoppers). Second, although our results contribute to the understanding of store entry effects in a product category where the physical examination of the product is important for consumer purchase, it is inherently limited to a selected product category of footwear. It would be worthwhile to pursue future research on more diverse product categories. The variation of complementarity and substitutability across product categories could be another meaningful extension. Third, while assortment and price are objective store characteristics (Williams 2002), subjective characteristics such as staffing competence, friendliness, ease of parking, store ambience, and checkout convenience may also affect consumers in navigating between channels (Helgesen and Nesset 2010). In addition, although we find a demand spillover effect on non-store brands overall when a narrow-assortment store opens, different brands may be affected differently. Future studies on pseudo-showrooming between products or brands can further account for similarities across competing brands. Finally, for some matched locations (Table 12), the treated locations tend to have lower online purchases than the matched control locations before the treatment, although the differences are mostly statistically insignificant. Future studies can include additional location characteristics in the PSM to further reduce such pre-treatment differences.

Notes

[1]All monetary amounts stated in this paper are in US dollars.
[2]Except for Red Wing Shoes, which sells specialty footwear only.
[3]For these major department store chains, we identified a total of 11 store closings during our data period, including one of Macy's, two of Dillard's, one of Neiman Marcus, and seven of JCPenney. These closings together affected 1,056 zip code locations (within a 30-mile radius). To control for the impact of store closings, these zip codes are excluded from our sample locations.
[4]Each footwear item refers to a pair of shoes.
[5]$\ln(Items_{it})$ is actually $+ \ln(Items_{it}1)$, where + 1 is used to retain 0 observations.
[6]We also confirm the results by double clustering the standard errors by both location and time (see Table B8 in Appendix B).
[7]Similar to *Items*, they are log transformed with one added to all values before transformation.
[8]$StoreDistance_i$ is capped at 30 miles for locations without any footwear store openings within the 30 miles and equals 0 for locations with footwear stores that opened within the location itself. Similarly, $MinDistance_i$ is also capped at 30 miles for locations without any footwear store within 30 miles and equals 0 for locations with footwear stores within the location itself.
[9]The main effect of $StoreDistance_{it}$ is not included because of collinearity with its interaction effect of $StoreEntry_{it}$* $StoreDistance_{it}$, and the main effect of $MinDistance_i$ is not included because it is not time-varying and thus collinear with the location fixed effects.

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Supporting Information

Additional supporting information may be found online in the Supporting Information section at the end of the article.

Appendix A: Balance Check by Entry Type.

Appendix B: Estimation Results of Robustness Checks with Alternative Specifications.