

Abstract

With the continual growth of e-commerce, many brands have opened up online sales channel alongside with their traditional brick-and-mortar (B&M) stores. Consumers usually incur lower shopping costs from purchasing online, so the presence of an online store tend to cannibalize sales of the corresponding B&M store. However, online sales may expand the market for the B&M store by increasing consumer awareness of the brand and transmitting product information. We use a unique dataset of 308 B&M stores matched with their online stores on Taobao to investigate the two countervailing effects. We utilize rainy days and Covid outbreaks as offline-exclusive demand shocks to identify the (negative) **cannibalization effect** of online sales on B&M stores. We use Double-11 online shopping festival as online-exclusive demand shocks to identify the (positive) **informative effect**. We estimate the magnitude of each effect and also analyzed the heterogeneity across different store categories. Our study unveil the complex relationship between online and offline sales and offer insights into the strategies and operations of store managers and shopping malls in the digital age.



Figure 1. Photo of the mall entrance



Figure 2. Photo of the mall center.

Cannibalization Effect

Cannibalization effect: In instances where an external shock makes traditional, offline shopping more challenging (such as inclement weather or a pandemic), the offline segment of a multi-channel retail store experiences a larger revenue loss compared to a similar sized offline-only store. This additional loss in revenue is termed the 'cannibalization effect' (Alba et al., 1997; Deleersnyder et al., 2002; Pozzi, 2013; Hernant and Rosengren, 2017).

We build a nested logit model to show the above statement. This statement holds true even when the model accounts for consumer behavior that defers consumption to future periods during offline disruptions.

To estimate the cannibalization effect, we first run a two-way fixed effect model and a PSM-DID model for rainy days. See the following regression equations. $Rain_t$ is a dummy that equals one if day t is rainy or snowy and 0 otherwise. $Taobao_{it}$ is a dummy that equals 1 if store i has an online branch on day t, and 0 otherwise. The cannibalization effect is measured by the coefficient of the interaction term $Rain_t * Taobao_{it}$. The results are shown in table 1 below. Multi-channel stores suffer from an additional 4.7% to 5.1% revenue losses on rainy days.

Similarly, we replace the $Rain_t$ with $Covid_t$ to test the cannibalization effect due to COVID threat (see table 2). $Covid_t$ equals 1 for four weeks after the initial lockdown in early 2020. We find that multi-channel suffers an additional 30% revenue losses compared to offline-only stores, implying a large group of consumers moving online due to health concerns.

► Regression (1):

$$R_{jt} = \beta_0 + \beta Rain_t * Taobao_{jt} + \eta_j + \eta_t + \epsilon_{jt}$$

► Regression (2):

$$R_{jt} = \beta_0 + \beta Rain_t * Taobao_{jt} + \beta_1 Rain_t + \beta_2 Taobao_{jt} + \eta_j + \eta_w + \eta_{weekday} + \epsilon_{jt}$$

$$R_{jt} = \beta_0 + \beta Rain_t * Covid_{jt} + \eta_j + \eta_t + \epsilon_{jt}$$

$$R_{jt} = \beta_0 + \beta Rain_t * Covid_{jt} + \beta_1 Covid_t + \beta_2 Taobao_{jt} + \eta_j + \eta_m + \epsilon_{jt}$$

	Dependent Variable: Store Daily Revenue	
	(1)	(2)
$Rain_t * Taobao_{jt}$	-508.038** (257.382)	-466.392* (261.545)
$Rain_t$		-339.114** (164.137)
$Taobao_{jt}$		706.588 (835.715)
Store FE	Yes	Yes
Day FE	Yes	No
Week FE	No	Yes
Weekday FE	No	Yes
Observations	159011	159011
R-Squared	0.587	0.561
$\Delta\%$ Revenue	-5.11%	-4.69%

Table 1: Cannibalization effect due to rainy days

	Dependent Variable: Store Daily Revenue	
	(1)	(2)
$Covid_t * Taobao_{jt}$	-9,664.603** (4,397.348)	-9,664.061** (4,391.002)
$Covid_t$		-19,440.435** (4,180.722)
$Taobao_{jt}$		-1,553.261 (3,053.443)
Store FE	Yes	Yes
Week FE	Yes	No
Month FE	No	Yes
Observations	7511	7511
R-Squared	0.656	0.644
Ave. Weekly Revenue	32233.43	32233.43
$\Delta\%$ Revenue	-29.98%	-29.98%

Table 2: Cannibalization effect due to COVID shock

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Information Effect

Informative effect refers to online sales channels causing revenue increase for corresponding B&M stores (Forman et al., 2009; Wang and Goldfarb, 2017; Avery et al., 2009; Bell et al., 2018). Online sales channels can increase brand awareness and transmit product information (Zhang, 2009; Pauwels et al., 2011).

To measure the informative effect, we run similar two way fixed effect model and PSM-DID mode. Here $Shop.Festival_t$ is a dummy variable that takes the value 1 when day t is during the shopping festival period, and it equals zero otherwise. We find that the offline revenue of multi-channel stores gets an additional 15%-16% increase during online shopping festivals. This finding provides strong evidence for the informative effect.

	Dependent Variable: Store Daily Revenue	
	(1)	(2)
$Shop.Festival_t * Taobao_{jt}$	1,491.569* (842.111)	1,377.289* (794.230)
$Shop.Festival_t$		40.434 (472.483)
$Taobao_{jt}$		-12.352 (1,768.240)
Store FE	Yes	Yes
Weekday FE	Yes	Yes
Month FE	Yes	Yes
Observations	78236	78236
R-Squared	0.591	0.582
Ave. Daily Revenue	9146.618	9146.618
$\Delta\%$ Revenue	16.31%	15.06%

Regression 1:

$$R_{jt} = \beta_0 + \beta Rain_t * Covid_{jt} + \eta_j + \eta_t + \epsilon_{jt}$$

Regression 2:

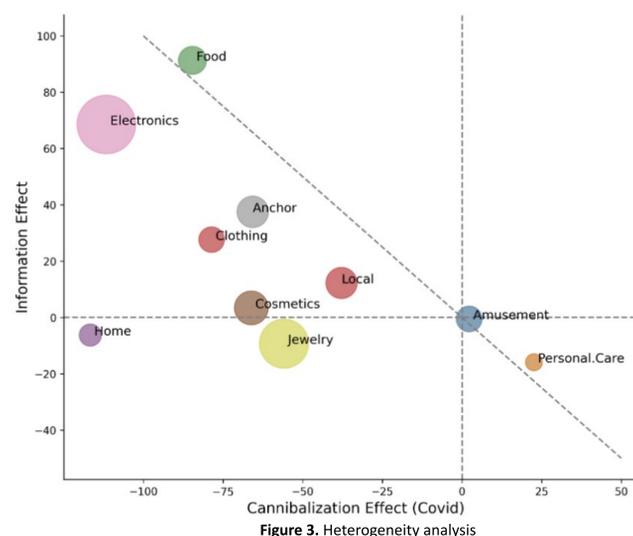
$$R_{jt} = \beta_0 + \beta Rain_t * Covid_{jt} + \beta_1 Covid_t + \beta_2 Taobao_{jt} + \eta_j + \eta_m + \epsilon_{jt}$$

Table 3: Information effect

Heterogeneity Analysis

In Figure 3 below, we present a graph that illustrates the magnitude of cannibalization and information effects across different categories. The circles on the graph represent the total revenue generated by each category. Upon conducting a heterogeneity analysis, we discovered that categories such as home, clothing, cosmetics, and jewelry are significantly impacted by the emergence of online stores. Conversely, amusement and personal care stores appear to be unaffected. Interestingly, local stores exhibit both substantial negative and minor positive effects.

Further examination using survey data allowed us to identify the primary mechanisms behind these heterogeneous results. We found that the discounted price difference, online store quality, and consumer online shopping habits play crucial roles in determining the impact experienced by each category.



Conclusions

1. Opening new online sales channels have both cannibalization and informative (market expansion) effects.
2. These effects are heterogeneous across categories.
3. Shopping mall can adjust rents and store space allocation accordingly.

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