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RESEARCH NOTE

COMPLEMENTARITY AND CANNIBALIZATION OF OFFLINE-TO-ONLINE TARGETING: A FIELD EXPERIMENT ON OMNICHANNEL COMMERCE[1]

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As the online channel is crucially important, traditional offline retail stores seek to induce their existing consumers to buy online with incentives (i.e., offline-to-online targeting). However, it is debatable whether such targeting is truly effective. While advocates argue that online shopping should complement a firm's store channel, critics counter that doing so may result in cannibalization. Drawing on the channel interplay literature and considering customers' travel costs, we examine whether and how inducing online shopping complements or cannibalizes a firm's offline sales. Using a randomized field experiment on over 11,200 customers of a large department store, we provide causal evidence for both the complementarity and cannibalization effects of online and offline channels. Offline-to-online targeting engenders higher online purchases (as intended) than no targeting. The local average treatment effects models suggest that once induced to buy online, consumers who live near the retailer's physical store tend to increase their offline spending and total sales by 47% (i.e., complementarity effects for nearby consumers). However, for consumers who live far away from the brick-and-mortar store, inducing them to buy online can backfire by reducing offline and total sales by approximately 5.7% for each additional kilometer of distance (i.e., cannibalization effects for distant consumers). Explorations of these mechanisms suggest that distant consumers who are induced to buy online may fail to return to shop in the offline store and purchase less experiential category products with a smaller basket size than other customers, thus leading to a negative net impact on the total sales. These findings alert managers to the dangers of improper targeting and investment in information technology and the importance of consumer heterogeneity for omnichannel commerce across online and offline channels.

Keywords: Omnichannel, online, offline, location distance, mobile promotions

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Introduction

The online channel has been crucially important for traditional offline retail stores since e-commerce transformed the retail landscape in the last decade (Brynjolfsson et al. 2009; Cao et al. 2018; Fang et al. 2014; Hui and Png 2015; Tam and Ho 2005). Recent advances in IT have empowered traditional retailers to integrate their new online sites with their long-established brick-and-mortar stores for omnichannel commerce (Gu and Tayi 2017; Hansen and Sia 2015; Piotrowicz and Cuthbertson 2014). Thus, many store-first retailers such as Walmart, Target, Macy's, and Home Depot leverage their omnichannel IT investments and induce their existing offline consumers to buy online by using incentives (i.e., offline-to-online targeting; Chao 2016; Forrester 2014; Garcia 2018).

However, it is debatable whether such offline-to-online targeting is effective. On the one hand, advocates argue that inducing offline customers to buy online may complement a firm's store channel. This is because as more channels are used to engage customers, the value of these customers increases (Gimpel et al. 2018), and multichannel shoppers are more loyal and spend more than single-channel shoppers (Chao 2016; Garcia 2018). Additionally, other synergies between online and offline channels can stem from having showrooms in the store and allowing customers to buy-online-pick-up-in-store (BOPUS), which improve the shopping experience (Bell et al. 2017; Gallino and Moreno 2014; Gao and Su 2016a, 2016b; Gu and Tayi 2017). Indeed, major retailers have invested in mobile-based loyalty program infrastructure and technologies to target their offline store customers with online incentives in hopes of boosting the overall purchases of consumers (Luo et al. 2014; Luo et al. 2019; Ghose et al. 2013; Ghose et al. 2019).

On the other hand, critics counter that inducing offline customers to buy online can be harmful because of the potential cannibalization of online and offline channels. For traditional retailers that have developed a new online channel, physical space limitations might constrain inventory and discourage store patronage, and BOPUS may not be profitable for products that sell well in stores and for stores that are not cost effective in terms of fulfillment (Gao and Su 2016b; Gu and Tayi 2017; Kumar et al. 2018). There could be significant substitution between offline bookstores and online purchases (Forman et al. 2009). The opening of online channels could even decrease profits for firms because they will be increasingly exposed to competition and excessive returns of products for which "touch and feel" are important for discerning quality (Ofek et al. 2011). Thus, online shopping could cannibalize offline shopping and become detrimental to the retailer's total sales.

Indeed, the tension between the complementarity and cannibalization debate of offline-to-online targeting is ostensively observed in many companies. For example, Nordstrom, a major store-first retailer, has long been at the center of the dispute. Industry analysts frequently point out that when Nordstrom incentivizes its store customers to shop online, these customers end up visiting the store less, so offline-to-online targeting may cannibalize store sales (Stevenson 2016; Tu 2017). Nevertheless, Nordstrom contends that it is not worried about cannibalization and counter argues that the more channels customers engage in with Nordstrom, the better the company should perform (Wischhover 2019). Similar disputes occurred regarding many of the iconic retailers such Macy's, Gap, Kohl's, and J. C. Penney (Boak and D'Innocenzio 2016; Marksjarvis 2016), consistently indicating uncertain payoffs for offline-to-online targeting.

Motivated by this debate, our research investigates whether and how inducing online shopping complements or cannibalizes a firm's offline sales. Drawing on the channel interplay literature and considering customers' travel costs, we examine how offline-to-online targeting influences the online, store and total sales (the sum of online and store sales) of an omnichannel retailer. Specifically, we first test the causal effect of online channel purchases induced by offline-to-online targeting on customers' offline channel spending. Then, we examine the net impact of induced online purchases on firms' overall sales. Finally, we explore the mechanism of how induced online shopping may complement or cannibalize customers' offline purchase activity.

Using a randomized field experiment on over 11,200 customers of a large department store, this study finds causal evidence for both the complementarity and cannibalization of online and offline channels. Specifically, offline-to-online targeting engenders higher online sales as intended than no targeting. However, using a local average treatment effects model (Imbens and Angrist 1994; Sun et al. 2019), we find that once induced to buy online, consumers who live near the retailer's physical store tend to purchase more offline, by 47%, than those who live further away (i.e., complementarity effects for nearby consumers). However, inducing consumers who live far away from the brick-and-mortar store to go online can backfire by reducing offline and total sales. On average, every additional kilometer of distance results in a reduction of 5.7% in total sales as a result of inducing these distant customers to buy online (i.e., cannibalization effects for distant consumers). Further, we reveal this mechanism by examining detailed transaction records. We find that for distant customers, the reduction in total sales due to offline-to-online targeting is driven by consumers making fewer trips to the brick-and-mortar store and purchasing fewer experiential category goods with a smaller basket size. This indicates that online sales can potentially cannibalize store sales, especially among experiential category purchases, by discouraging distant customers from returning to the offline store.

Our study contributes to the literature in several ways. First, *methodologically* speaking, we leverage a novel randomized field experiment setting, the gold standard to identify causal effects and address possible endogeneity and self-selection confounds. Most previous work relied on secondary data with propensity score matching, instrument variables, and natural experiments to infer causal effects (Ansari et al. 2008; Avery et al. 2012; Bell et al. 2017; Brynjolfsson et al. 2009; Langer et al. 2012; Overby and Ransbotham 2019). Therefore, we strengthen prior literature with a rigorous methodology to examine important, practical business problems (Gulati 2007; Vermeulen 2005). Furthermore, from the *substance* perspective, we reveal new insights into the omnichannel commerce literature by identifying both complementarity and cannibalization effects of offline-to-online targeting among different consumer segments. Extending previous research on showrooming and BOPUS (Bell et al. 2017; Gallino and Moreno 2014; Gao and Su 2016a, 2016b; Gu and Tayi 2017), we show that the offline-to-online targeting can create complementary for customers who live close to the store geographically. Also, advancing extant literature on travel costs (Bell et al. 2017; Forman et al. 2009; Ghose et al. 2019), we are among the first to uncover the cannibalization effects for customers who live far away from the brick-and-mortar store. The distant customers induced to buy online may fail to return to shop in the offline store and purchase less experiential category products with a smaller basket size, thus leading to a negative net impact on the total sales. These findings alert managers to the dangers of improper IT investments and potential pitfalls of promoting omnichannel commerce.

Literature Review

Researchers in the IS discipline and other fields broadly examine customers' use of offline and online channels and the interplay between them (Choudhury and Karahanna 2008; Gefen et al. 2003; Granados et al. 2012; Kumar et al. 2018; Kuruzovich et al. 2008; Langer et al. 2012; Yi et al. 2015). For example, Choudhury and Karahanna (2008) propose that the Internet has a multidimensional relative advantage in terms of information searches and transaction costs. Granados et al. (2012) find that the Internet increases both demand and price elasticity. In addition, Kumar et al. (2018) find that store openings increase online purchases by improving customer engagement and reducing the risk of returns. By and large, the prior literature elucidates both the complementarity and cannablization of online and offline channels.

Complementarity of Online and Offline Channels for Nearby Customers

Researchers study the return of IT investments in omnichannel commerce due to the potential complementarity of online and offline channels. IT that facilitates cross-channel promotions would improve total purchases because consumers who shop across multiple channels tend to purchase more and have a higher lifetime value than their single-channel counterparts (Ansari et al. 2008; Neslin and Shankar 2009). This notion has led traditional retailers to venture into the online world and invest considerable IT resources to facilitate online shopping for their traditional offline customers (Sebastian et al. 2017). There are some notable IT-enabled omnichannel practices that leverage these synergies. Examples include physical showrooming (physical locations where customers can view and examine products) with QR codes for online purchases, virtual showrooming (online customers can experience products as if they were in a physical store), pseudo-showrooming (customers experience one product at a physical store and then buy a related product online), and BOPUS (Bell et al. 2017; Gallino and Moreno 2014; Gao and Su 2016a, 2016b; Gu and Tayi 2017). Essentially, these omnichannel practices leverage the advantages of each channel to create complementarity. Showrooming enables online consumers to resolve their uncertainty about the value of products because consumers are allowed to visit the store and inspect and evaluate the product in person (Gu and Tayi 2017). For online-first retailers, physical showrooming is substantially beneficial (Bell et al. 2017). An omnichannel structure also allows consumers to buy online and pick up items in the store, reducing the waiting time of the offline checkout process and enabling the retailer to cross-sell additional items offline (Gallino and Moreno 2014). This is useful for digital customers who are skilled at navigating e-commerce (Hitt and Frei 2002; Koufaris 2002; Pavlou and Fygenson 2006). Furthermore, the online channel has fewer inventory limitations and thus can better support niche products than the offline channel (Brynjolfsson et al. 2009). In addition, the option for seamless offline returns might reduce the risk of online shopping (Kumar et al. 2018), leading to possible synergies between online and offline channels.

We contribute to this literature by proposing that offline-to-online targeting can have complementarity effects for a specific type of consumer: those who live close to the offline store. This is because the travel cost is an important consideration for customers wishing to leverage both online and offline channels (Bell et al. 2017; Forman et al. 2009; Ghose et al. 2019). For example, Forman et al. (2009) find that consumers who live close to a newly opened offline store tend to reduce their online purchasing, implying that proximal customers are more likely to use the offline channel than more distant customers. Ghose et al. (2013) and Luo et al. (2014) show that consumers are more responsive to promotions in stores that are close to their location than consumers who live further away. More recently, Ghose et al. (2019) find that trajectory-based mobile targeting online can improve promotional outcomes for in-store purchases. As a result, nearby customers who are targeted for making online purchases by the use of incentives can benefit from the advantages of online shopping but then easily return to the brick-and-mortar store to enjoy the synergies between online and offline channels due to the low travel cost associated with their distance to store. Thus, we test the following hypothesis:

H1: For offline customers who live near a physical store, online purchases induced by offline-to-online targeting have a positive effect on their offline and total purchases, implying a complementarity effect of offline-to-online targeting.

Cannabalizations of Online and Offline Channels for Distant Customers

However, cannibalization might also occur for firms that engage in offline-to-online targeting. Previous empirical studies caution that opening the online channel may actually reduce overall sales (Ansari et al. 2008). Researchers also assert that BOPUS implementation may not be profitable for products that sell well in stores and for stores that are not cost effective in terms of fulfillment. For traditional retailers with a new online channel, the limited physical space might constrain inventory and hence discourage store patronage (Bell et al. 2017; Gao and Su 2016b). In addition, Ofek et al. (2011) find that adding an online channel may decrease profits due to excessive returns for products for which "touch and feel" are important for determining quality. While consumers might buy more, they may also return more products to the offline store, which will decrease profits. Indeed, opening an online channel could even decrease firm profits because customers may be exposed to more competing brands and better prices from other online merchants (Ofek et al. 2011).

We extend this literature by proposing that cannibalization can occur for certain types of customers: those who live far from the offline store. Online shopping reduces or eliminates travel costs, which can be particularly attractive for customers who live far away from physical stores (Bell et al. 2017; Forman et al. 2009; Luo et al. 2014). However, once online, it is relatively more costly for distant customers to return to the brick-and-mortar store due to their high travel costs (Forman et al. 2009; Ghose et al. 2013). In addition, the online channel generally does not allow customers to touch and feel merchandise that is experiential in nature or products with high quality uncertainty (Chiang and Dholakia 2003; Dinner et al. 2014; Kushwaha and Shankar 2013). In this sense, distant consumers who are induced to buy online by incentives may purchase fewer products in experiential categories with a smaller basket size (Ghose et al. 2019; Hong and Pavlou 2014; Koufaris 2002; Overby and Jap 2009), leading to a net negative impact on their total spending. As such, although offline-to-online targeting motivates offline customers to buy online, because of their high travel costs, distant customers may fail to return to shop in the offline store and purchase fewer experiential category products with a smaller basket size, leading to a potential cannibalization effect of offline-to-online targeting on the retailer's store sales. Thus, we test the following hypothesis:

H2: For offline customers who live far away from a physical store, online purchases induced by offline-to-online targeting have a negative effect on their offline and total purchases, implying a cannibalization effect of offline-to-online targeting.

Randomized Field Experiment and Data

A field experiment is conducted in collaboration with a large department store ("the firm") located in a midsized city in Asia. The firm is one of the largest physical retail outlets in the city, with six-decade history of long-term trust and reputation in the local market. The firm also operates an online retail website that sells products that are also available in the offline store. The firm's offline store is a large complex that spans multiple levels. It has departments selling products in a diverse set of categories such as general merchandise, electronics, household appliances, men's and women's apparel, shoes, jewelry, and cosmetics. This feature allows us to identify different product categories (e.g., experiential or search) in the purchase records. The company executives assured us that the assortment and prices were the same in the offline and online channels at the time of our field experiment. This alleviates concerns regarding the use of different stock keeping units (SKUs) for products sold in the online and offline channels. The firm is interested in leveraging targeted promotions to integrate the physical and digital channels so that its customers can buy both online and offline.

The firm has also invested in a mobile loyalty platform. The firm's customer relationship management includes a unified loyalty member system that is tied to customers' mobile ID for individual identification. This mobile loyalty infrastructure has unique advantages: it can use both online and offline data for the same individuals. For both online and offline purchases, customers can earn reward points that are automatically stored in the mobile loyalty system. Another feature of the mobile loyalty system is that the firm can deliver promotions via mobile short-message services (SMS). Delivering mobile promotions via SMS can be effective because SMS is the second most effective tool behind email for encouraging customers to make purchases in North America.[2] Further, because regulations are less strict in Asia, SMS may surpass email as the most effective promotional method in our setting (i.e., having the highest consumer reach rates and fastest response rates—approximately 90% of SMSs are read within 3 minutes; Andrews et al. 2016; Fang et al. 2015; Luo et al. 2019). Mobile promotions have many other advantages: they are low cost and can be quickly distributed, scaled, and personalized (Danaher et al. 2015; Fong et al. 2015; Lamberton and Stephen 2016; Li et al. 2017; Luo et al. 2014). However, consumers may not see the SMS or may ignore it when they receive it. This is why a randomized experimental design is necessary: if such a risk were to exist, it would be the same across both the treatment and control groups. In this sense, our findings are free from such risk and other confounding aspects such as seasonality, competition, changes in the company's IT investment, or macro economy shocks (randomized experiments are the gold standard for identifying causal effects).

Using mobile promotions, the firm can target offline customers with online promotions (offline-to-online targeting) at the individual level to induce online spending. By using the customers' mobile ID, the firm can send promotions to individual consumers via one-on-one attribution within one channel and across both channels, thus avoiding the contamination or interference of our experimental design. Notably, mobile promotions are automatically applied to loyalty member accounts, thus alleviating selection bias in the usage and redemption of traditional promotions (e.g., Erdem et al. 1999). In other words, mobile promotions are stored in the loyalty system regardless of where the customers are or whether they shop online or offline and are automatically authenticated and redeemed online and offline. This is a unique feature of mobile promotions directly tied to loyalty member accounts used by hybrid retailers. Akin to a grocery store membership, customers provide their phone number and home address and obtain a loyalty member ID through which they can take advantage of in-store or online promotions.

[2]https://www.emarketer.com/Article/Mobile-Email-Most-Likely-Drive-Purchase/1008512.

For our experiment, the company randomly sampled 11,200 shoppers with loyalty memberships. This sample accurately represents the average shoppers of the firm because more than 90% of the firm's customers are loyalty membership card holders. As shown in Table 1, the vast majority of shopper spending is in the traditional offline channel, with small amount of spending and purchase incidences occurring online. Thus, most customers are frequent offline shoppers. The focal company seeks to boost online channel sales by using offline-to-online incentives to target these shoppers. Note that this online and offline sales distribution pattern and the tendency to promote frequent offline shoppers to buy online are common in the retail industry. Traditional retailers such as Walmart, Target, and Macy's attain more than 80% of the total sales from the physical store (Table A1 in the Appendix). So our results would apply to such store-first retailers.

The sampled customers were randomly assigned into treatment and control conditions on January 30, 2015. Customers in the treatment condition received an SMS indicating that he or she would receive 2,000 reward points in their loyalty membership account (worth of 20 RMB) for purchasing any product on the company's web channel. Because consumers spend 576 RMB each offline shopping trip on average, 20 RMB is equivalent to a 3.7% price discount, which represents a moderate level because the firm has a low profit margin and generally avoids giving price discounts that are too high and signal low quality to consumers. Nevertheless, the purchase power of 20 RMB is sufficient because the prices of many items in the department store are below 20 RMB. The promotional incentives were valid for one week before they expired. When customers check out, they input their membership ID, and the incentives are automatically applied to deduct the due amount, owing to the mobile loyalty membership program of the focal omnichannel retailer.

In contrast, customers in the control condition did not receive a promotion. This randomized control condition is used as the baseline to rule out alternative explanations due to seasonality, competition, changes in the company's IT investment, macro economy shocks, and any other confounding issues. If alternative explanations exist, they should be the same across the treatment and control conditions and thus are randomized away in our study. During the time of the field experiment and the subsequent three months, the firms did not have any other promotion targeted at the sample customers. Thus, the customers did not experience more discounts in one channel than the other, and our results are not contaminated by other promotions.

Table 1. Summary Statistics

	Mean	SD	Minimum	Maximum
Pretreatment Online Sales	21.17	320.59	0.00	1932.58
Pretreatment Offline Sales	1153.31	4116.77	0.00	176781.10
Pretreatment Offline Incidence	0.47	0.50	0.00	1.00
Pretreatment Online Incidence	0.06	0.25	0.00	1.00
Offline Sales (month 1)	237.84	1407.62	0.00	100317.10
Offline Sales (month 2)	335.96	1990.64	0.00	90988.00
Offline Sales (month 3)	301.24	1900.95	0.00	89900.00
Total Sales (month 1)	242.35	1410.60	0.00	100317.10
Total Sales (month 2)	479.92	3118.18	0.00	223700.00
Total Sales (month 3)	356.29	2135.47	0.00	89900.00
Induced Online Sales (1 week)	4.15	96.00	0.00	3907.70
Induced Online Incidence (1 week)	0.25	0.43	0.00	1.00
Distance	7.24	15.34	0.00	100.00
Frequent Shopper Type	0.89	0.31	0.00	1.00
Age	32.38	5.04	0.00	85.00

Data, Randomization Check, and Results

We obtained data on all pre- and post-treatment purchases for both the online and offline channels from the unified mobile loyalty member reward system. In our analyses, we have two months of pretreatment data. Because the targeting promotion incentive was valid for one week, we first gauge online sales (consumer spending using the online channel) within the first week as an immediate response to offline-to-online targeting. Additionally, to test any lasting effects, we analyze the data with month 1 (excluding the first week), month 2, and month 3 post-treatment. Given that the inter-purchase time period is approximately two weeks, our month 3 data should be sufficient for evaluating the promotions' delayed effects. Total sales represents the sum of online sales and offline sales (consumer spending in the brick-and-mortar store channel). All sales values here are continuous and measure the sales revenues net the cost of the promotional offer.

Table 1 reports the summary statistics of our data. As shown in Table 1, most of the pretreatment spending is offline (1,153.31) rather than online (21.17). Additionally, in the pretreatment period, shopping incidence occurs more offline (0.52) than online (0.03). This result is expected because the customers are frequent offline shoppers, confirming the face validity of the offline-to-online targeting. The average age of the customers is approximately 32. Further, we use membership information to retrieve data on the customers' home address (required by the firm's membership card registration process) to gauge the distance between their home and the store. Thus, we can calculate a proxy for consumer travel costs by using digital maps. The average travel distance (from the home address to the physical store) is 7.24 km.

Randomization Check

We conduct randomization checks. The results are reported in Table 2. The t-test results suggest that the treatment and control conditions are not significantly different from each other in terms of the subjects' pretreatment online and offline sales and incidences, their age, frequent shopper type, and travel distance (all p >.05). These results suggest that the experimental data passed the randomization checks.

Results for the Complementarity and Cannibalization Effects of Offline Sales

Intent-to-treat effects. We first assess the causal effect of the online promotion treatment on both online and offline sales. In this analysis, we measure the intent-to-treat effect of offering an online promotion to offline customers. Thus, we avoid accounting for customers who choose to go online and compare all customers in the treatment group with those in the control group regardless of their purchase channel. Because our data have exogenous variations due to the randomized field experiment, the modeling analyses are straightforward. However, we do estimate a Tobit model given that there is a

Table 2. Randomized Check

	Treatment (Offline-to-Online Targeting)		Control			
	Mean	SD	Mean	SD	Difference	*p*-value
Age	32.38	5.10	32.39	4.93	-0.01	0.91
Distance	7.29	15.26	7.14	15.51	0.15	0.63
Frequent Shopper Type	0.89	0.31	0.89	0.32	0.01	0.26
Pretreatment Online Sales	21.68	299.26	20.15	359.71	1.53	0.82
Pretreatment Online Incidence	0.06	0.24	0.07	0.26	-0.009	0.07
Pretreatment Offline Sales	1181.87	4649.84	1095.73	2742.46	86.14	0.22
Pretreatment Offline Incidence	0.47	0.50	0.47	0.50	0.01	0.40
N	7486		3714			

zero-inflated distribution in the sales data.[3] Table 3 presents the results of the Tobit regression in which the dependent variable is online sales during the one-week promotional period and offline sales in month 1 (excluding the one-week promotional period), month 2, and month 3. The focal independent variable is the treatment indicator (equal to one if the customer was in the group with the targeted online promotion and zero, otherwise) and its interaction with distance. We also include covariates such as the pretreatment online and offline sales amounts, sales incidence, age, and frequent shopper type. Again, distance measures the geographic distance in kilometers between the customer's home address and the physical store. The first column reports the results where the dependent variable is online sales. Consistent with expectations, we find that the treatment has a significant and positive impact on online sales. The second column reports the impact of the treatment and its interaction with distance on offline sales. The results suggest that the online treatment is effective for increasing online sales but can potentially cannibalize offline sales for distant customers (distance × treatment = -52.7, -25.5, and -31.4 for month 1, month 2, and month 3, respectively). For customers who live near the store, the online treatment complements offline sales (treatment = 517.1, 434.2, and 387.1 for month 1, month 2, and month 3, respectively). Thus, we find evidence for both the complementarity (H1) and cannibalization (H2) effects.

Local average treatment effects (LATE) model. Next, we test the treatment effect for the sample of users who complied with the treatment and made an online purchase. This allows us to assess whether the online purchases induced by the promotion drive our results. We apply the LATE model and leverage the randomized online promotion treatment as an instrument for the induced online purchase incidence (Imbens and Angrist 1994; Sun et al 2019). In this analysis, we run a two-stage least square regression:

First-Stage Models:

$$InducedOnline_i = \gamma_1 \times Treat_i \times Distance_i + \gamma_2 \times Treat_i + \gamma_3 \times Distance_i + \gamma_4 \times X_i + v_i$$

$$InducedOnline_i \times Distance_i = \gamma_5 \times Treat_i \times Distance_i + \gamma_6 \times Treat_i + \gamma_7 \times Distance_i + \gamma_8 \times X_i + \zeta_i$$

Second-Stage Model:

$$y_i = \beta_1 \times InducedOnline_i \times Distance_i + \beta_2 \times InducedOnline_i + \beta_3 \times Distance_i + \delta \times X_i + \varepsilon_i$$

where the second-stage dependent variable is the post-treatment (one, two, and three months after treatment) offline sales revenues net the promotional costs and is a vector of covariates: pretreatment online and offline sales amount, sales incidence, age, and frequent shopper type. Again, *distance* is the geographic distance in kilometers between the customer's home address and the physical store. Additionally, we use two first-stage dependent variables: *induced online purchase incidence* and its interaction with *distance*. In our context, induced online purchase incidence is an indicator variable that is equal to 1 if we observe individual i making a purchase during the one-week post-treatment period (the valid period for the promotion) and 0 otherwise.

In our LATE model, the induced online purchase incidence variable is endogenous and instrumented by the randomized

[3]We also use a two-part model to relax the assumption that the covariates have the same impact on both the decision to buy and the amount of the purchase. The results (see Table A2 in the Appendix) suggest that the impact of the treatment reduces the likelihood that a distant consumer will go to the offline store and make a purchase. The treatment also reduces the number of immediate sales in Month 1 but has no impact on the amount of the purchases, conditional on a purchase being made in months 2 and 3.

Table 3. Intent-to-Treat Effects of Offline Sales

	DV = Online Sales	DV = Offline Sales (Month 1)	DV = Offline Sales (Month 2)	DV = Offline Sales (Month 3)
Model	**Tobit**	**Tobit**	**Tobit**	**Tobit**
Distance ×Treatment	31.780909 (34.071362)	-52.727065*** (9.563770)	-25.462152* (10.192821)	-31.426865** (11.338077)
Treatment	645.054517*** (177.883088)	517.103269*** (139.041062)	434.275766** (166.072957)	387.117743* (172.177726)
Pretreatment Online Sales	0.242575*** (0.068327)	0.747564*** (0.150650)	0.320175+ (0.191918)	-0.410148 (0.329799)
Pretreatment Offline Sales	-0.041785 (0.025766)	0.083937*** (0.011280)	0.125233*** (0.013686)	0.1027885*** (0.014201)
Pretreatment Online Incidence	1018.814918*** (164.508190)	-937.539077* (396.864381)	-47.600097 (455.204622)	151.408607 (492.691668)
Previous Offline Incidence	43.789124 (100.6563988)	32.827355 (121.805366)	-328.466653* (145.920157)	-320.113181* (151.506921)
Age	-16.928758* (8.350699)	-8.032034 11.802328)	24.845699+ 14.041700)	18.574018 (14.391886)
Frequent Shopper Type	-41.08542 (144.039084)	130.926066 (186.449104)	880.685519*** (215.256682)	1590.710717*** (216.405494)
Distance	-32.670713 (33.972668)	2.834067 (6.596309)	0.443705 (7.958665)	-9.039719 (8.598414)
Constant	-2674.526464*** (382.9249)	-4421.304420*** (413.763507)	-6055.398217*** (495.055079)	-6180.394111*** (506.479619)
N	11200	11200	11200	11200
Chi-sq.	143.29	163.75	131.97	144.78

Notes: The baseline is the holdout group. ****p* < 0.001; ***p* < 0.01; **p* _ 0.05; +*p* < 0.10.

promotion treatment (Imbens and Angrist 1994). We also instrument the interaction between induced online purchase incidence × distance using the interaction between the randomized promotion treatment × distance. As a valid instrument, the randomized promotion should be related to online sales. This inclusion rule is satisfied because the treatment with incentives for online purchases significantly increases online purchase, while the control condition has no such incentives. Further, as a valid instrument, the treatment should satisfy the exclusion rule. That is, there is no direct impact of the treatment on the error term associated with offline sales in the second stage. In the promotion treatment, the message mentions that the incentive is only for the online channel and not for offline sales. Additionally, this incentive expired in one week, so we used only the induced online purchase during the first week as the instrument, as in Sun et al. (2019). Further, in our analysis, the offline sales during the first month exclude the offline purchase activity during the first week in which the promotion is valid. We also use two alternative dependent variables: offline sales during the second and third months. These variables exclude the first month and the first two months, respectively, and provide further robustness checks in conditions where awareness is less of a concern due to the time that has elapsed after the initial promotional message. Additionally, our data should satisfy the monotonicity assumption of LATE models: the promotion affects online purchase incidence in a monotone way. This means that consumers in the control group who go online would also have gone online if they received the treatment. In our setting, a consumer who purchased online in the control group would also purchase in the treatment condition because they had more incentives to buy online. A consumer who did not purchase online in the control group might have purchased in the treatment condition, again due to the greater incentives. Thus, our data satisfy the monotonicity condition. We note that the causal results of the LATE model apply to "compliers," who were induced to buy online. This is the exact population of interest for the company for the purpose of evaluating whether offline-to-online targeting can induce online purchase and, conditional on complying, can boost or reduce store purchases and total sales. The LATE model assures that offline sales are causally driven by the induced online purchases due to offline-to-online targeting rather than by any other issues, such as seasonality, competition, changes in the company's IT investment, and macro economy shocks (Imbens and Angrist 1994; Sun et al. 2019).

First-stage results of induced online purchase incidence. We first report the impact of offline-to-online targeting on online purchase incidence and the interaction between online purchase incidence and distance (first stage). The dependent variable for this analysis is online purchase incidence during the one-week post-treatment period (when the promotion deal was valid) and its interaction with distance. Table 4 presents the OLS results. Column 1 reports the first-stage results for the models without the treatment × distance interaction. We find that consumers who received an online promotion were more likely to buy online ($p < .01$), as expected. Specifically, the treatment coefficients are positive and significant (0.620 for online purchase incidence). Thus, traditional offline firms can use promotions to significantly increase the chance that consumers will make online purchases by 62% and induce 13.7% (= 2.962/21.17) more online spending than would occur without these promotions. We note that the coefficient of distance is positive for online purchase incidence ($p < .01$). This indicates that customers who live far away from the store are more likely to shop in the online channel than customers who live near the store, which is consistent with the literature on consumer travel costs (Forman et al. 2009; Ghose et al. 2013). Columns 2 and 3 report the first-stage results for the models with the treatment x distance interaction. We again find that customers who received the treatment are more likely to buy online (estimate on treatment = 0.61) than those who did not receive the treatment. Moreover, the impact of the treatment is stronger for customers who live far away (estimate on treatment × distance = 0.001) than those who live near the store. In addition, treatment x distance is positively related to online purchase incidence x distance (estimate = 0.73).[4]

Second-stage results for the effect of induced online purchase incidence on offline sales. Here, we directly test whether induced online shopping leads to the complementarity or cannibalization of offline sales. Table 5 presents the results. The left three columns use log(offline sales + 1) as the dependent variable to correct for the skewness of the data (see Figure A1 in the Appendix), and the right three columns provide the results for offline sales using a Tobit model with endogenous regressors to correct the left censoring of the sales data at zero. The results for the impact of induced online purchase incidence on offline sales are mixed. For month 1, there is no significant impact ($p > .10$). For month 2, we find a significant and positive impact on log offline sales and a marginal impact on offline sales ($p < .10$). For month 3, we find a marginal, positive impact on log offline sales ($p < .10$). Overall, these results suggest that the induced online purchase incidence seems to play a role in driving offline sales.

The moderating role of distance. To further shed light on the results, we explore the heterogeneous effects of the distance from the consumer's home to the offline store. Because online shopping reduces or eliminates travel costs, it can be particularly attractive for customers who live far away from physical stores (Forman et al. 2009; Ghose et al. 2013). As shown in Table 6, the effect of the interaction between distance and the online promotion treatment on online purchase incidence is significant and positive ($p < .05$). This finding confirms that distant consumers are more likely to be induced by an online promotion to buy online, as expected (Bell et al. 2017; Fang et al. 2015; Forman et al. 2009).

More importantly, the results in Table 6 suggest that across all time periods, there is a significant and negative coefficient for distance × induced online purchase incidence ($p < .01$). This finding suggests that for customers who live far away from the offline store, the induced online purchase incidence can lead to a significant reduction in offline sales. Thus, the LATE model finds causal evidence that the induced online purchasing cannibalizes offline sales. This cannibalization result is robust when we use a Tobit model (the right three columns). We also calculate the effect size. Inducing consumers who live far away from the brick-and-mortar store to buy online can backfire by reducing offline and total sales by approximately 5.7% for each additional kilometer in distance (i.e., cannibalization for distant consumers).

Interestingly, the main effect of induced online purchase incidence is significant and positive ($p < .05$), suggesting that for consumers who live close to the store (e.g., the extreme case of distance = 0), induced online purchase incidence actually increases offline sales. Thus, this result suggests that inducing online shopping can potentially be synergetic and boost offline sales for consumers who live near the store. In terms of the effect size, once nearby consumers have been induced to buy online, they tend to increase their offline spending and total sales by 47% (complementarity for nearby consumers).

[4]The correlation between our treatment instrument and online purchase incidence is 0.6. The correlation between our treatment × distance instrument and online purchase incidence x distance is 0.8. To test the suitability of our IVs, we further run an underidentification test. The Kleibergen and Paap (2006) test statistic is 42.70, indicating we can reject the null hypothesis and the instruments are sufficiently correlated with the endogenous variables. We also applied a weak instruments test based on the Kleibergen–Paap Wald rk F statistic and compared the values with the corresponding critical values compiled by Stock and Yogo (2005). The Kleibergen–Paap rk Wald F statistic is 54.62, rejecting the hypotheses that our instruments are weak.

Table 4. Induced Purchasing by Offline-to-Online Targeting			
	DV = Online Sales Incident	**DV = Online Sales Incident**	**DV = Online Sales Incident × Distance**
Model	**OLS**	**OLS**	**OLS**
Distance × Treatment		0.001602** (0.000517)	0.731448** (0.008066)
Treatment (Targeted Online Promotion)	0.620470*** (0.007974)	0.608940*** (0.0089792)	-0.438221** (0.137281)
Pretreatment Online Sales	0.000007 (0.000013)	0.000007 (0.000013)	0.000093 (0.000200)
Pretreatment Offline Sales	0.000001 (0.000001)	0.000001 (0.000001)	0.000013 (0.000015)
Pretreatment Online Incident	0.023455 (0.024382)	0.023479 (0.024361)	0.172736 (0.380392)
Previous Offline Incident	-0.003511 (0.007852)	-0.004032 (0.007848)	0.023494 (0.122536)
Age	0.000021 (0.000745)	0.000042 (0.000744)	0.014701 (0.011620)
Frequent Shopper Type	-0.005374 (0.012012)	-0.005761 (0.012002)	-0.157804 (0.187413)
Distance	0.000998*** (0.000245)	-0.000061 (0.000420)	-0.000060 (0.006558)
Constant	-0.003333 (0.025366)	0.003835 (0.025450)	-0.478583 (0.397388)
N	11200	11200	11200
R-sq.	0.3521	0.3526	0.6975

Notes: The baseline is the holdout group. ***$p < 0.001$; **$p < 0.01$; *$p < 0.05$; +$p < 0.10$.

Table 5. Impact of Induced Purchase Incident on Offline Sales

Model	DV = Log Offline Sales (Month 1) 2SLS	DV = Log Offline Sales (Month 2) 2SLS	DV = Log Offline Sales (Month 3) 2SLS	DV = Offline Sales (Month 1) TOBIT w/ Endogenous Regressor	DV = Offline Sales (Month 2) TOBIT w/ Endogenous Regressor	DV = Offline Sales (Month 3) TOBIT w/ Endogenous Regressor
Induced Online Incidence	0.042873 (0.03403)	0.074291* (0.036658)	0.066896+ (0.035087)	211.317187 (202.053184)	413.905321+ (242.192455)	(303.847766 (251.660491)
Pretreatment Online Sales	0.000121*** (0.000034)	0.000039 (0.000037)	-0.000049 (0.000035)	0.749956*** (0.149841)	0.316450+ (0.191955)	-0.416918 (0.332229)
Pretreatment Offline Sales	0.00007** (0.000003)	0.000020*** (0.000003)	0.000015*** (0.000003)	0.085013*** (0.011255)	0.125709*** (0.013677)	0.103402*** (0.014198)
Pretreatment Online Incidence	-0.138469* (0.064539)	-0.037181 (0.069557)	0.002592 (0.066576)	-946.606637* (395.462643)	-57.351337 (455.064789)	154.550304 (492.894094)
Pretreatment Offline Incidence	-0.004816 (0.020782)	-0.071329** (0.022398)	-0.053639* (0.021439)	6.051935 (121.248444)	-377.895500* (145.795748)	-323.997410* (151.468230)
Age	-0.002527 (0.001971)	0.004623* (0.002124)	0.002138 (0.002033)	-6.328963 (11.741832)	25.190089+ (14.032441)	18.828970 (14.386842)
Frequent Shopper Type	0.032842 (0.031794)	0.12894** (0.000700)	-0.2313*** (0.033)	111.7464 (185.756)	870.1904*** (215.099)	1587.2784*** (216.343)
Distance	-0.003945*** (0.000649)	-0.001894*** (0.000700)	-0.003251*** (0.000670)	-24.770025*** (4.568975)	-15.868629** (4.952983)	-28.314432*** (5.572863)
Constant	-.538840*** (0.067112)	0.381531*** (0.072330)	0.406564*** (0.069230)	-4232.079094*** (409.522106)	-5946.335161*** (492.258688)	-6062.732789*** (503.922863)
N	11200	11200	11200	11200	11200	11200
R-sq.	0.0085	0.0084	0.0100	NA	NA	NA
Chi-sq.	65.20	90.72	115.93	131.09	129.15	137.42

Notes: The baseline is the holdout group. ***$p < 0.001$; **$p < 0.01$; *$p < 0.05$; +$p < 0.10$.

Table 6. Distance Moderates the Impact of Induced Online Purchase Incidence on Offline Sales

Model	DV = Log Offline Sales (Month 1) 2SLS	DV = Log Offline Sales (Month 2) 2SLS	DV = Log Offline Sales (Month 3) 2SLS	DV = Offline Sales (Month 1) TOBIT w/ Endogenous Regressor	DV = Offline Sales (Month 2) TOBIT w/ Endogenous Regressor	DV = Offline Sales (Month 3) TOBIT w/ Endogenous Regressor
Distance × Induced Online Incidence	-0.008113*** (0.001901)	-0.005711** (0.002052)	-0.005965** (0.001964)	-90.619422*** (14.880447)	-37.116700** (14.214029)	-45.259565** (15.815815)
Induced Online Incidence	0.105975** (0.037558)	0.118706** (0.040545)	0.113287** (0.038817)	728.251086** (224.103751)	681.445131* (267.965828)	606.776745+ (277.801156)
Pretreatment Online Sales	0.000122*** (0.000034)	0.000040 (0.000036)	-0.000049 (0.000035)	0.744520*** (0.149710)	0.316691+ (0.191892)	-0.410371 (0.329032)
Pretreatment Offline Sales	0.000007** (0.000003)	0.000020*** (0.000003)	0.000015*** (0.000003)	0.084305*** (0.011194)	0.125191*** (0.013668)	0.102963*** (0.014197)
Pretreatment Online Incidence	-0.138637* (0.064405)	-0.037299 (0.069527)	0.002468 (0.066565)	-898.311746* (393.233083)	-58.811982 (454.861323)	144.016612 (492.495622)
Pretreatment Offline Incidence	-0.002476 (0.020747)	-0.069682** (0.022397)	-0.051918* (0.021442)	18.607506 (121.098444)	-325.615881* (145.798822)	-317.592681* (151.487893)
Age	-0.002485 (0.001967)	0.004652* (0.002124)	0.002169 (0.002033)	-6.904794 (11.717318)	25.3758 (14.024392)	19.145529 (14.385784)
Frequent Shopper Type	0.033334 (0.031728)	0.126021*** (0.034252)	0.231704*** (0.0327892)	125.746294 (185.333254)	882.756094*** (214.984929)	1586.237455*** (216.376808)
Distance	-0.000086 (0.001111)	0.000822 (0.001199)	-0.000424 (0.001148)	3.002206 (6.516643)	0.486546 (7.952427)	-8.995178 (8.599754)
Constant	0.508619*** (0.067404)	0.360260*** (0.072765)	0.384346*** (0.069664)	-4384.184423*** (411.370104)	-6068.592603*** (495.435234)	-6199.013523*** (507.316741)
N	11200	11200	11200	11200	11200	11200
R-sq.	0.0126	0.0092	0.0104	NA	NA	NA
Chi-sq.	83.30	98.11	124.74	156.00	135.25	143.26

Notes: The baseline is the holdout group. ***$p < 0.001$; **$p < 0.01$; *$p < 0.05$; +$p < 0.10$.

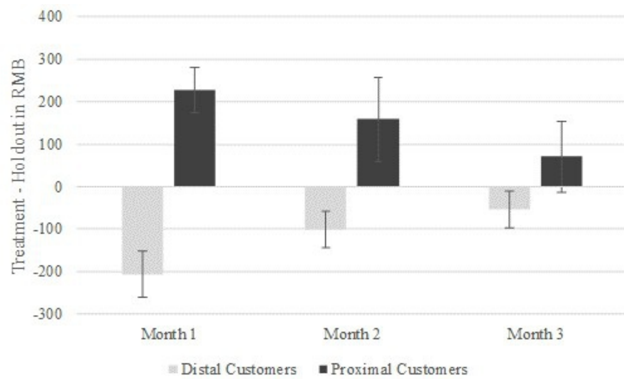

Figure 1. Incremental Offline Sales Revenues by Travel Distance Over Time

Figure 1 provides a visualization of the effects of both complementarity and cannibalization. For customers who live far away from the store by median split, there is a cannibalization effect: the impact on offline sales is negative over time (months 1, 2, and 3) after the treatment. In contrast, for customers who live near the store, there is a complementarity effect: the impact on offline sales is positive over time (month 1, 2, and 3) after the offline-to-online treatment.

Results for total sales. One important consideration for the firm is whether this cannibalization is simply a shift in the purchase channel (from offline to online) or whether it actually reduces total sales. We test for this by including the total sales (=offline + online – promo cost) as our dependent variable in the LATE model. Table 7 reports the results, which suggest that inducing distant customers to buy online can significantly decrease total sales.

Thus, paradoxically, successful online promotions targeting offline customers to buy online can backfire if the customers live far away from the brick-and-mortar store. Managers may also erroneously conclude that this targeting is effective because the impact on online sales is positive; however, the impact on total sales is actually negative.

Overall, these results provide empirical support for not only H1 (for offline customers who live close to a physical store, online purchases induced by offline-to-online targeting have a positive effect on their offline and total purchases, implying a complementarity effect of offline-to-online targeting) but also H2 (for offline customers who live far away from a physical store, online purchases induced by offline-to-online targeting have a negative effect on their offline and total purchases, implying a cannibalization effect of offline-to-online targeting).

Results for the Mechanisms of the Complementary and Cannibalization Effects

Here, we seek to identify the mechanisms by examining detailed transaction records. Because offline sales are made up of several components, trips to the store, basket size per trip, and product categories purchased during the trip, we use these components as the second-stage dependent variables.[5] In this way, we can empirically examine whether the complementarity and cannibalization effects are driven by these components.

***Trips to the offline store*.** Table 8 reports the results of the LATE model using offline channel purchase incidence, that is, whether or not the customers make at least one trip to the physical store (left three columns with Probit models), and the number of trips to the store (right three columns with Poisson models) as the dependent variables. Indeed, we find that distant customers who are induced to buy online are less likely to return to the store to buy during the 1, 2, or 3 months post-treatment periods (most cases $p < .05$). Thus, the cannibalization effect for distant customers (complementarity effect for nearby customers) is indeed driven by a reduction (or increase for nearby customers) in the number of trips the customers make to the store as a result of offline-to-online targeting.

***Basket size per trip to the offline store*.** Table 9 reports the results of the LATE model using the basket size per offline trip as the dependent variable. We find that for distant customers, induced online purchase incidence reduces their basket size per trip ($p < .01$). In other words, for distant customers, the cannibalization effect (complementarity effect for nearby customers) is also driven by the smaller (larger) basket size per trip as a result of the offline-to-online targeting.

[5]We acknowledge one anonymous reviewer for offering this insight.

Table 7. Impact of Induced Online Purchase Incidence on Total Sales

	DV = Log Total Sales (Month 1)	DV = Log Total Sales (Month 2)	DV = Log Total Sales (Month 3)	DV = Total Sales (Month 1)	DV = Total Sales (Month 2)	DV = Total Sales (Month 3)
Model	**2SLS**	**2SLS**	**2SLS**	**TOBIT w/ Endogenous Regressor**	**TOBIT w/ Endogenous Regressor**	**TOBIT w/ Endogenous Regressor**
Distance × Induced Online Incidence	-0.007767*** (0.001918)	-0.007909*** (0.002303)	-0.006587** (0.002103)	-75.246368*** (13.294734)	-51.475483** (16.755291)	-40.593803** (15.017960)
Induced Online Incidence	0.129256*** (0.037897)	0.138376** (0.045503)	0.130805** (0.041559)	807.991058*** (216.387681)	853.7219** (324.813634)	553.963936* (266.747480)
Pretreatment Online Sales	0.000219*** (0.000034)	0.000034 (0.000041)	-0.000055 (0.000037)	0.853694*** (0.138785)	0.333388 (0.247769)	-0.480510 (0.346393)
Pretreatment Offline Sales	0.000006* (0.000003)	0000017*** (0.000003)	0.000015*** (0.000003)	0.082688*** (0.010879)	0.121466*** (0.017651)	0.10638*** (0.014126)
Pretreatment Online Incidence	-0.066891 (0.064986)	-0.010590 (0.078030)	-0.052900 (0.071266)	-251.748072 (353.955949)	32.126141 (546.777222)	-167.295283 (486.463038)
Pretreatment Offline Incidence	-0.003675 (0.020934)	-0.040363 (0.025136)	-0.047359* (0.022957)	7.201602 (116.901006)	-266.346820 (176.801901)	-282.662523+ (145.601085)
Age	-0.002975 (0.001985)	0.006260** (0.002383)	0.001567 (0.002177)	-10.090626 (11.275453)	27.305715 (17.027522)	10.892111 (13.830573)
Frequent Shopper Type	0.030155 (0.032015)	0.195192*** (0.038441)	0.256291*** (0.035109)	112.204496 (178.779236)	1484.500950*** (260.071033)	1711.023544*** (208.877522)
Distance	-0.000176 (0.001121)	0.002404+ (0.001346)	-0.000446 (0.001229)	2.751328 (6.338679)	9.786831 (9.414556)	-9.8460 (8.2476)
Constant	0.527051*** (0.068012)	0.454031*** (0.081664)	0.492027*** (0.074585)	-4150.180088*** (395.443278)	-6737.852984*** (595.786164)	-5406.618061*** (484.412336)
N	11200	11200	11200	11200	11200	11200
R-sq.	0.0168	0.0081	0.0115	NA	NA	NA
Chi-sq.	112.02	84.02	126.38	175.10	105.94	158.68

Notes: The baseline is the holdout group. ***$p < 0.001$; **$p < 0.01$; *$p < 0.05$; +$p < 0.10$.

Table 8. Impact of Induced Online Purchase Incidence on Trips to the Offline Store

	DV = Offline Sales Incident (Month 1)	DV = Offline Sales Incident (Month 2)	DV = Offline Sales Incident (Month 3)	DV = Number of Trips to Store (Month 1)	DV = Number of Trips to Store (Month 2)	DV = Number of Trips to Store (Month 3)
Model	**PROBIT w/ Endogenous Regressor**	**PROBIT w/ Endogenous Regressor**	**PROBIT w/ Endogenous Regressor**	**POISSON w/ Endogenous Regressor**	**POISSON w/ Endogenous Regressor**	**POISSON w/ Endogenous Regressor**
Distance × Induced Online Incidence	-0.017873*** (0.003521)	-0.005481* (0.002687)	-0.007383* (0.002929)	-0.010275* (0.004941)	-0.007068+ (0.003646)	-0.010302* (0.004601)
Induced Online Incidence	0.071799 (0.054649)	0.083026 (0.051781)	0.096438+ (0.052931)	0.060473 (0.074226)	0.114139 (0.069949)	0.243390*** (0.067286)
Pretreatment Online Sales	0.000096* (0.000047)	0.000043 (0.000042)	-0.000043 (0.000058)	0.000098*** (0.000025)	0.000031 (0.000032)	-0.000101 (0.000067)
Pretreatment Offline Sales	0.000002 (0.000003)	0.000015*** (0.000003)	0.000010** (0.000003)	-0.000008 (0.000009)	0.000006** (0.000002)	0.000006** (0.0000002)
Pretreatment Online Incidence	-0.142071 (0.096901)	-0.018947 (0.089043)	-0.020603 (0.094238)	0.006597 (0.118293)	-0.034974 (0.123710)	0.008556 (0.130543)
Pretreatment Offline Incidence	0.006592 (0.029903)	-0.083888** (0.028588)	-0.065751* (0.029163)	0.027277 (0.043936)	-0.031112 (0.038959)	-0.097455* (0.038496)
Age	-0.001312 (0.002870)	0.006219* (0.002716)	0.000628 (0.002761)	0.008648* (0.003635)	0.010422** (0.003563)	0.007435* (0.003513)
Frequent Shopper Type	0.023632 (0.045629)	0.147428*** (0.042125)	0.232440*** (0.043193)	0.094804 (0.057966)	0.276550*** (0.058937)	0.116062* (0.053558)
Distance	-0.000305 (0.001603)	0.000543 (0.001523)	-0.001473 (0.001623)	0.001552 (0.002184)	0.002529 (0.001695)	0.001448 (0.002303)
Constant	-0.955683*** (0.098827)	-1.0815*** (0.0934)	-0.969012*** (0.094615)	-1.452370*** (0.123747)	-1.580646*** (0.122239)	-1.421064*** (0.119658)
N	11200	11200	11200	11200	11200	11200
Chi-sq.	51.90	53.44	71.02	NA	NA	NA

Notes: The baseline is the holdout group. ***$p < 0.001$; **$p < 0.01$; *$p < 0.05$; +$p < 0.10$.

Table 9. Impact of Induced Online Purchase Incidence on Basket Size per Trip to the Offline Store

Model	DV = Log Per Trip Basket Size (Month 1) 2SLS	DV = Log Per Trip Basket Size (Month 2) 2SLS	DV = Log Per Trip Basket Size (Month 3) 2SLS	DV = Per Trip Basket Size (Month 1) TOBIT w/ Endogenous Regressor	DV = Per Trip Basket Size (Month 2) TOBIT w/ Endogenous Regressor	DV = Per Trip Basket Size (Month 3) TOBIT w/ Endogenous Regressor
Distance × Induced Online Incidence	-0.008014*** (0.001883)	-0.005791** (0.002036)	-0.005901** (0.001951)	-89.180484*** (14.611985)	-37.328259** (14.091657)	-44.560872** (15.658800)
Induced Online Incidence	0.105223** (0.037217)	0.120790** (0.040226)	0.111779** (0.038552)	711.439070** (219.660516)	695.247384** (265.835975)	599.777729* (274.838850)
Pretreatment Online Sales	0.000123*** (0.000033)	0.000039 (0.000036)	-0.000048 (0.000035)	0.744642*** (0.146611)	0.314629+ (0.190175)	-0.408436 (0.325347)
Pretreatment Offline Sales	0.000007** (0.000002)	0.000020*** (0.000003)	0.000015*** (0.000003)	0.084628*** (0.010953)	0.124986*** (0.013548)	0.102888*** (0.014036)
Pretreatment Online Incidence	-0.139234* (0.063821)	-0.034534 (0.068980)	0.004380 (0.066111)	-913.478063* (386.281435)	-45.893804 (450.878486)	161.722338 (486.939410)
Pretreatment Offline Incidence	-0.003778 (0.020559)	-0.069016** (0.0022221)	-0.052811* (0.021296)	6.601908 (118.694151)	-318.524112* (144.612193)	-324.852523* (149.973079)
Age	-0.002576 (0.001949)	0.004456* (0.002107)	0.002009 (0.002019)	-6.909997 (11.48568.3)	24.118273+ (13.910364)	19.105312 (14.231933)
Frequent Shopper Type	0.033242 (0.031441)	0.121937*** (0.033982)	0.229606*** (0.032569)	128.708667 (181.610200)	871.763440*** (213.247004)	1558.662109**** (214.100064)
Distance	-0.000086 (0.001101)	0.000868 (0.001190)	-0.000439 (0.001140)	3.059771 (6.384335)	0.869228 (7.881923)	-9.147223 (8.515237)
Constant	0.507106*** (0.066795)	0.360380*** (0.072193)	0.386755*** (0.069189)	-4296.032272*** (403.169260)	-6006.851436*** (491.346851)	-6138.579900*** (501.852571)
N	11200	11200	11200	11200	11200	11200
Chi-sq.	84.04	99.04	125.09	160.46	136.34	143.94

Notes: The baseline is the holdout group. ***$p < 0.001$; **$p < 0.01$; *$p < 0.05$; +$p < 0.10$.

Product categories purchased during the offline trips. Here, we test whether the complementarity and cannibalization effects are driven by product categories purchased during offline purchasing trips. The literature suggests that products that are experiential in nature and products with high quality uncertainty have relative advantages in the offline (versus online) channel because consumers are able to "touch and feel" the merchandise (Chiang and Dholakia 2003; Dinner et al. 2014; Hong and Pavlou 2014; Koufaris 2002; Kushwaha and Shankar 2013; Overby and Jap 2009). Following Chiang and Dholakia (2003) and Kushwaha and Shankar (2013), we classify each product as either an experiential or non-experiential (or search) product. In the context of our research, experiential products require the customers to see, inspect and touch the product before its quality and fit can be ascertained (Avery et al. 2012; Wright and Lynch 1995). Examples of experiential products include adult clothing, cosmetics, and groceries. In contrast, search products are those with observable attributes that do not require that the customer physically touch the product (Huang et al. 2009; Neslin et al. 2014). Examples of search attributes include price, color, shape, dimensions, and other standard product specifications.[6] The LATE model results shown in Table 10 suggest that the negative impact of induced online purchases is much stronger for experiential products ($p < .01$) than for products with search attributes. In other words, the cannibalization effect for distant customers (complementarity effect for nearby customers) is also driven by whether the customers make less (or more for nearby customer) experiential category purchases rather than search category purchases as a result of offline-to-online targeting. Figure 2 provides a visualization of the change in the distribution of product categories in the

[6] We also test the robustness of our categorization by using categories coded by actual department store customers. We recruited twelve independent research assistants from the company (who are also regular loyalty card members of the firm) to rate each of the 529 subproduct categories with search/experiential attributes using a seven-point scale. The inter-rater reliability is 0.937 for the search attributes and 0.915 for the experiential attributes; both are within acceptable levels. We then classify the search or experience product category based on the higher scores of the rated search or experience attributes. For more than 96% of the cases, a search (experience) product indeed has a much higher search (experience) attribute scores, as expected. We resolved the rest of the cases by having discussions with the raters. The results of this alternative categorization are consistent with our main results.

Table 10. Impact of Induced Online Purchase Incidence on Experiential Product Category Purchases during the Offline Trips

	DV = Log Experiential Product Sales (Month 1)	DV = Experiential Product Sales (Month 1)	DV = Log Non-Experiential Product Sales (Month 2)	DV = Non-Experiential Product Sales (Month 3)
Model	**2SLS**	**TOBIT w/ Endogenous Regressor**	**2SLS**	**TOBIT w/ Endogenous Regressor**
Distance × Induced Online Incidence	-0.017390*** (0.004049)	-75.619062*** (13.524496)	-0.004965 (0.003089)	-11.881237* (4.839603)
Induced Online Incidence	0.312222*** (0.080009)	841.195401*** (217.690749)	0.031627 (0.061042)	10.422600 (77.700475)
Pretreatment Online Sales	0.000486*** (0.000072)	0.829993*** (0.136719)	0.000209*** (0.000055)	0.143607** (0.048480)
Pretreatment Offline Sales	0.000015** (0.000005)	0.081864*** (0.010661)	0.000004 (0.000004)	0.006289 (0.0040786)
Pretreatment Online Incidence	-0.100055 (0.137201)	-159.491681 (351.460976)	-0.232473* (0.104676)	-264.945390+ (144.808516)
Pretreatment Offline Incidence	-0.004542 (0.044197)	18.791886 (117.292334)	0.007539 (0.033719)	8.711083 (42.605746)
Age	-0.007854+ (0.004190)	-13.7073443 (11.308507)	0.000430 (0.003197)	1.362044 (4.154284)
Frequent Shopper Type	0.070706 (0.067591)	115.258565 (179.298080)	-0.039456 (0.051568)	-46.499334 (67.080528)
Distance	-0.000396 (0.002367)	2.559763 (6.406196)	-0.002682 (0.001806)	-3.281460 (2.487219)
Constant	1.084605*** (0.143591)	-4221.301842*** (396.531880)	0.531858*** (0.109551)	-1693.649180*** (151.399935)
N	11200	11200	11200	11200
R-sq.	0.0190	NA	0.0040	NA
Chi-sq.	118.33	167.22	42.55	38.46

Notes: The baseline is the holdout group. ***$p < 0.001$; **$p < 0.01$; *$p < 0.05$; +$p < 0.10$.

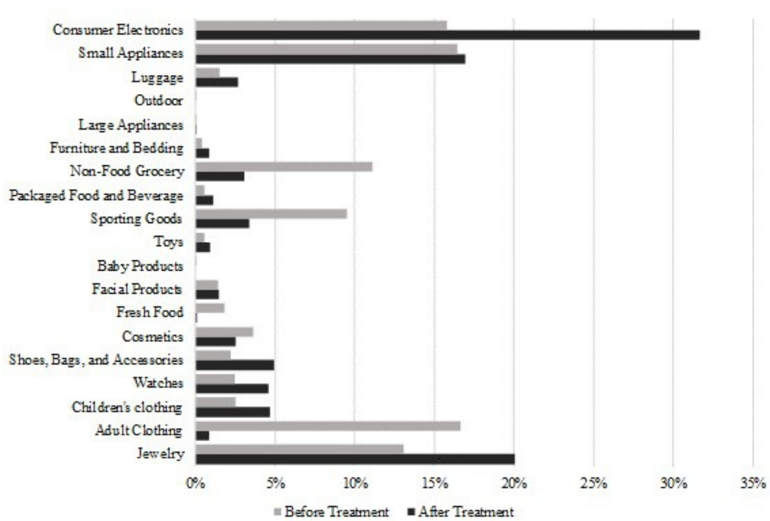

Figure 2. Distribution of Product Categories in the Store Shopping Baskets of Distant Customers

shopping basket for distant consumers before and after the promotion treatment. These results show that distant customers purchase fewer experiential category products (e.g., adult clothing, grocery, and hot foods) and more search category products (e.g., consumer electronics) after offline-to-online targeting than before it, providing more evidence for our main results.

Indeed, the cannibalization that occurs for distant customers makes sense because once distant consumers buy online, they are less likely to return to the physical store due to their high travel costs, leading to fewer experiential purchases offline (experiential purchases often occur in the offline channel due to the difficulty in confirming the quality and fit of experiential products in the online environment). Additionally, the complementarity that occurs for proximal customers is also reasonable because the store can act as a showroom and affirm the quality and fit for nearby consumers who might start the purchase journey online but can easily return to the store to touch and feel the experiential product before completing the purchase.

Additional Results

Alternative explanation for the awareness effects of the promotion. In this section, we test a potential alternative mechanism. One may argue that the promotion might, in addition to providing a discount to buy online, serve as a reminder for all customers and increase offline purchases. However, our LATE results show a decrease, rather than an increase, in total purchases for distant customers after the promotion treatment, suggesting that our estimates are conservative. We further test the effects by using an alternative model that directly assesses the impact of the online promotion treatment on offline sales. If it were the case that the promotion acted as a reminder and increased the awareness of consumers, then we would find an increase in offline sales incidence for customers receiving the treatment. Table A3 in the Appendix reports the results of the Probit model, which suggest that offline sales incidence has a nonsignificant impact ($p > .10$) on average and a negative impact on customers who live far away from the store ($p < .01$ for month 1). Thus, these findings are in direct contrast to the awareness-based alternative explanation.

Alternative sample of customers. In the main results above, we use frequent offline shoppers. Now, we limit the sample to customers who *only* shop offline (no prior online purchases). This sample of customers is more likely to have robust and lasting effects than the sample with all customers because this will be their first time to buy online as a result of offline-to-online promotion incentives.[7] The LATE results consistently provide causal evidence for both the complementarity and cannibalization of the online and offline channels (Tables A4, A5, and A6 in the Appendix) and the mechanisms with respect to trips to the store, basket size per trip, and product categories purchased during the trip (Tables A7, A8, and A9 in the Appendix). Again, once induced to buy online with the promotion, consumers who live near the retailer's physical store tend to make more offline purchases. However, inducing consumers who live far away from the brick-and-mortar store to purchase online can reduce offline and total sales. Thus, these additional results corroborate our main findings.

Difference-in-differences modeling. Finally, we use differences to control for unobserved time constant fixed effects. Specifically, we estimate a model in which the dependent variable is the difference in offline sales, online sales, or total sales between the month pre- and post-treatment:

$$y_{i,t} - y_{i,t-1} = \beta_1 \times Treatment_i \times Distance_i + \beta_2 \times Treatment_i + \beta_3 \times Distance_i + \varepsilon_i$$

With this specification, the time-invariant variables drop from the equation, allowing us to control for these unobservable factors. Table A10 in the Appendix reports the results, which are consistent with our main findings. Specifically, we find a negative coefficient for distance x treatment on the change in offline and total sales, indicating that distant customers who receive the online treatment buy less. Distance × treatment did not impact the change in online sales, although the main effect of the treatment has a marginal positive impact on the change in online sales.

Conclusion

Since the online channel is crucially important, traditional offline retail stores tend to induce their existing consumers to buy online. We conduct a randomized field experiment on over 11,200 customers of a large department store and provide causal evidence for both the complementarity and cannibalization effects of online and offline channels. The key findings of this study are as follows:

- Offline-to-online targeting leads to higher online purchase incidence and spending (as intended) than no targeting.

[7]We acknowledge one anonymous reviewer for offering this insight.

- The results of the LATE models suggest that once induced to buy online, consumers who live near the retailer's physical store tend to increase their offline spending and total sales by 47% (complementarity for nearby consumers).

- Inducing consumers who live far away from the brick-and-mortar store to buy online can backfire by reducing offline and total sales by approximately 5.7% for each additional kilometer in distance (cannibalization for distant consumers).

- The analysis of the mechanisms suggests that distant consumers who are induced to buy online may fail to return to shop in the offline store and purchase fewer experiential category products with a smaller basket size, leading to a negative net impact on total sales.

Theoretical Implications

Our study makes several contributions to the literature. First, the results reflect a novel phenomenon of offline-to-online targeting, contributing to the omnichannel literature. A large body of the e-commerce literature focuses solely on online channels (Chiu et al. 2014; Fang et al. 2014). This study demonstrates that it is crucial to recognize the new trend of omnichannel commerce, as focusing only on the online channel and neglecting the interplay between the online and offline channels can substantially limit outcomes (Gu and Tayi 2017; Piotrowicz and Cuthbertson 2014). While some studies consider potential channel synergies such as showrooming and BOPUS (Bell et al. 2017; Gallino and Moreno 2014; Gao and Su 2016a, 2016b; Gu and Tayi 2017), our findings provide evidence of a cannibalization effect for customers who live far away from the physical store. This negative cannibalizing effect is nontrivial for several reasons. First, this study suggests that, paradoxically, successful online promotions that induce offline customers to buy online can backfire if customers live far from the store. One may erroneously conclude that this type of targeting is effective because the impact on online sales is positive; however, the impact on total sales is actually negative. In other words, counterintuitively, despite noble intentions and an increase in online sales as intended, offline-to-online targeting significantly reduces total sales for distant customers compared to that of no targeting, thus wasting omnichannel budgets. While online commerce has received the lion's share of attention and motivated traditional retailers to nurture customer relationships on the web, it is dangerous to ignore the impact of online sales on offline sales and customer heterogeneity in terms of travel costs. Second, it is important to design effective IT targeting strategies. Many omnichannel firms are making IT investments that enable them to make channel-specific targeting decisions in the hopes of achieving higher returns. However, retailers may fail to reap value from their IT investments and become worse off by targeting the wrong segment (i.e., use offline-to-online promotions to target distant customers).

Furthermore, our identification of the complementarity and cannibalization of online and offline channels is causal based on our randomized field experiment and LATE model (Imbens and Angrist 1994; Sun et al 2019). This study extends the vast majority of the literature and uses observational data to infer the causal effects. Methodologically speaking, estimates with observational data lacking exogenous variations may be biased because of possible endogeneity and self-selection confounds. Thus, it is crucial to leverage randomized field experimental data and the LATE model to identify the causal effects of the induced online purchases on offline sales in a nonbiased manner (Ghose et al. 2019; Sun et al. 2019).

Moreover, this study provides some insights into the underlying mechanisms of complementarity and cannibalization effects. Extant research generally concentrates on channel attributes and focuses less on customer heterogeneity such as travel distance, although consumer travel costs are fundamentally embedded in the interplay between online and offline channels (Bell et al. 2017; Chintagunta et al. 2012; Dube et al. 2017; Forman et al. 2009). We demonstrate that although consumers who live far away from physical stores can be induced to buy online, they may fail to return to shop in the offline store and purchase fewer products in experiential product categories with a smaller basket size, thus resulting in a net negative impact on total sales revenues.

Practical Implications

Our findings offer useful implications for managers. In omnichannel commerce, customers may make both online and offline purchases from the same company. However, companies that invest in omnichannel commerce should not simply assume that offline-to-online targeting is universally effective. Indeed, because of the complementarity effect of offline-to-online targeting for nearby customers, a payoff strategy hybrid retailers can use is to coax nearby customers to buy online. However, we caution managers that offline-to-online targeting might have varying effects. Since targeting distant offline customers for online shopping can have a negative impact, managers should note the caveat of this targeting, especially when promoting products in experiential categories that require consumers to physically see, touch, or inspect the products in a traditional store (Chao 2016; eMarketers 2016; Garcia 2018). We also recommend that managers conduct randomized field experiments and leverage mobile targeting IT for precise omnichannel attribution with causal effects.

Indeed, as companies implement IT strategies to drive omnichannel commerce, there is an urgent need for efforts that involve testing the sales impact of promoting the online channel to offline shoppers. Although offline-to-online targeting appears to be a common industry practice, our findings regarding its positive and negative effects should alert managers that they should prudently consider consumer heterogeneity and design more sophisticated targeting strategies to boost total sales revenues in omnichannel commerce.

Limitations and Future Research

Our work has several limitations, which are avenues for future research. First, our study focuses on net sales revenue rather than the profitability of one retailer. While one might expect that the online channel may be associated with lower cost of delivering the product, in practice for a hybrid company, shifting sales to the online channel does not necessarily lead to significantly lower costs at the firm level because much of the cost associated with the physical store is fixed, and there are additional costs associated with processing an online order (e.g., picking, packing, and shipping).[8] Given this cost structure, increasing sales revenues should indicate increased profits. While we believe that our findings could apply to most department stores, we caution against over generalization to all omnichannel settings. Future research can extend our study and examine other companies that can substantially reduce their cost structure by funneling consumers from the offline channel to the online channel (i.e., a bank trying to migrate its customers from branches to online banking for the cost-saving benefits of online operations).

Additionally, our study is limited to mobile loyalty card holders and existing customers who are primarily offline customers (approximately 90% of the customers). Many omnichannel strategies focus on attracting new customers to avoid cannibalization. Simply allowing the existing customers to shift between channels does not tell the whole story, and on many occasions, may not be the best strategy. Hence, future research could investigate how firms can target new customers who have never made online or offline purchases or existing customers who are not loyalty card members.

Moreover, we do not examine how to make online shopping more experiential with more cross-selling opportunities via new IT such as virtual reality, endless shopping aisles, smart shelves, and smart dressing rooms. Thus, future works could address the effectiveness of these IT technologies.

Finally, we focus only on offline-to-online targeting. Future research can examine the reversed direction with online-to-offline targeting. However, studies directly comparing these two types of targeting should be careful because different stores may have different types of customers. Digital-first retailers such as Amazon or Warby Parker have begun to open their own physical stores and promote offline sales (online-to-offline targeting), which may affirm the strategic importance of the in-store shopping experience for total sales. Thus, it would be fruitful for future works to examine different omnichannel settings and different promotional incentives.

Conclusion

In conclusion, this study is among the first to use a unique randomized field experiment in omnichannel commerce research to scientifically identify causal effects and account for endogeneity and self-selection confounds. It also contributes to the literature by adding new insights with complementarity and cannibalization effects of offline-to-online targeting. Omnichannel commerce is the future of retailing, and the future is here. Our study reveals that omnichannel retailers should be cautious when targeting distal customers due to potential cannibalization effects that might reduce the total sales revenues. We hope our research can stimulate more field experiments on the important topic of omnichannel commerce.

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[8]An online-only retailer might have a lower cost structure than an offline only retailer given the lack of its brick-and-mortar presence. However, an omnichannel retailer with a brick-and-mortar location may not be able to reduce a significant amount of its cost unless it closes the offline store (the firm did not reduce staffing cost as a result of increasing online revenues). In our context, the firm has one large department store. Thus, its closure is not in consideration. Also, the focal firm affirmed that they do not differentiate costs between online and offline but rather consider a sale in either channel to be an omnichannel sale and combine the costs of both channels. This concept is consistent with other omnichannel retailers such as Macy's, who does not distinguish whether consumers made online or offline purchases but rather recognize that both channels are valuable touchpoints for generating sales.

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Appendix

Table A1. Distribution of Online and Offline Sales for Top Store-First Retailers (% of Total Sales)

	Online Sales	Offline Sales
Wal-Mart	3%	97%
Costco	3%	97%
Target	3%	97%
Best Buy	9%	91%
Kohl's	12%	88%
Gap Inc.	15%	85%
L Brands	15%	85%
Macy's	17%	83%
Nordstrom	19%	81%

Source: eMarketer (2015).

Table A2. Two-Part Model to Estimate Treatment Effects on Sales Incident and Amount

	DV = Online Sales		DV = Offline Sales (Month 1)		DV = Offline Sales (Month 2)		DV = Offline Sales (Month 3)	
Model	**Logit (Sales Incident)**	**GLM (Sales Amount)**	**Logit (Sales Incidence)**	**GLM (Sales Amount)**	**Logit (Sales Incidence)**	**GLM (Sales Amount)**	**Logit (Sales Incidence)**	**GLM (Sales Amount)**
Distance × Induced Online Incidence	0.078633 (0.082484)	-3.945176 (54.352889)	**-0.02188***** (0.004456)	**-35.42193**** (12.195902)	**-0.007585*** (0.003437)	-17.556395 (13.016102)	**-0.011721**** (0.004040)	-5.736279 (15.045432)
Treatment	**1.57207***** (0427074)	**3.174298** (287.344170)	**0.188154**** (0.060513)	**450.47490**** (166.373851)	**0.145881**** (0.056241)	**144.887315** (208.623654)	**0.173666**** (0.058585)	**-167.123701** (217.997822)
Pretreatment Online Sales	0.000387** (0.000137)	0.140953* (0.065262)	0.000148* (0.000075)	0.459119*** (0.126450)	0.000065 (0.000072)	0.240746 (0.208963)	-0.000089 (0.00011)	-0.384124 (0.546925)
Pretreatment Offline Sales	-0.000076 (0.000056)	-0.036897 (0.031304)	0.000004 (0.000006)	0.161876*** (0.012302)	0.000027*** (0.000007)	0.114008*** (0.013478)	0.000015** (0.000006)	0.111754*** (0.014458)
Pretreatment Online Incidence	2.251881*** (0.279882)	19.457063 (184.913439)	-0.230793 (0.174031)	-882.793977+ (470.225747)	-0.042241 (0.156674)	241.601004 (578.966452)	0.001242 (0.167645)	327.324273 (663.301433)
Pretreatment Offline Incidence	0.114547 (0.237026)	62.990776 (158.929028	-0.001235 (0.053132	211.825563 (145.295050)	-0.141547** (0.050776)	127.006308 (181.094152)	-0.111334* (0.051525	26.579239 (189.974526)
Age	-0.039035* (0.018565)	-3.692296 (12.164774)	-0.003737 (0.005064)	-1.491947 (14.739805)	0.009347* (0.004710)	3.845302 (17.940257)	0.002364 (0.004882)	34.32714+ (17.885506)
Frequent Shopper Type	0.040460 (0.324547)	-207.213369 (211.788162)	0.055780 (0.080586)	6.476551 (221.355037)	0.231528** (0.072211)	668.452437* (260.885777)	0.403936*** (0.072139)	1344.8008*** (261.414609)
Distance	-0.082476 (0.082206)	6.33763 (54.262162)	-0.000577 (0.002937)	9.673253 (8.010321)	0.000929 (0.002671)	-5.383550 (9.918506)	-0.002747 (0.003009)	-7.122670 (10.863425)
Constant	-4.919954*** (0.717018)	403.594576 (468.104738)	-1.546855*** (0.173020)	936.462790+ (508.550064)	-1.757779*** (0.161924)	1241.387002* (626.371606)	-1.653268*** (0.167431)	370.678935 (618.769566)
N	11200	11200	11200	11200	11200	11200	11200	11200

Notes: The baseline is the holdout group. ****p* < 0.001; ***p* < 0.01; **p* < 0.05; +*p* < 0.10.

Table A3. Direct Effect of the Offline-to-Online Treatment on the Offline Sales Incidence

	DV = Offline Sales Incident (Month 1)	DV = Offline Sales Incident (Month 2)	DV = Offline Sales Incident (Month 3)
Model	**PROBIT**	**PROBIT**	**PROBIT**
Distance × Induced Online Incidence	**-0.010047***** (0.002257)	**-0.003773+** (0.001926)	**-0.005214*** (0.002108)
Treatment (Online Promotion)	0.047751 (0.033601)	0.052600 (0.032069)	0.061955+ (0.032853)
Pretreatment Online Sales	0.000096* (0.000047)	0.000044 (0.000042	-0.000043 (0.000058)
Pretreatment Offline Sales	0.000002 (0.000003)	0.000015*** (0.000003)	0.000009** (0.000003)
Pretreatment Online Incidence	-0.149720 (0.097054)	-0.017884 (0.089027)	-0.019292 (0.094267)
Pretreatment Offline Incidence	0.008845 (0.029851)	-0.084448** (0.028583)	-0.066496* (0.029173)
Age	-0.001442 (0.002870)	0.006152* (0.002716)	0.000520 (0.002762)
Frequent Shopper Type	0.024582 (0.045574)	0.147637*** (0.042128)	0.233272*** (0.042213)
Distance	-0.000322 (0.001607)	0.000538 (0.001522)	-0.001480 (0.001622)
Constant	-0.956785*** (0.098179)	-1.079021*** (0.093355)	-0.965965*** (0.094651)
N	11200	11200	11200
Chi-sq.	59.88	55.44	73.61

Notes: The baseline is the holdout group. ****p* < 0.001; ***p* < 0.01; **p* < 0.05; +*p* < 0.10.

Table A4. Induced Online Purchasing by Offline-to-Online Targeting (Offline Only Customers)

	DV = Online Sales Incidence	DV = Log Online Sales	DV = Online Sales
Model	**OLS**	**2SLS**	**TOBIT**
Treatment (Targeted Online Promotion)	**0.619130****** (0.009592)	**0.019270****** (0.005021)	**805.115692****** (192.630929)
Distance	0.001043*** (0.000255)	0.000029 (0.000134)	-2.070645 (3.259590)
Constant	-0.000565 (0.030494)	0.031175* (0.015963)	-2855.176191*** (452.018869)
N	7676	7676	7676
Covariates	YES	YES	YES
R-sq.	0.3534	0.0436	NA
Chi-sq.	NA	NA	123.218323

Notes: The baseline is the holdout group. ***$p < 0.01$; **$p < 0.05$; *$p < 0.10$.

Table A5. Impact of Induced Online Incidence on Offline Sales (Offline Only Customers)

	DV = Offline Sales (Month 1)	DV = Offline Sales (Month 2)	DV = Offline Sales (Month 3)	DV = Log Offline Sales (Month 1)	DV = Log Offline Sales (Month 2)	DV = Log Offline Sales (Month 3)
Model	**2SLS**	**2SLS**	**2SLS**	**TOBIT w/ Endogenous Regressor**	**TOBIT w/ Endogenous Regressor**	**TOBIT w/ Endogenous Regressor**
Distance × Induced Online Incidence	**-0.007526****** (0.002065)	**-0.005096***** (0.001920)	**-0.004861****** (0.001844)	**-79.906820****** (13.160281)	**-41.538315**** (20.006627)	**-49.662346**** (21.816465)
Induced Online Incidence	**0.129968***** (0.047353)	**0.074872+** (0.044026)	**0.106936**** (0.042304)	**715.875711****** (204.275476)	523.262239 (461.828083)	716.265641 (451.385993)
Distance	-0.001425 (0.001218)	0.001998+ (0.001133)	0.000003 (0.001089)	-2.385263 (5.411385)	10.911096 (11.265626)	-8.753304 (12.018677)
Constant	0.770413*** (0.084512)	0.143964+ (0.078575)	0.302739*** (0.075500)	-2112.148056*** (370.347799)	-10553.20*** (879.265500)	-8679.82*** (836.969073)
N	7676	7676	7676	7676	7676	7676
Covariates	YES	YES	YES	YES	YES	YES
R-sq.	0.0196	0.0145	0.0126	NA	NA	NA
Chi-sq.	NA	NA	NA	158.99	98.39	99.29

Notes: The baseline is the holdout group. ***$p < 0.01$; **$p < 0.05$; *$p < 0.10$.

Table A6. Impact of Induced Online Purchase Incidence on Total Sales (Offline Only Customers)

	DV = Offline Sales (Month 1)	DV = Offline Sales (Month 2)	DV = Offline Sales (Month 3)	DV = Log Offline Sales (Month 1)	DV = Log Offline Sales (Month 2)	DV = Log Offline Sales (Month 3)
Model	**2SLS**	**2SLS**	**2SLS**	**TOBIT w/ Endogenous Regressor**	**TOBIT w/ Endogenous Regressor**	**TOBIT w/ Endogenous Regressor**
Distance × Induced Online Incidence	**-0.007199****** (0.002083)	**-0.006181***** (0.0021782)	**-0.005712***** (0.001994)	**-62.600754****** (11.261898)	**-38.028622**** (16.438248)	**-44.432417**** (18.681525)
Induced Online Incidence	**0.155360***** (0.047765)	0.02130+ (0.049811)	**0.126871***** (0.045741)	**772.841921****** (196.6673675)	442.365032 (386.692896)	687.608656+ (395.275284)
Distance	-0.001514 (0.001229)	0.003185* (0.001282	0.000343 (0.001177)	-2.407773 (5.250657)	15.026868 (9.333963)	-5.263878 (10.358735)
Constant	0.798390*** (0.085247)	0.165676+ (0.088899)	0.370759*** (0.081635)	-1949.16*** (355.113606)	-8860.06*** (727.205950)	-7376.16*** (727.624740)
N	7676	7676	7676	7676	7676	7676
Covariates	YES	YES	YES	YES	YES	YES
R-sq.	0.0236	0.0114	0.0133	NA	NA	NA
Chi-sq.	119.76	82.46	97.82	182.84	96.83	108.93

Notes: The baseline is the holdout group. ***$p < 0.01$; **$p < 0.05$; *$p < 0.10$.

Table A7. Impact of Induced Online Purchase Incidence on Trips to the Offline Store (Offline Only Customers)

	DV = Offline Sales Incidence (Month 1)	DV = Offline Sales Incidence (Month 2)	DV = Offline Sales Incidence (Month 3)	DV = Number of Trips to Store (Month 1)	DV = Number of Trips to Store (Month 2)	DV = Number of Trips to Store (Month 3)
Model	**PROBIT w/ Endogenous Regressor**	**PROBIT w/ Endogenous Regressor**	**PROBIT w/ Endogenous Regressor**	**PROBIT w/ Endogenous Regressor**	**PROBIT w/ Endogenous Regressor**	**PROBIT w/ Endogenous Regressor**
Distance × Induced Online Incidence	**-0.021012***** (0.004163)	**-0.005216+** (0.002912)	**-0.006808*** (0.003254)	**-0.010408+** (0.005504)	-0.005559 (0.004101)	**-0.009990+** (0.005302)
Induced Online Incidence	0.105865 (0.065296)	0.046305 (0.068561)	0.112229 (0.069305)	**0.162626+** (0.087026)	0.078334 (0.101900)	**0.201640*** (0.096703)
Distance	-0.002118 (0.001742)	0.002630 (0.001657)	-0.000740 (0.001823)	0.001066 (0.002575	0.004221* (0.001982)	0.003253 (0.002631)
Constant	-0.606302*** (0.117314)	-1.529291*** (0.124472)	-1.129918*** (0.124033)	-1.478071*** (0.148602)	-2.178106*** (0.170523)	-1.768049*** (0.165112)
N	7676	7676	7676	7676	7676	7676
Covariates	YES	YES	YES	YES	YES	YES
Chi-sq.	62.44	53.11	47.85	NA	NA	NA

Notes: The baseline is the holdout group. ****p* < 0.01; ***p* < 0.05, **p* < 0.10; +*p* < .10.

Table A8. Impact of Induced Online Purchase Incidence with Basket Size (Offline Only Customers)

	DV = Log Per Trip Basket Size (Month 1)	DV = Log Per Trip Basket Size (Month 2)	DV = Log Per Trip Basket Size (Month 3)	DV = Per Trip Basket Size (Month 1)	DV = Per Trip Basket Size (Month 2)	DV = Per Trip Basket Size (Month 3)
Model	**2SLS**	**2SLS**	**2SLS**	**TOBIT w/ Endogenous Regressor**	**TOBIT w/ Endogenous Regressor**	**TOBIT w/ Endogenous Regressor**
Distance × Induced Online Incidence	**-0.007403***** (0.002052)	**-0.005180**** (0.001906)	**-0.004852**** (0.001837)	**-77.564075***** (12.903834)	**-41.634626*** (19.899338)	**-49.326981*** (21.718457)
Induced Online Incidence	**0.128604**** (0.047063)	**0.075682+** (0.043714)	**0.105999*** (0.042142)	**689.151013***** (199.624867)	534.271808 (459.556045)	702.277555 (449.326749)
Distance	-0.001444 (0.001211)	0.002036+ (0.001125)	0.000010 (0.001084)	-2.322866 (5.287250)	11.102552 (11.203909)	-8.723689 (11.963467)
Constant	0.767452*** (0.083995)	0.145847+ (0.078018)	0.305155*** (0.075211)	-2058.883174*** (361.969731)	-10478.622853*** (874.655623)	-8613.173845*** (833.149261)
N	7676	7676	7676	7676	7676	7676
Covariates	YES	YES	YES	YES	YES	YES
Chi-sq.	100.54	108.62	102.21	163.93	98.79	99.43

Notes: The baseline is the holdout group. ****p* < 0.01; ***p* < 0.05, **p* < 0.10; +*p* < .10.

Table A9. Impact of Induced Online Purchase Incidence on Experiential Product Categories (Offline Only Customers)

	DV = Log Experiential Product Sales (Month 1)	DV = Log Experiential Product Sales (Month 2)	DV = Log Non-Experiential Product Sales (Month 2)	DV = Log Non-Experiential Product Sales (Month 3)
Model	**2SLS**	**TOBIT w/ Endogenous Regressor**	**2SLS**	**TOBIT w/ Endogenous Regressor**
Distance × Induced Online Incidence	**-0.017048***** (0.004410)	**-61.352352***** (10.821563)	-0.003227 (0.003356)	**-9.776229+** (5.586079)
Induced Online Incidence	**0.359791***** (0.101156)	**743.546354***** (187.891609)	0.071547 (0.076969)	74.189439 (93.623988)
Distance	-0.002323 (0.002603)	-0.761242 (4.975466)	-0.004984* (0.001981)	-7.249281* (2.988913)
Constant	1.643559*** (0.108535)	-1950.537893*** (338.385936)	0.996090*** (0.137368)	-1131.643965*** (175.514842)
N	7676	7676	7676	7676
Covariates	YES	YES	YES	YES
R-sq.	0.258	NA	0.0091	NA
Chi-sq.	131.85	189.66	61.89	51.79

Notes: The baseline is the holdout group. ***p < 0.01; **p < 0.05, *p < 0.10; +p < .10.

Table A10. Impact of Treatment on the Change in Offline, Online, and Total Sales

	DV = Change in Offline Sales	DV =Change in Online Sales	Change in Total Sales
Model	**OLS**	**OLS**	**OLS**
Distance × Treatment	**-5.873820**** (2.053626)	0.084874 (0.124892)	**-5.788946**** (2.057141)
Treatment	**102.856049**** (34.958693)	**3.764898+** (2.126033)	**106.620947**** (35.018529)
Distance	2.165528 (1.669554)	-0.021795 (0.101535)	2.143733 (1.672412)
Constant	110.508136*** (28.516286)	1.724667 (1.734234)	112.232803*** (29.565095)
N	11,200	11,200	11,200
R-sq.	0.0013	0.0005	0.0013

Notes: The baseline is the holdout group. ***p < 0.01; **p < 0.05, *p < 0.10; +p < .10.

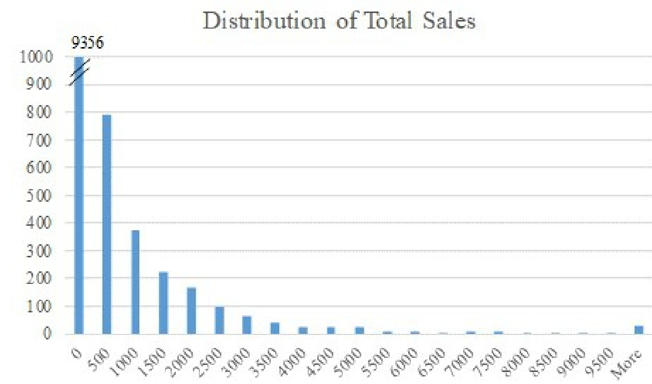

Figure A1. Distribution of Sales

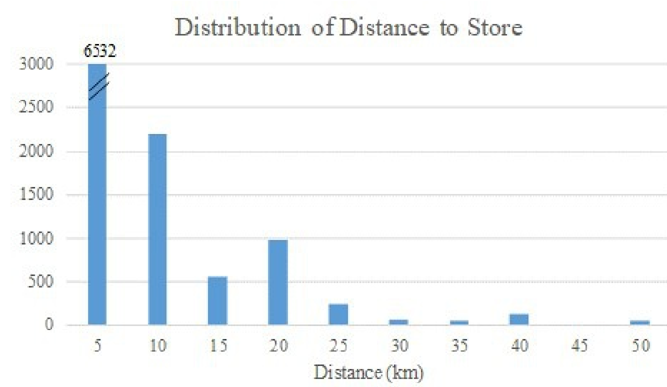

Figure A2. Distribution of Distance to the Brick-and-Mortar Store