Effect of Stores on Online Sales

Case written by

Anuj Kumar (akumar1@ufl.edu)
Warrington College of Business, Univ. of Florida
&
Amit Mehra (Amit.mehra@utdallas.edu)
Naveen Jindal School of Management, UT Dallas

INTRODUCTION

Kevin Hu, CEO of a multichannel apparel and home goods retailer in the US (hereafter called the firm), looked at the deserted flagship store of the firm on 5th Avenue in NY City. The firm has suffered massive losses due to the closure of its stores during COVID-19 pandemic. Kevin has to decide now whether to close stores permanently or wait till the economy opens up. The COO of the company warned Kevin that their online sales are highly interdependent with their stores. He argued that the firm acquires loyal customers through stores, and these customers create word of mouth publicity for their brand. By closing their stores permanently, they risk losing their customers to the competitors. Kevin also recalled the demand of Angela Perry, representative of the firm's employee union. Angela resented that store employees are not rewarded for the firm's online sales that originate due to customers' store visits. She argued that sales associates help customers find desired products on the firm's website if they cannot find them in the store. Therefore, a substantial portion of the firm's online sales is attributable to the stores.

Kevin put together a team of marketing executives and data analysts to seek an answer to the general question– what is the effect of the firm's stores on its online sales?

EFFECT OF STORES ON ONLINE SALES

To validate Angela's claim, Kevin asked his team to measure the effect of stores on customers' online purchases. The firm captured data on each sale/return interaction of a customer in its point of sales (POS) database. However, if a customer does not purchase anything during her store visit, the store visit is not recorded in the firm's database. Moreover, a customer's interaction with the sales associate during the store visit was not recorded. Kevin wondered how he should measure the effect of stores on customers' online purchase behavior with this data.

A team member suggested that the effect of stores on customers' online purchases can be estimated by simply subtracting the average online purchases of customers who visit stores from that of customers who do not visit stores. However, another team member argued that customers who use both channels are high value and loyal customers of the firm. These customers will be different from single-channel customers. Therefore, comparing the purchases of these two types of customers may not be appropriate.

Kevin wondered then how to find the true effect of stores on customers' online purchases.

A team member suggested If they could find an event that affects a customer's access to stores, then the difference in her online purchases with the change in store access would indicate the effect of stores on customer's online purchases. Kevin realized that the store openings by the firm create such variation in the store access for customers residing in nearby areas. Kevin asked his team to find statistical methods to evaluate the effect of store openings on customers' online purchases.

The experimental evaluation of policies in economics seemed promising to Kevin. In these evaluations, economists design experiments to compute the average treatment effect of government policies in terms of their benefits to the citizens. There are three types of experiments.

(1) **Randomized experiments** – In a randomized experiment, the treatment is assigned to a sample of randomly selected subjects and not assigned to the remaining subjects. Thus, subjects who get the treatment are similar to those who do not get it. The average treatment effect (ATE) is the difference in average outcome for treated subjects from that of the untreated subjects.

    It is not possible for the firm to execute such experiments because it would to too expensive to open new stores in randomly chosen locations just for the purpose of doing the experiment.

(2) **Natural experiments** – In a natural experiment, some subjects may randomly receive the treatment due to a natural event while other subjects do not receive it. Since the natural event occurs randomly, its assignment is not correlated to the characteristics of the subjects. The average treatment effect (ATE) is the difference in the average outcome of treated subjects from that of the untreated subjects.

    An example could be a tornado that hits a store closing it down for several months or longer. Since the tornado hit is not a selected one, we can consider a random selection of customers who are affected by it as the treatment group and other customers who are not affected by store closures as the control group.

    Such events occur due to forces of nature and may not be easy to find when one wants to do the analysis.

(3) **Quasi-natural experiment –** In a quasi-natural experiment, the treatment effect is estimated by computing the difference of the behavior of treated subjects who receive the treatment due to an

event (e.g. store openings by the firm) from that of untreated subjects. The benefit of these experiments is that they can use a firm's transactional data. However, these experiments require statistical methods to account for the differences between the treated and untreated subjects.

The team was unanimous that designing a quasi-experiment was the feasible option for them. Accordingly, the team designed the following quasi-experimental field study.

QUASI-EXPERIMENTAL FIELD STUDY

The firm mainly sells its products through physical stores and a website.[1] To understand the effect of the store on the firm's sales, the team decided to use the event of store opening by the firm. The team identified six stores opened by the firm in the year 200X. Data on all customer interactions for four years around 200X, two years prior and two years after 200X, were collected. The distance from the nearest store was computed for each customer using the great-circle distance formula (called *store distance*).[2] As a result of these store openings, the store distance reduced for 17,277 existing customers (called *affected customers*) but remained the same for over 1.5 million remaining customers (called *unaffected customers*). A random sample of 50,000 customers was chosen from a total population of unaffected customers to keep the sample size manageable for the present analysis.

Detailed data about the past purchases and returns on the store and online channels for the selected sample of customers were collected.[3] The data on the age and income category of each customer were also collected. Figure 1 diagrammatically describes the experiment.

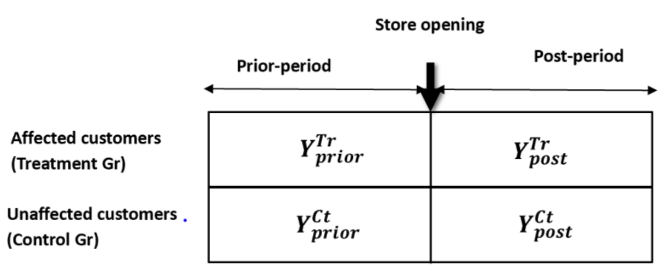

Figure 1: quasi-Experiment

Where Y indicates the outcome variables of interest – the number of purchase interactions, purchase quantity and purchase revenue on the online and store channels.

[1] Store and online sales put together account for roughly 95% of the total sales of the retailer.
[2] Great circle distance formula available at https://en.wikipedia.org/wiki/Great-circle_distance#:~:text=The%20great%2Dcircle%20distance%20or,line%20through%20the%20sphere's%20interior).
[3] The store opening would also result in acquisition of new customers, and hence an additional sales for the firm. However, the present case only estimates the effect of stores on the online purchases of the existing customers.

The data from this experiment is provided in the attached *MS Exel workbook titled "DataFinal."* This workbook has a worksheet titled "Data dictionary" that describes the different variables covered in the data and a worksheet titled "Raw Data" that has the data on those variables.

Kevin and his team explored several options for the treatment effect of store openings on customer online purchases.

OPTION 1 (ATE ON ONLY TREATED CUSTOMERS) – The change in average values of online purchase revenue of affected customers (Y_i) from pre- to post-period.

$$\text{ATE} = \text{Y}^{\text{Tr}}_{\text{post}} - \text{Y}^{\text{Tr}}_{\text{prior}} \quad \text{--(1)}$$

Question 1 (2 points)

Students should compute the ATE from equation (1) and analyze its statistical significance using a t-test. Why is this treatment effect estimate biased?

OPTION 2 (DIFFERENCE-IN-MEANS ATE) – The difference in average values of online purchase revenue of affected customer and unaffected customer in the post store opening period is the treatment effect of stores.

$$\text{ATE} = \text{Y}^{\text{Tr}}_{\text{post}} - \text{Y}^{\text{Ct}}_{\text{post}} \quad \text{--(2)}$$

Question 2 (2 points)

Students should compute the ATE using equation (2) and analyze its statistical significance using a t-test. Why is this treatment effect estimate biased?

OPTION 3 (POST-PERIOD MATCHING ESTIMATOR)

One way to account for differences in characteristics of the two groups of customers is to only consider those control customers who have similar purchase behavior as the treated customers before store opening. The average treatment effect can be computed as the difference in purchase behavior of treated customers from that of their matched control customers.

The main issue in finding matched control customers was the difficulty in matching customers on multiple variables (such as age, income etc.). Kevin learned that different types of functions are available to reduce the multiple variables into a single number. Then the customers can be matched based on this single number. One can use a linear probability model, or the logit probability function, and the matching of customers based on this type of function is called propensity score-based matching.

The propensity score is the probability that a customer (c) is treated, given their socio-demographic characteistics and past purchase variables is computed as $PropScore_c = \frac{e^{\beta X_c}}{1+ e^{\beta X_c}}$ (if using the logit function). Coefficients β are the weights for different variables used in the computation of propensity scores.

The values of coefficients β should be such that the affected customers have propensity score values closer to one (get the treatment of store opening), and the unaffected customers have the propensity score values close to zero. Once the coefficients β are estimated, the propensity scores of each customer c ($PropScore_c$) can be computed. Then, using the propensity scores a matched sample of consumers can be created by matching one control customer to each treatment customer. The idea of matching can be extended by matching multiple control customers to a single treatment customer also. However, we will stick to the use of using a single matched customer.

Question 3 (2 points)

What variables should be included in the computation of propensity scores and Why? Explain.

Question 4 (2 points)

Students should estimate the effect of store opening by finding a matched sample of customers and conducting a t-test to compare online purchase revenue of treated and control customers in the post-period. Why would the estimate of treatment effect be biased in this case?

OPTION 4 (DIFFERENCE-IN-DIFFERENCE OR DID ATE) –

The propensity score matching accounts for the differences in the observed characteristics between the treated and control customers but not their unobserved characteristics. The differences in unobserved characteristics between the two groups of customers can be controlled for by taking the difference in their behavior from pre- to post-period, using a diff-in-diff approach.

Question 5 (2 points)

We cannot use the data in the provided format to run a regression analysis to find the DiD estimator. Explain how the format of the data needs to be changed so that we can run the regression analysis using the DiD estimator.