Multi-channel Stores in Shopping Malls: How Opening the Online Sales Channel Affects Physical Stores?

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Abstract

With the rise of e-commerce, more and more stores in shopping mall have opened up online sales channel. It is intuitive that many consumers will shift from physical stores to online sales due to lower shopping costs and convenient search tools. However, from our novel data on multi-channel stores, we find that revenue and rental values of many stores increase after opening online sales channel. One reason is the online sales channel has advertisement effect that attract previously uninformed consumers. We empirically study how online sales affect offline sales. The rainy days and COVID-19 shock provide exogenous variation on shopping costs and help us identify and separate the switching effect and advertisement effect.

Keywords: Shopping mall, multichannel store, switching effect, advertisement effect

JEL classification: D43, L11, L13

1 Introduction

Online sales have been continuously increased in the past few decades. In 2019, the scale of online retail sales reached US$602 billion, accounting for 14.9% of total US retail sales. In China, the country with the largest scale and highest rate of e-commerce development, online retail sales reached US$1563 billion and account for 20.7% of total retail sales in 2019. More and more consumers make daily purchases by scrolling down computer or smartphone screens instead of walking inside Brick-and-Mortar (B&M) shopping malls. Consumers typically incur lower shopping costs and search costs in online sales channel. This phenomenon has drawn considerable managerial attention and has been widely studied in the literature (Daunt and Harris (2017), Gensler et al. (2017), Basak et al. (2017)).

Consumers who visit the shopping mall often purchase goods in many stores and make unplanned purchases (Johnson, 2017). Non-anchor stores in the shopping malls often rely on consumer flows attracted by anchor stores. As consumers switch from offline consumption to online, it hurts the interest of shopping malls by reducing consumer traffic and rental values of store spaces. For example, 68% of US internet users indicate that they showroom at least occasionally (Statista). Retailers such as Toys"R"Us, Bed, Bath Beyond and Best Buy often appear to be showrooms for Amazon.com. Such showrooming phenomenon harms the B&M store and retailer performance, while online retailers benefit from it.

However, as a B&M store opens an online store, it can attract consumers who are uninformed. The online sales channel has an advertisement effect that brings in more consumers to its physical sales channel. In addition, the B&M store can provide consumers the opportunity to experience the goods (e.g., trying the clothes) and provide services (e.g., fixing electronic devices). Some consumers may search for products and make comparison using information online while choose to purchase in physical stores for immediate delivery and additional services (Jing, 2018).

For a particular consumer, the shopping costs and search costs in B&M stores are affected by distance, weather and other factors, but the shopping costs of online sales channel, such as delivery time and shopping fee, are typically fixed in distance and weather. Therefore, the online platform is used as an information disclosure channel, and consumers can obtain the price service information of each store on the platform at a low search cost, and ultimately increase the income of offline stores. Finally, the placement of online advertising has significantly increased the revenue of offline stores. Consider the search cost. Considering the search cost, the cost of consumers contacting this advertisement online is less than going to offline shopping malls, and online platforms can often attract more customers than a single shopping mall. Therefore, the efficiency of online advertising is higher than offline advertising, which enables the online store to increase the passenger flow and revenue of the offline store.

In this paper, we gather a unique data set that matches B&M stores in shopping malls with their corresponding online sales channels. Most studies in the literature have information about either the online sales channel or the physical stores but not both. With this novel data set, we separate and quantify the switching effect and advertisement effect about how offline sales and rental values of physical store spaces. Moreover, in facing with these two counterveiling effects, we explore how the shopping mall should adjust its rental contracts and business strategies.

Specifically we study the following research questions:

- How can we separate and quantity switching effect and advertisement effect?
- What factors determine the relative magnitude and trade-off between the advertisement effect and switching effect?
- From the shopping mall's perspective, what is the implication when stores switch from having a single channel to multiple sales channels? How should the shopping mall adjust the contractual agreement?

To address these questions, we construct a model with stores that can operate dual channels. Each store offers a certain product and chooses its price. For consumers, the shopping costs of purchasing in the physical stores rise faster than purchasing online. As a benchmark, we begin by analyzing the case of a monopolist retailer and compare its strategy and profits under different distances that lead to different search costs of consumers. To explore externalities of offline stores, we then modify the discrete choice model and accommodate multiple stores in the value calculation. Subsequently, we introduce different exogenous shocks, such as COVID-19, online festival, and weather, to test trade-off effects. After deriving the equilibrium solutions of these cases, we obtain the equilibrium strategies and gain some novel insights.

First, we find that the advertisement effect generated by the online store is stronger than the switching effect when online stores discount. Specifically, because online stores can influence some uninformed consumers and attract them to choose offline channels for shopping. Correspondingly, through the analysis of the online discount day, we explore that on the day of the online store's discount day, the revenue of the offline store will also increase significantly. In addition, since such online discount days have been implemented in China for more than ten years, consumers have formed the habit of making a lot of consumption on this day, so they will save in advance for discounted daily consumption. Therefore, the influence of online stores on offline stores is mainly based on the advertising effect.

Second, switching effect generated by online stores is stronger than advertising effect during the COVID-19. We compared the income of offline stores with and without online stores after COVID-19. In detail, we find that the revenue of offline stores with online stores dropped sharply after the outbreak of COVID-19, while the revenue of offline stores without online stores showed a leap-forward growth. This is because, consumers are worried about being infected due to the impact of COVID-19, making them prefer to choose online channels for shopping, which has led to a decline in the revenue of offline stores. The demand accumulated during the COVID-19 period of the stores without online stores was released after the COVID-19, and thus the income jumped.

The remainder of this paper is organized as follows. In section 2 we briefly review the related literature. In section 3 we discuss the theoretical framework that guides the empirical results. Section 4 introduces the data and reports descriptive statistics, followed by a discussion of the econometric framework and discuss our results in section 5. Section 6 discusses an extension where we built a structural estimation model.

2 Literature review

Our research links and contributes to two streams of literature: (i) externalities between stores, (ii) multi-channel effect. Next, we describe how our research relate to the literature in these areas.

Externalities between stores has been extensively researched in the literature. Research on this problem processes from various focuses. Such as the relationship between contract incentives and externalities (Gould et al. (2005); Benjamin et al. (1992); Benjamin et al. (1990); Yuo et al. (2011); Eppli (1993)), store space allocation and agglomeration effect (Melo et al. (2009); Brueckner

(1993); Zhu et al. (2011); Pashigian and Gould (1998); Koster et al. (2019); Benmelech et al. (2014); Damian et al. (2011); Chung and Kalnins (Chung and Kalnins)). Our work is in the specific stream of store space allocation and agglomeration effect. In this field, Melo et al. (2009) put forward new thinking about the agglomeration effect, believing that the agglomeration effect of different countries and regions is different, so the spillover effect brought by agglomeration is heterogeneous among different regions. Chung and Kalnins (Chung and Kalnins) believe that the geographically closest store will generate externalities, that is, increased production efficiency or increased demand, thereby increasing rents. Brueckner (1993) relate the externality of the stores to the space allocation of the shopping mall and believes that a given store's sales depend on its own space as well as the space allocated to other stores in the mall. The sales of a given store increase as other stores grow in size. Pashigian and Gould (1998) measure that shopping mall traffic generated by anchor stores indirectly increased the sales of less-known stores, and propose that shopping mall developers can internalize these externalities by providing rent subsidies to anchor stores and charging rent premiums to other shopping mall tenants. Zhu et al. (2011) assess how the entry of new stores affects the pricing of existing stores and the role played by the entrantâs location, and identify how traditional retailers respond to the new low-cost retail. Benmelech et al. (2014) identify a new channel through which bankrupt companies impose negative externalities on non-bankrupt counterparts. This negative externality weakens the agglomeration in any given region and reduces the attractiveness of retail centers to remaining stores.Damian et al. (2011) explore that a greater presence of anchors in a mall directly increases the sales, and therefore increases the rent of non-anchor stores in shopping malls. The total sales of shopping malls are directly affected by the number of anchor stores. It also proves that externalities are internalized by effectively allocating space and incentives between stores. Koster et al. (2019) argue that the reason for the agglomeration of stores in shopping streets is that retail firms benefit from shopping externalities such as footfall. Contrary to previous views, they propose such externalities cannot be completely internalized.

In this paper, we combine the externalities of stores with the opening of online stores. Since the opening of an online store by a store will not only affect its offline store revenue but also affect other offline stores through an external transmission mechanism. Therefore, we combine the externalities with the opening of online stores through study the sales changes of other stores at different distances after the online store is opened by a given store. It can more comprehensively measure the impact of the opening and existence of online stores on shopping mall revenue. Our work is also related to the literature that explores multi-channel effect, which can be divided into four strands: switching effect, advertisement effect, trade-off effect, price differences.

For the switching effect, Perea y MonsuwÃ© et al. (2004) show that peopleâs attitudes towards online shopping and their willingness to shop online are not only affected by ease of use, practicality, and entertainment, but also by consumer characteristics, situational factors, product characteristics, previous online shopping experience, and other external factors impact.

For the advertisement effect, Lewis and Reiley (2014) evaluate the positive causality of major retailersâ online advertising: online advertising increased total purchases by 5%. 93% of the increase occurred in offline stores and 78% of the increase came from consumers who never clicked on the advertisement, which shows the existence of an advertisement effect generated by online stores. Dinner et al. (2013) analysis shows that online display, especially search advertising, is more effective than traditional advertising, and believes that online advertising can strongly increase the revenue of offline stores. Zhang (2009) study the effectiveness of promotions in online and offline markets and found that loyalty promotions in online stores are more profitable than offline stores, while competitive promotions are the opposite. And for categories that are promotion sensitive, individual-level customized promotions can lead to a meaningful profit increase over segment- and mass-marketâlevel customized promotions in online stores. Kuksov and Liao (2018) propose the threat of showrooming ignored the manufacturer's strategic role in the distribution channel. When considering the manufacturerâs decision, engage in showrooming may lead to an increase in the profitability of BM retailers rather than a decrease. Thus, the retail industry's efforts to restrict showrooming behavior may be misguided.

Trade-off effect between switching effect and advertisement effect is the core of our paper, Ofek et al. (2011) study the pricing strategies and profits of competing retailers that can operate dual channels and conclude that when the differentiation between competing retailers is not too high, having an online channel can increase investment in store assistance levels and reduce profits. Jing (2018) concludes that for showrooming, reduce the intermediate search profits of traditional retailers. The opening of online stores has expanded the demand of traditional retailers, but has intensified competition, thereby reducing their profits under certain conditions. For webrooming resolves partial match uncertainty, it may increase both online and offline firmsâ profits by inducing more consumers to participate. Yan et al. (2018) develop that online channels allow manufacturers to fully control prices, thereby helping to protect offline channels. However, due to the inefficiency of online platform fees and manufacturersâ direct retail sales, marketing channels have not been used in some cases.

Multi-channel price difference is an area that has been well studied. Cavallo (2017) makes the first large-scale comparison of the prices charged by online and offline stores at the same time and found that the price levels were the same about 72% of the time. Also, price changes are not synchronized but have similar frequency and average size. Fassnacht and Unterhuber (2016) propose that consumers are unwilling to accept that retailers charge higher prices for the same physical goods in their online stores than their traditional offline stores. Price differences and lower online prices have been accepted by consumers. Meanwhile, the size of the price difference that consumers can tolerate depends on the product category. Kireyev et al. (2017) self-matching can dampen competition online and enable price discrimination in-store. Its effectiveness depends on consumersâ decision-making stages and their perception of online channels and store channels.

In our paper, we mainly explore the trade-off effect between switching effect and advertisement effect. Although the previous literature has studied the switching effect and the advertising effect, due to the difficulty in obtaining sales data from shopping malls, there is almost no literature that specifically analyzes the impact of these two effects on the income of offline stores. Specifically, we combine online and offline store data to study the changes in offline store revenue after opening an online store, as well as changes in offline store revenue data due to a series of exogenous shocks (such as COVID-19, weather), to study the trade-off between switching effect and advertising effect.

3 The Model

3.1 Model Setup

Individual store: Assume each store is a profit maximize. Think of, for instance, a restaurant. There is a continuum of consumers located from $[0, \infty]$ and the density follows a PDF $f(d)$ where $d \in [0, \infty]$ is the location of the consumer. Assume the shopping mall is located at point 0. This is a generally harmless assumption. It is equivalent to assume all the consumers are located on a circle of some radius and the shopping mall is in the center. The density of consumers follows some $g\theta, r$ in the polar coordinates. You can always normalize the density and put the model on a line segment. So d stands for the distance of the consumer from the shopping mall. Assume there is a cost for consumer to travel to the shopping mall. The cost function is denoted as $c(d)$, which is increasing in d and weakly convex. The implicit assumption here is that the transportation cost only depend on the distance from the consumer to the store, and does not depend on the store type, or the quantity of goods that the consumer buys. This assumption enables us to identify parameters of the transportation cost by exploiting the heterogeneous shocks among stores.

Assume, for a store s, it sells a bundle of value v_s to a average consumer at price p_s. If the store only has an offline selling channel, a consumer located at place d will buy the goods offline if

(1) $$v_s - c_{off}(d) \geq p_{s,off}$$

Here, we will refer $p_{s,off} + c_{off}(d)$ as the total offline consumer cost at distance d, and $v_s - c_{off}(d)$ as consumer's willingness to pay offline at distance d.

When there is an online store, assume the transportation cost now becomes $c_{on}(d)$. (Might add wait cost for online shopping, and then assume consumers are different in patience level) Assume the online price is $p_{s,on}$. So a consumer will shop online if

(2) $$v_s \geq p_{s,on} + c_{on}(d)$$

Again, I will refer $p_{s,on} + c_{on}(d)$ as the total online consumer cost at distance d, and $v_s - c_{on}(d)$ as consumer's willingness to pay offline at distance d.

Assume the first order derivative of $c_{off}(d)$ is strictly larger than the first order derivative of $c_{on}(d)$. This assumption guarantees that there exists a distance after which online shopping is strictly less costly than offline shopping. Denote this distance d^* which satisfies equation $p_{s,off} +$

$c_{off}(d^*) = p_{s,on} + c_{on}(d^*)$ as the switching distance, then we need to discuss two cases: 1. $v_s > p_{s,off} + c_{off}(d^*)$. 2. $v_s \leq p_{s,off} + c_{off}(d^*)$.

case 1 $v_s > p_{s,off} + c_{off}(d^*)$ This is the case in which the increment of offline transportation cost is relatively slow, so it requires a very long distance before the online total consumer cost gets past the total offline consumer cost. The critical distance is so long that all the customers who are willing to buy the goods will buy it offline. Thus offline stores will not have incentive to open an online branch when we do not include other benefits such as the advertisement effect.

case 2 $v_s \leq p_{s,off} + c_{off}(d^*)$ This is the main case of interest. let d_1 be the distance such that $v_s = p_{s,off} + c_{off}(d_1)$; And let d_2 be the distance such that $v_s = p_{s,on} + c_{on}(d_2)$. From the model setting, we can find that $d^* < d_1 < d_2$. With these three cutoffs we can study the switching of shopping channels before and after the opening of a consumers. Then we can calculate the change in consumer size and thus the shop's profit.

Assume the marginal cost for the shop to supply certain quantity is the same no matter the goods is sold online or offline (the difference in cost is absorbed by the different transportation cost). Denote the marginal cost as $MC(q)$ for supply a quantity of q. Assume both the online and offline markets are perfectly competitive, so the price is set to be equal to the marginal cost. There are 4 predictions of movement of consumers before and after the online stores opening:

1. Before a store s opens its online branch, so the total demand is $q(d) = \int_0^{d_1} f(x)dx$. Since we have assumed a competitive market, the price of offline is determined by where the demand curve $V_s - c(d) = MC(q(d))$. Denote this price of offline as p_1, we can thus derive the profit function

$$\pi_{s,1} = p_1 q(d_1) - \int_0^{q(d_1)} MC(x)dx \tag{3}$$

2. After opening an online store, the demand curve changes to the online channel. Still, by the competitive market assumption, the new price p_2 is obtained by equating $V_s - c_{on}(d) = MC(q(d))$. These cases complete both the base model.

3. When the online consumer total cost is always lower than the offline consumer total cost, then all the shopping will be done online, and thus the store would exit the shopping mall and thus such store will not be in our sample. If we assume all stores are profit maximizing, then we should not expect store of such cost structure to be observed in our sample.

4. If the online consumer total cost is always higher than that the offline total consumer cost, then this case should be captured by case 1, in which all consumer buy the goods offline. However, if the advertisement effect is significant for such store is large, then the store will still have the incentive to open an online branch to expand the consumer base.

3.2 Crowd out effect and the advertisement effect

As a main theme of this paper, we want to estimate the size of switching effect and advertisement effect, both of which are important focus of this literature on online and offline sales. However, before we proceed, it is important that we formally define these two effects.

Given a fixed distribution of the customers, the switching effect is the percentage change in the quantity sold from the offline channel after the store open the online store. The advertisement effect is the distribution of uninformed customer that becomes informative of the store after the online branch opens. More mathematically, the advertisement effect is measured by the distribution $g(d)$. We assume this fraction of people does not know the existence of the store, so originally, even if their value of buying goods from the store is higher than the price plus transportation, they will not go to the store. However, when the online branch opens, the those uninformed consumers can learn about the store by doing online search. Assume they can form correct belief about the value of the goods in each store. One additional assumption to facilitate the estimation of the advertisement effect is that we assume the distribution of uninformed customer is a fixed fraction of the total customer distribution: $g(d) = \rho f(d)$. It is still possible to estimate the advertisement effect even if we assume different distribution of g(d), however in any case, we need to assume some functional form for g(d).

The identification of these two effects hinges on the fact that the advertisement effect does not change all the critical distances solved in the model. I will be more specific later.

In this base model, we assume linear cost curve for online and offline. However, as long as we have a functional form for the cost function, it should be fine. let the offline cost function be

$$c_{off}(d) = a_{off}d \tag{4}$$

And let the online cost function be

$$c_{on}(d) = a_{on}d + b \tag{5}$$

As mentioned before, to ensure an interior solution, we assume $a_{on} < a_{off}$ so as the distance gets large enough, there will be a cutoff point that it is less costly to shop online than offline. Denote this critical point as

$$d^* = \frac{b}{a_{off} - a_{on}} \tag{6}$$

There is a value corresponding to this critical distance.

$$v^* = v - a_{off}d^* = v - \frac{a_{off}b}{a_{off} - a_{on}} \tag{7}$$

For the estimation purpose, we can put an error term into the valuation term.

Before the opening of the online branch, all the consumers can only buy the good via the offline channel. So there is another critical distance d'' such that all customers will be willing to go to the store while customers who lives further will not buy the goods.

$$d'' = \frac{v_s - MC}{a_{off}} \tag{8}$$

Here, V_s is consumer's willingness to pay for the goods or services of the store s. This equation is used to estimate MC and V for offline only store, but is not necessary when we want to estimate a_{on}, a_{off} and b. Next, I will proceed to show how to solve for those three parameters.

After making some assumption of the functional form of $f(d)$, we will be able to get all distances d from the corresponding quantity in quantity soled (Q).

Then, we can estimate the parameter for the offline cost by exploiting exogenous online price shocks and offline price shock. We first normalize the consumer's value at distance d^* to be 1. So we would only need to solve a_{on}, a_{off} and b. We also normalize the quantity of goods sold at the offline store at this point to be 1. $v^* = 1$ and $Q^* = 1$ is represents the case of a normal day with sunny weather and no discount or promotion.

So the first equation we can use to solve is:

$$v - a_{off}d^* = v - a_{on}d^* - b \tag{9}$$

Then when there is an online discount specifically, we can observe the percentage of the price change, or, in other word, we observe the new price with discount. We can write the discount in comparing to the original unit price that we observed before. Denote the value of the discount as δ, for instance, if there is a 30% decrease of the price level from the original equilibrium, then $\delta = 0.3$ in this case. A discount of online price is equivalent to a decrease of the online transportation cost by 0.3 unit of utility. Then, we can derive a new online offline switching distance with such discount. Denote this new distance as d' and then we have

$$v - a_{off}d' = v - a_{on}d' - b + \delta \tag{10}$$

or equivalently:

$$d' = \frac{b - \delta}{a_{off} - a_{on}} \tag{11}$$

Again, we can back out this distance from the pdf of offline customer and the observed offline quantity sold. observe the offline quantity change because we observe the offline revenue change and there is no change in the offline price. So all the offline fluctuation in revenue can be attribute to offline customers switching to the online platform. Thus, the online shock will result in a sequence of points that is a movement along the offline demand curve.

Here, the critical assumption is that the online discount or promotion is independent of the offline transportation cost, the value from shopping or the marginal cost. In the data, we would be able to observe the change in the offline changes.

Similarly, we can use the offline price change to estimate the online cost curve. Again, without online or offline discount, the critical point is at d^* and the consumer's willingness to pay at this distance is v^* which is normalized to 1.

Now, suppose there is a offline discount that is equivalent to reduce the offline transportation cost by ϵ. In the absence of the online price shock, there will be online consumers switching to offline shopping. since we observe the price change and the offline change, we can back out the quantity change before and after the price shock. Then using the consumer distribution $f(d)$ to get the critical distance before and after the price shock. So, we observe d^* and d'' in which d'' is the critical point with offline discount.

Then, we can derive expression for d''.

$$v - a_{off}d'' + \epsilon = v - a_{on}d'' + b \tag{12}$$

Combining the equation 9,10 and 12, we have the following matrix expression, and we can solve for the three parameters easily:

$$\begin{bmatrix} d^* & -d^* & -1 \\ d' & -d' & -1 \\ d'' & -d'' & -1 \end{bmatrix} \begin{bmatrix} a_{off} \\ a_{on} \\ b \end{bmatrix} = \begin{bmatrix} 0 \\ \delta \\ -\epsilon \end{bmatrix}$$

After we identify those parameters, it is possible to estimate the advertisement effects of going online. Then we would be able to calculate the counterfactual revenue of a purely offline store, but with the advertisement effect realized. Due to the competitive market assumption, the price of goods does not change before and after going online, so we can still back out the quantity sold in this model and then by comparing the observed purely offline quantity soled in the market with the counterfactual purely offline case after the advertisement effect is realized, then we can identify the advertisement effect.

3.3 A simplified Micro foundation for offline externality

Now the consumer faces a consumption bundle problem. The intuition is the follow: assume that a consumer wants to buy more than one type of goods. If she buys all of them together, then she only pays for the transportation cost once. However, if she buys each of the goods online, then she has to pay the shipping fee for each good separately (because things are sold by different stores, and thus cannot be shipped together)

We can modify the discrete choice model and accommodate multiple stores in the value calculation. The consumer surplus from going to the shopping mall now becomes:

$$U_{off}(d) = \sum_j \mathbb{1}(V_j > P_j)(V_j - P_j) - c_{off}(d) + \epsilon_{it} \tag{13}$$

While shopping online gives utility level:

$$U_{on}(d) = \sum_j \mathbb{1}(V_j > P_j)(V_j - P_j - c_{on}(d)) + \epsilon_{it} \tag{14}$$

Still, V_j is the consumer i's valuation of the goods and services of the store j that depends on a vector of store characteristics. The error term is assumed to be independent of the value of each store's goods and services i. The value of external choices are normalized to zero in this model. However, in the later structural estimation section, we will not assume the external choices to have zero value.

Thus, a consumer will go to the offline branch if and only if $U_{off}(d) \geq U_{on}(d)$ and $U_{off}(d) \geq 0$. She goes to the online branch if and only if $U_{on}(d) \geq U_{off}(d)$ and $U_{on}(d) \geq 0$. Otherwise the consumer goes to the external choice.

Using the above assumptions, we can solve for the individual demand curve for each store. And we will see, when one store opens an online branch (assume no advertisement effect), the total size of consumers going to the shopping mall will decrease and thus profit for the other stores should decrease.

4 Data and description

Our data consists of several parts. The first data set is detailed information on the population of stores in a shopping mall (A mall) located in Ningbo, China. This is the largest shopping mall in Ningbo that has 389 stores. The second data set is a shopping mall (B mall) located in Hangzhou that has 136 stores. For each store in these two shopping malls, we observe the daily income, rent, passenger flow and other characteristics. The third data set contains the information about online stores constructed by web scraping. For each store in these two shopping mall, we find its corresponding online store (if there is one). For each online store, we record its opening time, number of viewers, promotion information. Part of the above data are still under construction and analysis. In this writing sample, our results are incomplete.

Table 1: Summary of Two Shopping Malls

	A Mall	B Mall
City	Ningbo	Hangzhou
County Population	686,000	801,000
Open time	2016 Sept	2016 August
Area (m^2)	100,000	35,841
N. shops	389	136
Market Size	6km (main consumers)	5km (80% consumers)
Ave.consumption (RMB)	100	123
Ave. Month Revenue (RMB)	54,951,603	21,987,731
Data advantage	store level daily revenue	consumer tracking data

Table 1 summarizes the descriptive statistics of these two malls. For mall A, our statistic result shows that for physical stores in different category, the proportion of opening online stores differ. For food and beverage stores, the proportion is the lowest, while clothing stores has the highest proportion.we find among all rent contracts the number of proportional rent contracts is much lower than the number of fixed rent contracts. On the other hand, the proportion of proportional rent contracts has been declining year by year, from 16% in 2016 to 11% in 2019, and the proportion of fixed rent contracts has increased year by year, from 80% in 2016 to 85% in 2019.

We can roughly see the switching effect in these data pattern. Due to the presence of the showrooming effect, offline demand has been more transferred to online channels, resulting in a gradual decrease in offline store sales. The decrease in-store sales will reduce shopping malls' revenue when they charge a store with proportional rents. Therefore, shopping malls are more inclined to provide stores with fixed rent contracts (Cho and Shilling (2007)), which also explains why in all contracts, the proportion of rents is relatively small and the fixed rents are relatively large. Besides, when consumers try to purchase online, their consumption habits may change. Driven by the low search cost of online shopping, consumers may choose more online shopping in subsequent consumption, resulting in a decrease in offline store sales. This drives shopping malls to charge more fixed rents rather than proportional rents in future contracts, which explains why the proportion of proportional contracts has decreased year by year while the proportion of fixed contracts has increased year by year in all contracts.

5 Data Evidence of switching effect and advertisement effect

5.1 Online store opening

Event study for shop i which opens the online store on week τ_i

$$LRE_{it} = \beta_0 + \beta D_t + \beta_1 D_t t + \eta_i + \theta_t + \nu_f c + \zeta_{my} + \epsilon_{it} \tag{15}$$

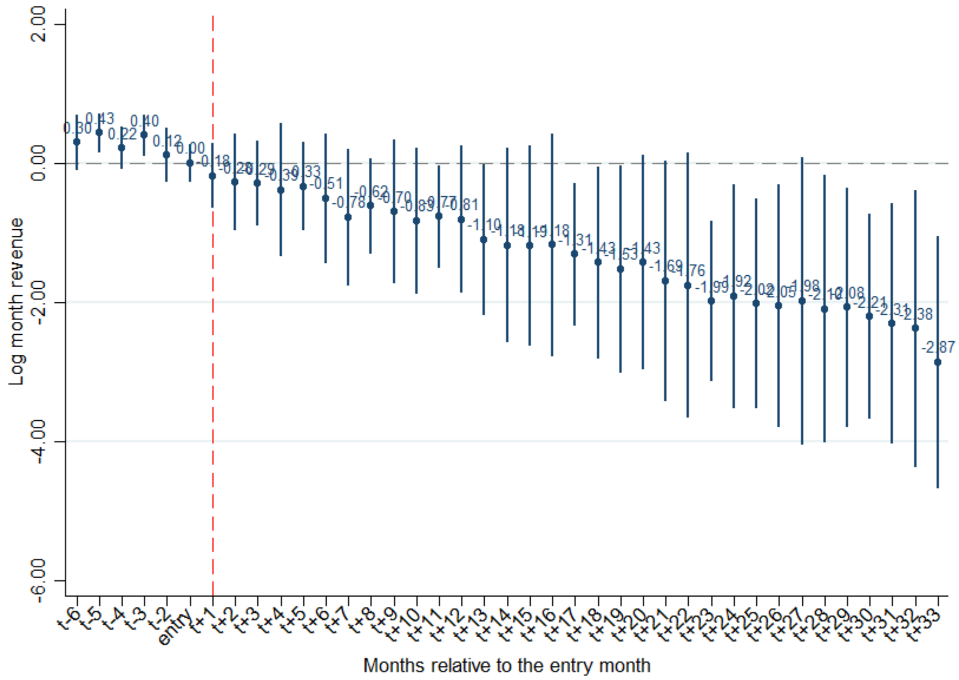

Figure 1: Event study: Online store opening

where LRE_{it} is the log revenue for shop i on week t, D_t is the dummy for online store opening on week τ_i if week t is after τ. We restrict the range of weeks as $[\tau - 10, \tau + 30]$. η_i is shop i's characteristics (anchor store, date of entry, area...). θ_t denotes week t's characteristics (number of rain days, number of festival days). $\nu_f c$ denotes categorycategory fixed effect. ζ_m denotes month and year fixed effect. We want to estimate β and result is shown in Figure 3.

5.2 11-11 Festival

Event study for 11-11 Festival analysis:

(16) $$LRE_{it} = \beta_0 + \beta D_t + \beta_1 D_t t + \eta_i + \zeta_t + \nu_f c + \zeta_{my} + \epsilon_{it}$$

where LRE_{it} is the log revenue for shop i on week t, D_t is the dummy for 11-11 festival if date t is after November 11th. We restrict the range of weeks as a week before and a week after the 11-11 festival. η_i is shop i's characteristics (anchor store, date of entry, area...). ζ_t denotes date t's characteristics (i.weather, i.weekday, i.festival). $\nu_f c$ denotes categorycategory fixed effect. ζ_m denotes month year fixed effect. We want to estimate β. Results are shown in Figure 4 and 5.

DID regression for 11-11 Festival analysis: We regard shops with Taobao store as the treatment group. And other stores as the control group.

(17) $$LRE_{it} = \beta_0 + \beta D_t \kappa_{it} + \beta_1 D_t t + \eta_i + \zeta_t + \nu_f c + \zeta_{my} + \epsilon_{it}$$

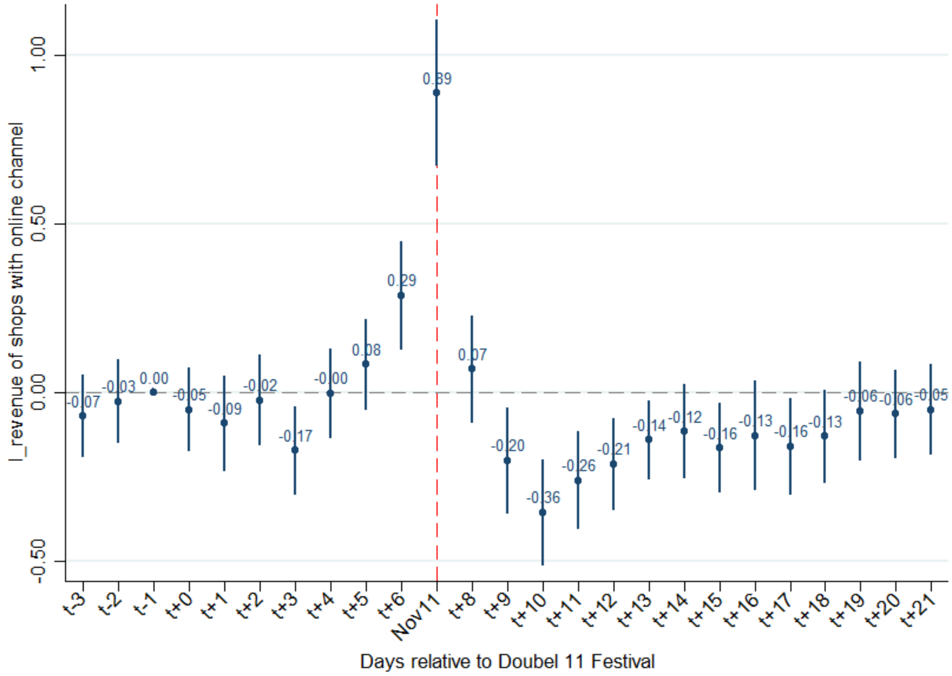

Figure 2: 11-11 event study: Shops with online selling channel

where

$$\kappa_i = \begin{cases} 1, & \text{shop } i \text{ has a Taobao shop} \\ 0, & o.w. \end{cases}$$

5.3 Offline shock: Rain weather

We denote $R_t = 0, 1$ as the rain dummy of date t. $R_t = 0$ when there is no rain (sunny or clouded). $R_t = 1$ when date t is raining. $\gamma_i = 1$ when store i has an online channel. The result is shown in Table 2,

$$LRE_{it} = \beta_0 + \beta\gamma_i + \beta_1 R_1 \gamma_i + \beta_2 R_1 + \eta_i + \theta_t + \zeta_{cf} + \zeta_{ymw} + \epsilon_{it} \tag{18}$$

5.4 COVID-19 shock

Event study for COVID-19 analysis:

$$LRE_{it} = \beta_0 + \beta D_t + \beta_1 D_t t + \theta_t + \eta_i + \nu_f c + \zeta_{my} + \epsilon_{it} \tag{19}$$

where LRE_{it} is the log revenue for shop i on week t, D_t is the dummy for 11-11 festival if

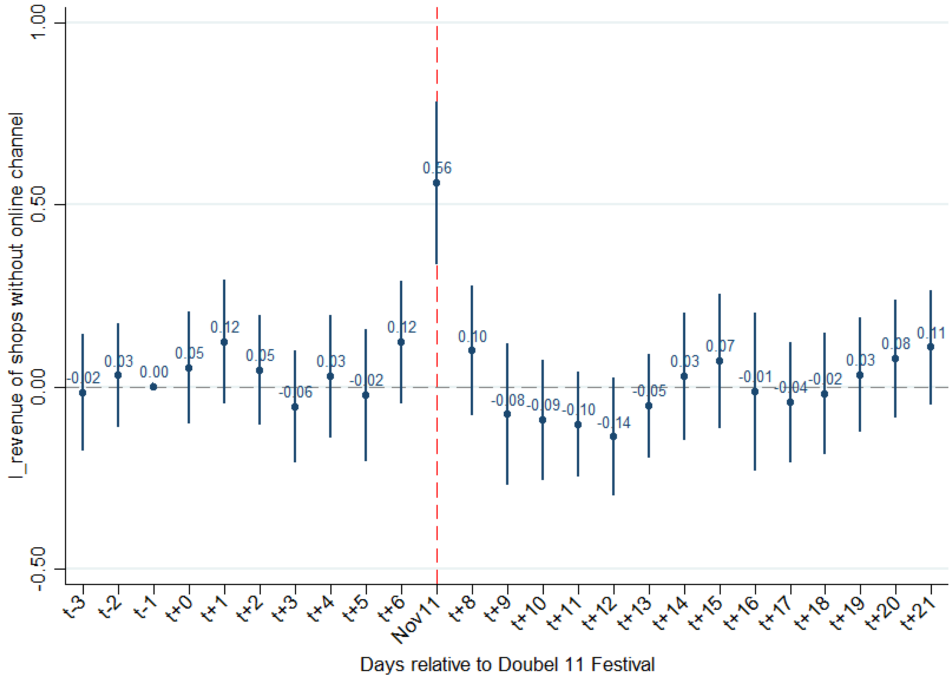

Figure 3: 11-11 event study: Shops without online selling channel

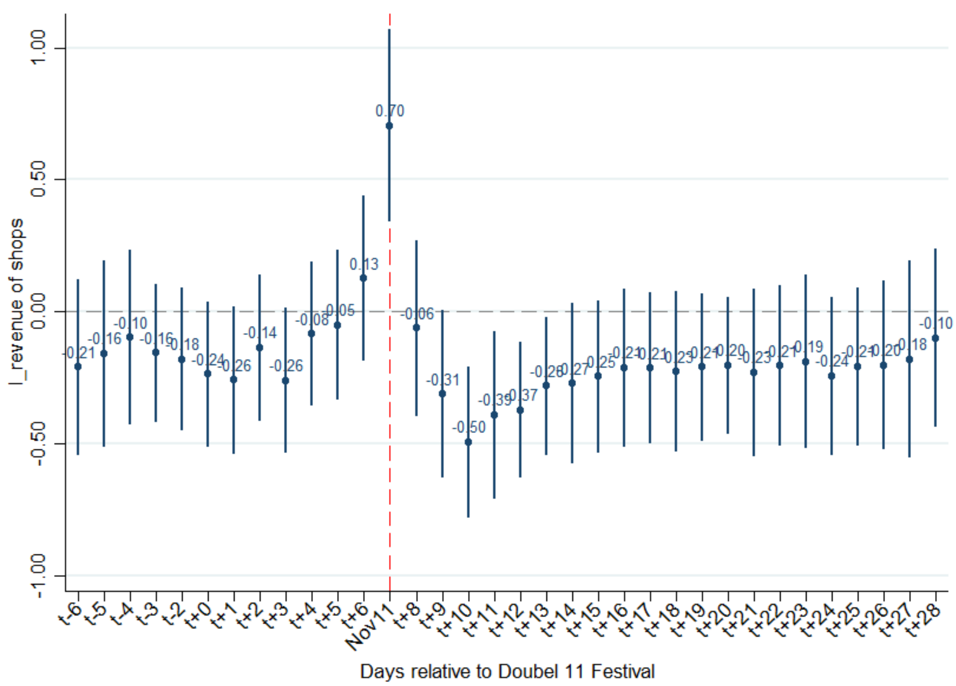

Figure 4: DID analysis: 11-11 Festival

Table 2: Rain Weather FE regression

Dependent Variable:	(Log Shop Daily Revenue)		
	(1)	(2)	(3)
β_1	-0.028**	-0.025*	-0.025*
	(0.013)	(0.013)	(0.013)
β_2	-0.016*	-0.031***	-0.027***
	(0.009)	(0.009)	(0.009)
β	0.239	0.238	0.236
	(0.154)	(0.154)	(0.153)
Shop control	Yes	Yes	Yes
Day control	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Month FE	Yes	Yes	No
Weekday FE	Yes	No	No
Category-Floor FE	Yes	Yes	Yes
Observations	170091	170091	170091
R-Squared	0.520	0.509	0.489

Note: Festival=1 if the date is a festival day.

date t is after Jan 24th. We restrict the range of weeks as Oct.24th, 2019 until May 25th, 2020. θ_t denotes week t's characteristics (number of rain days, number of festival days). $\nu_f c$ denotes categorycategory fixed effect. ζ_m denotes month and year fixed effect. We want to estimate β.

DID regression for COVID-19 analysis: We regard shops with Taobao store as the treatment group. And other stores as the control group.

$$LRE_{it} = \beta_0 + \beta D_t \kappa_{it} + \beta_1 D_t t + \theta_t + \eta_i + \nu_f c + \zeta_{my} + \epsilon_{it} \tag{20}$$

where

$$\kappa_i = \begin{cases} 1, & \text{shop } i \text{ has a online shop} \\ 0, & o.w. \end{cases}$$

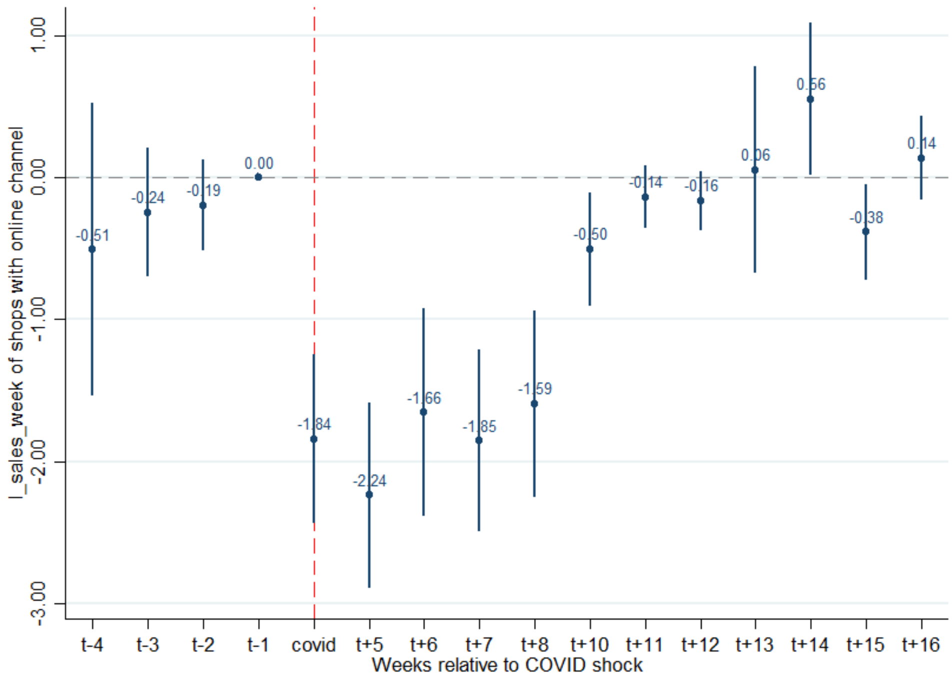

Figure 5: Event study: Shops with online selling channel

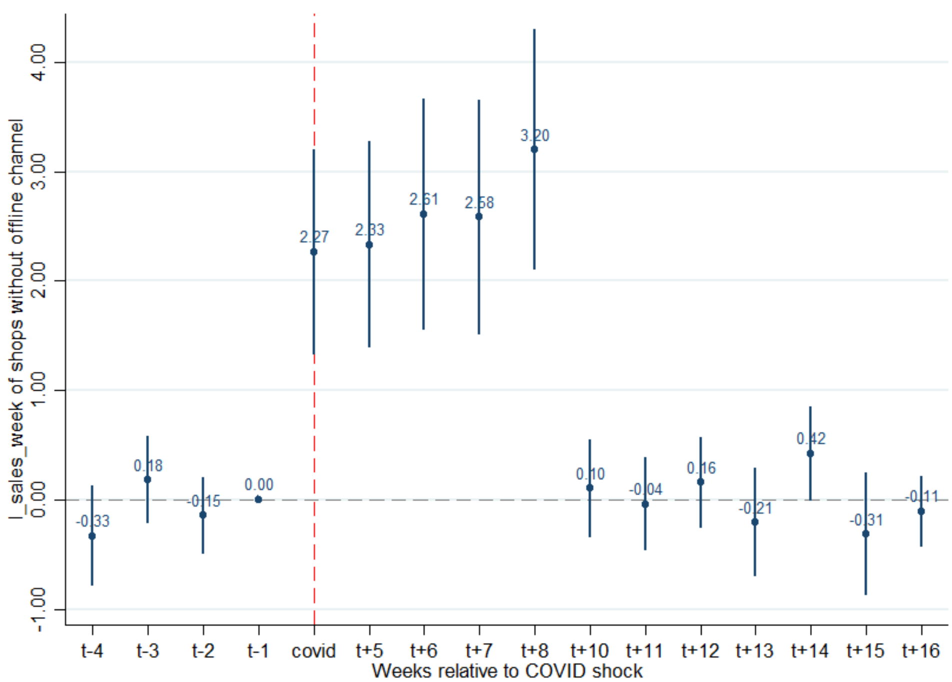

Figure 6: Event study: Shops without online selling channel

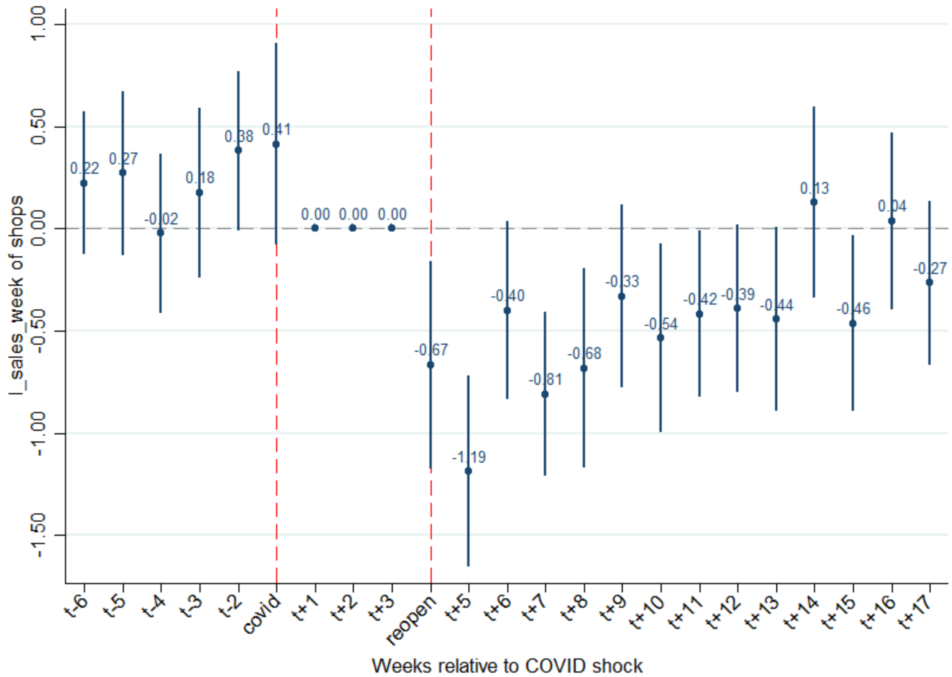

Figure 7: DID analysis: COVID-19 Shock

6 Structural estimation model

Following Holmes (2011) and Zheng (2016), we will construct a discrete choice model for the structural estimation part. We closely follow the standard literature in existing literature and put it into out shopping mall case. First, we assume all consumers can choose from three alternatives: shopping in the store offline, shopping online or going to an outside option. We assume the utility derived from each choice is derived from a vector of separable attributes and an error term ϵ_{ijmt} that follows a Gumbel and type I extreme value distribution. The probability density function of the following form:

$$f(\epsilon_{ijmt}) = e^{-\epsilon_{ijmt}} e^{-e^{-\epsilon_{ijmt}}}$$

and cumulative distribution of:

$$F(\epsilon_{ijmt}) = e^{-e^{-\epsilon_{ijmt}}}$$

.

The consumer i shopping at store j's offline branch inside shopping mall m at time t derives utility

$$\begin{aligned} u_{ijmt} &= \beta x_{jmt} + r_1 d_{im} + r_2 d_{im} popden_{it} + \epsilon_{ijmt} \\ &= v_{ijmt} + \epsilon_{ijmt} \end{aligned} \tag{21}$$

where β is a vector of parameters to estimate. x_{jmt} is the attribute of store j in shopping mall m at time t. It includes the category of the store, a brand dummy, the size, the floor in which the store is located at, promotion and advertisement at day t, number of employee, weather of the day and so on. d_{im} is the distance from where the customer i lives to the shopping mall. In our model, we do not observe the address of each consumer, so we use a representative individual for each region of Ninghai city. so d_{im} measure how far the center of each region is to the shopping mall. We also include an interaction term of $d_{im}popden_{it}$ which is a interaction term between the population density of where i lives $popden_{it}$ and the distance from i's location to the shopping mall. This arrangement is to capture the heterogeneity in consumers' preferences with respect to distance to the shop. We can put random coefficients to capture the heterogeneity, but to reduce the computational burden, we choose this setup.

The utility for consumer i to shopping at online branch of store s generates a different utility level

$$\begin{aligned} u_{ijot} &= \delta_1 x_{jot} + \delta_2 w_i + \epsilon_{io} \\ &= v_{ijot} + \epsilon_{io} \end{aligned} \tag{22}$$

x_{jot} is a vector of online store characteristics. w_i is a vector of co-varieties of region i that include a constant, population density, population density squared, per capitaL income, and share of African-American, elderly, and young people in the population. (I think we should also include something related to the distance in this part)

Finally, the utility from shopping in the outside option is the following:

$$\begin{aligned} u_{iot} &= \alpha_1 w_i + \alpha_2 locationChara_{lt} + \epsilon_{iot} \\ &= v_{iot} + \epsilon_{iot} \end{aligned} \tag{23}$$

Again, w_i is region i's characteristics. $locationChara_{lt}$ in our setting is how many other similar type of store is within the city

Finally, we can write down the equation for store j's revenue on a day t. This is what we observe. Let p_{ijot} denote the probability of the consumer i buying in the offline store j at day t, then the store's revenue can be written as:

$$R_{jlt} = \sum_i \lambda p_{ijot} n_{it} \tag{24}$$

where λ is the average spending per consumer which is what we can observe through a brief survey or asking for the administrative data. n_{it} is the total population of block group i, which is also observable using the census data. So, it is possible to back out p_{ijot} using this formula.

Lastly, we can solve for the utility of going to the offline store j using the relative utility from the three choices and the distribution of the error term.

$$\begin{aligned} p_{ijmt} &= Pr(u_{ijot} > max\{u_{iot}, u_{ijot}\}) \\ &= \frac{e^{v_{ijmt}}}{e^{v_{ijmt}} + e^{v_{iot}} + e^{v_{ijot}}} \end{aligned} \tag{25}$$

Similar equation also applies for p_{ijot} and p_{iot}. We can start the estimation from looking only at the stores that does not have an online branch. For those stores $v_{ijot} = 0$. So, we will be able to identify the parameters that are related to the offline branch and the outside choice. Then, plugging those estimated parameters to the online branch, we would be able to identify the rest of the model parameters in the online utility model.

7 Conclusion

With the rise of the online channel, shopping mall often needs to consider how to deal with this new threat to their revenue. In detail, the presence of spillover from online sales, which can be divided into switching effect and advertisement effect, will affect offline store in different ways.

To explore the trade-off effect of switching effect and advertisement effect, we have established a consumer decision-making model. By distinguishing the effects of changes in consumer search costs under different channels on their consumption behavior, the store's channel selection is affected. Specifically, when the search cost of consumers is low, the utility brought by online stores is strictly less than offline stores, so there will be no online stores. The switching effect mainly occurs after the search cost crosses the equilibrium point. After the equilibrium point, the original offline demand was transferred to the online. But at the same time, because the marginal cost of online search costs for consumers is lower, the opening of online stores has also expanded consumer demand.

Also, the results of the measurement regression show that the opening of the online store mainly brings the advertisement effect. Although the regression results of rain shock and COVID shock both show that the switching effect is stronger than the advertisement effect, this is because an online store is an alternative option, and consumers will choose online consumption when offline channels are blocked, not Demand shift due to the opening of online stores.

Despite the encouraging results obtained in this paper, there are numerous other factors to be considered regarding advertisement effect and switching effect. Since there is no price data, we cannot explore why the advertising effect is stronger than the switching effect. And The open impact of online stores and externality between stores still needs to be measured. The sales growth of offline stores may be caused by the simultaneous discounting of online and offline stores. Besides, our structural estimation model does not build in the positive externalizes among all the stores inside the shopping mall. It might take some additional assumptions to make it work.

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