

Integration of Online and Offline Channels in Retail: The Impact of Sharing Reliable Inventory Availability Information

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Increasingly, retailers are integrating their offline and online channels to reduce costs or to improve the value proposition they make to their customers. Using a proprietary dataset, we analyze the impact of the implementation of a buy-online-pickup-in-store project. Contrary to our expectations, the implementation of this project is associated with a reduction in online sales and an increase in store sales and traffic. We interpret the results in light of recent operations management literature that analyzes the impact of sharing inventory availability information online. The implementation of a buy-online-pickup-in-store project provides an exogenous shock to the verifiability of the inventory information that the firm shows to their customers. The fact that inventory information becomes more credible reduces the risk that customers face when deciding whether to visit the store. This is consistent with a shift of some online customers to the store channel. Our analysis illustrates the challenges of drawing conclusions about complex interventions using single channel data.

Key words: retail operations, inventory availability, empirical operations management, business analytics, online retail

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1. Introduction

Online retailing has grown steadily over the last few years. Some retailers operate exclusively through online channels, and traditional brick and mortar (B&M) retailers have incorporated online sales channels since the early stages of the commercial Internet (e.g., the Barnes and Noble website launched in May 1997). Today, retailers' online channels are no longer an experiment but a relevant and growing part of their business. Originally, most of the B&M retailers decided to separate the operations of traditional and online channels. Now, some B&M retailers are exploring integration strategies for their online and B&M channels to enrich the customer value proposition and/or reduce costs. Online-offline integration efforts can occur in a variety of configurations. For example, B&M

retailers often show in-store inventory availability information online. More advanced integration includes shipping the product ordered from the store closest to its destination, or offering the option to buy products online and pick them up in the store.

In particular, over the last few months, a number of traditional B&M retailers across different categories (e.g., The Home Depot, Apple, Crate & Barrel, Toys "R"Us, among others) have implemented buy-online-pickup-in-store (BOPS) functionality. The retailer shows online viewers the locations at which the item is available, and gives customers the option to close the transaction online and then pick up the product at one of the locations within two hours of closing the purchase¹.

The integration of online and offline channels provides an opportunity to empirically study issues that have been the subject of theoretical research in operations management. In this paper, we use an online-offline integration project that implements BOPS functionality as a natural experiment to study the impact of sharing reliable inventory availability information with the customers. Implementing a buy-online-pick-up-in-store project provides an exogenous shock to the verifiability of the inventory information that the firm shows to their customers; because the inventory information becomes more credible, the risk that customers face when deciding whether to visit the store is reduced.

We have collected a novel proprietary dataset from a nationwide retailer that has been among the pioneers in implementing BOPS functionality. Using this dataset and a series of natural experiments, we make the following contributions:

First, we evaluate the impact of BOPS implementation on company sales and customer behavior, and give the first piece of empirical evidence on this emerging trend in retailing². We study the impact of the deployment of a BOPS project on both the online and brick and mortar channels. Conventional wisdom within the industry suggests that offering the BOPS functionality will improve online channel revenue (since BOPS transactions are considered online revenue), and that the traditional B&M stores will carry the burden of having the item ready for the customers to pick up, without receiving any significant benefit in their sales. However, as we will describe in detail, a series of natural experiments leads us to conclude that these assumptions are not correct. Our results show that, contrary to what we would expect, sales transacted online *decrease* and B&M sales *increase* when the BOPS functionality is deployed.

¹ Most retailers announce that they need a two hour window to have the item ready to pick up. In some cases this time can be less but two hours is representative of the most common commitment. This short lead-time restricts the retailer to fulfill the order with in store inventory

² See, for example, <http://operationsroom.wordpress.com/2012/05/16/macys-warehouse-at-the-mall/> and <http://operationsroom.wordpress.com/2010/08/25/pooling-inventory-at-nordstrom/>

Second, we show how the increase of inventory information verifiability affects customer behavior. The impact of availability information and its verifiability on customer behavior has been the subject of recent modeling research in the field of operations management (e.g., Allon and Bassamboo (2011), Su and Zhang (2009)) but to our knowledge, no empirical results were available prior to this paper. Implementing BOPS functionality can be seen as a shock to the verifiability of inventory information online. To implement BOPS functionality, the online system must have access to accurate real-time information about availability of in-store inventory. If the retailer offers the option to pick up an online order at a particular store, the customer knows with very high certainty that the item ordered is available at that store. Therefore, inventory availability information is perceived as very reliable. This contrasts with situations whereby the store simply shows inventory information but does not offer the option to close the transaction online. For example, consider a car dealership showing information online about their inventory. This information is typically unverifiable; if a customer visits the dealer and the product is not available, the dealer can claim that the online information was not updated in real time. We find that increased reliability of in-store availability information increases the probability that customers will visit the store. We present an explanation consistent with empirical evidence we observed regarding the impact of BOPS functionality: Providing BOPS functionality increases the reliability of the inventory information, resulting in an increase in the number of customers visiting the stores to purchase items after checking product availability online. This provides an explanation to the counterintuitive finding described above. We further check the validity of this explanation by presenting further evidence from the shopping cart abandonment behavior.

Finally, we use this project as an example of the evaluation of an online-offline strategy, illustrating the complex interactions between the online and offline channels and the challenges of relying on single channel data to evaluate the impact of interventions that affect multiple channels. Retailers often run experiments in their online channel (for example, A/B testing) to evaluate the impact of interventions on their conversion rates or other measures of interest. In our case, an isolated evaluation of the online channel would have considered the impact of the BOPS implementation to yield negative results. Only when closing the loop and looking at the effects in the brick and mortar channel we can quantify the net effects of the BOPS implementation, which are positive.

The rest of the document is organized as follows: Section 2 reviews the literature related to our problem of interest; Section 3 describes the empirical setting and data; Section 4 shows the impact of the deployment of BOPS functionality on the online channel and the brick-and-mortar channel. Section 5 provides an interpretation of the results based on information verifiability and tests the validity of this interpretation with additional analyses. Finally, Section 6 concludes by highlighting the managerial insights that can be drawn from our analysis.

2. Context and Related Literature

Integration of online and offline retail channels is a very recent phenomenon. In the early stages of online business, many traditional B&M retailers developed online branches of their traditional businesses. In some cases, they saw in online stores a new version of their traditional catalog channel since there were, and still are, several similarities.

Today, the online channel has developed characteristics of its own. The relevance of this channel in the retail sector and the pressure from customers that want to interact with the company in a cohesive way have pushed B&M retailers to consider channel integration efforts with varying characteristics. Integration is not always evident to the customer, as is the case when a retailer ships an online purchase from a store rather than the warehouse. In other cases, integration is driven by the need to offer a homogenous and more rewarding online-offline customer experience. Examples include offering customers the possibility to return to a store items that were bought online, place online orders from the store and have the products shipped to the customer address, buy items online and pick them up later at the store in which they are stocked, or buy an item online and pick it up at the store once it has been delivered to the store.

Online-offline integration efforts are challenging for companies. The retailer must integrate inventory systems, warehouses, marketing campaigns, pricing strategies, etc. Even before these integration attempts are made, retailers often struggle to discern what is really available at their stores or warehouses, as has been studied in previous empirical research documenting substantial inventory record inaccuracy (DeHoratius and Raman 2008). Another challenge faced in the implementation of some of these integration efforts is an increased complexity in store execution (Fisher et al. 2006). Store processes are designed to sell and not necessarily to support the quick delivery or shipment of goods, activities that these integration strategies allocate to physical stores.

Given that online-offline integration is a recent phenomenon, it is not surprising that there is limited literature that studies it. Some recent work in marketing and information systems has explored related issues, such as the difference in price elasticity between the online and brick and mortar channels (Chu et al. 2008, Granados et al. 2011), customer channel migration (Ansari et al. 2008), the choice between online and offline channels in grocery stores (Chintagunta et al. 2012), the impact of product returns on a multi-channel retailer (Ofek et al. 2011), or customer behavior in multi-channel customer service (Jerath et al. 2012). To our knowledge, no previous work has considered a buy-online-pickup-at-store channel. The competition between brick and mortar and online channels has been studied by Brynjolfsson et al. (2009) and Forman et al. (2009), among others.

In operations management, some work has examined fulfillment and supply chain choice on the Internet. For example, Netessine and Rudi (2006) study the effects of inventory ownership in

online channels, and Randall et al. (2006) empirically study the decision to invest in fulfillment capabilities, although we are not aware of any work that has explored the integration of online and offline channels. We contribute to the literature by studying the impact of the implementation of an online-offline integration strategy, namely the "buy-online-pickup in store" functionality, on the online and brick and mortar channel.

When consumers decide to visit a physical store to buy a product, they face the risk that the product is out of stock. Fitzsimons (2000) and Anderson et al. (2006) study how customers respond to stockouts and how to measure and mitigate stockout costs. Substitution effects and its consequences for demand estimation are studied by Kok and Fisher (2007) and Musalem et al. (2012).

Some models in operations management consider the costs that of visiting a store (Dana and Petrucci 2001). Recent work has modeled the impact of inventory availability information in attracting consumer demand. In this stream, Su and Zhang (2009) study the value of commitment and availability guarantees when selling to strategic consumers. In a related work, Allon and Bassamboo (2011) explore the issue of cheap talk when the information shared is not verifiable. Our paper contributes to this stream of literature by providing the first empirical analysis of the impact of sharing *verifiable* inventory information. In our case, implementing the BOPS functionality can be interpreted as providing a commitment device to the inventory availability information, which is perceived by the customer as more credible. In this context, customers are able to "reserve" inventory that exists in the store. We can establish an analogy between the "inventory reservation" aspect of BOPS functionality and a restaurant reservation system; Alexandrov and Lariviere (2012) show that a reservation system reduces the uncertainty that customers face and may attract more people to the restaurants in certain situations.

3. Empirical Setting and Data

We have partnered with one of the leading nationwide retailers in the US that has implemented buy-online-pickup-at-store (BOPS) capabilities. This retailer specializes in housewares, furniture (indoor and outdoor), and home accessories, and has more than 80 B&M stores in the US and Canada. In addition to traditional B&M stores, this retailer has an online store that ships to ship to anywhere in the US.

We have obtained data spanning April 2011 to April 2012. Throughout this period, the online store offered information about the availability of inventory at each of the stores. After October 11, 2011, the retailer offered the option of placing orders online and picking them up at a B&M store. Under the BOPS mode of interaction, customers pay for the items through the online store (and therefore sales are considered *online* sales), but the order is fulfilled using inventory from

the store. The pickup option was available simultaneously for every store in the US, but was not implemented for stores in Canada. The period of analysis considered in our analysis covers six months before the store pickup implementation (since April 11, 2011) and extends six months after the implementation (until April 11, 2012).

The information used in our analysis comes from two main data streams, one related to the online channel and the other related to the brick and mortar channel.

Data related to the online channel

We obtained daily data from the online channel at the designated market area (DMA)³ level. For our main analysis of the impact of BOPS, we used data on total number of transactions, total dollar sales, and total number of unique visitors in the US for each day. Our data includes a total of 210 DMAs that completely cover the US populated areas. Table 1 shows the main summary statistics for these variables. We also obtained data about online shopping cart abandonment behavior for each DMA and day, using them in Section 5 to validate our interpretation of the findings.

Data related to the brick and mortar channel

We obtained daily data for each of the stores in the US and Canada. During the period of analysis, the retailer had a total of 83 stores in the US and Canada. For our analysis of the impact of the BOPS implementation on the B&M channel, we collected data on the total number of transactions, total dollar sales, and total visitors for each day and store in the US and Canada. Table 1 shows relevant summary statistics for these variables.

In addition, we collected data specifically related to the BOPS orders. We obtained information on the date that a BOPS transaction was placed online and the date and store where each one of these pickup transactions was collected by the customer. We use this data in Section 4.3.

4. Evaluating the Impact of BOPS

A naive approach to evaluating the impact of BOPS would look at the difference in the variables of interest between the pre-implementation period and the post-implementation period. Clearly, this approach would be flawed; many things can differ in the pre-implementation and post-implementation period that are completely unrelated to the BOPS implementation. For example, there might be seasonal factors that cause a change in sales. In order to deal with this challenge, we consider a difference-in-differences approach (DiD).

In general, to implement a DiD approach we need to identify a portion of the population that is not affected by the intervention for which we are trying to estimate the causal effect (the BOPS

³ A designated market area (DMA) is a region where the population can receive the same (or similar) television and radio station offerings, and may also include other types of media including newspapers and Internet content. They can coincide or overlap with one or more metropolitan areas, though rural regions with few significant population centers can also be designated as markets. They are widely used in audience measurements, which are compiled in the United States by Nielsen Media Research (television) and Arbitron (radio) (from Wikipedia)

implementation in our case). In other words, we need a control group. After identifying a control group, we can measure the effect of the treatment by comparing the differences between treatment and control groups before and after the treatment is applied. Figure 2 shows a schematic summary of the DiD approach. For a more detailed discussion on this topic, see Angrist and Pischke (2008).

The rest of this section applies a DiD approach to evaluate the impact of BOPS in the online and brick and mortar channels. Subsection 4.1 estimates the effect of BOPS on the online channel using a control group based on the distance between the online customers and the closest store. Customers that visit the website from locations that are very far from a store are used as a control group in the DiD framework. Subsection 4.2 uses Canadian stores, where the BOPS functionality was not deployed, as a control group for the DiD framework. Subsection 4.3 studies whether BOPS transactions lead to cross-selling of additional in-store purchases by customers who ordered goods online.

4.1. Impact on the Online Channel

We start our analysis of the impact of BOPS by focusing on its effects on traffic and sales observed in the online channel. For this purpose, we use data from the online business that covers the six months preceding the implementation of BOPS and the six months following the implementation.

As mentioned before, if we simply compared what happened before and after the intervention, we would not be able to find a causal effect of the intervention, because the pre and post-implementation periods might differ in aspects other than the intervention. For example, the post-intervention period includes the Christmas season, which we can expect to have higher sales independent of the BOPS project. In order to control for differences not related to the BOPS implementation, we define two different groups in our population. The first group includes the portion of the population that was affected by the BOPS implementation (the treatment group); the second group includes the portion of the population that was not affected by this decision (the control group). In the definition of a control group, we take into account the fact that customers who live far from physical B&M stores will be unaffected by the deployment of the BOPS capabilities.

More specifically, we conduct our analysis for the online channel at the DMA level. The retailer has a total of 79 B&M stores in the U.S.; this relatively small number of stores helps us to identify a treatment and control group in our population. Our treatment group is defined to include those DMAs within the area of influence of a B&M store. The control group includes DMAs that are not within the area of influence of a B&M store. As a baseline, we assume that the area of influence of a B&M store covers a radius of 50 miles, but our results are robust to choosing different distances. This classification is used because customers visiting the online store from DMAs that are not within the area of influence of a B&M store will find no use for the pickup implementation. The

store's inventory information shown online and the option to pick up online purchases at a store should not affect customer behavior within those DMAs, as it is not practical for customers to visit a physical store. Hence, it is reasonable to assume that customers within these DMAs can behave as a control group, in the sense that they will be affected by the general dynamics of behavior of the online channel (for example, they will respond to the seasonal Christmas period), but not by the BOPS implementation. In contrast, online customers who visit the website from DMAs that are in the area of influence of a store can benefit from this new alternative. It is possible for customers in those DMAs to actually visit a store to pick up the items they bought online, or decide to go to the store shown online to have the item desired in order to make their purchase.

Figure 1 shows the location of the B&M stores and the geographic center of each of the DMAs. From the total of 210 DMAs, 162 of those DMAs do not include a B&M store within their geographic area and the other 48 DMAs have at least one store within their geographic area⁴. In our analysis, following the company's practice, we considered all the pickup sales as online sales.

In the first place, we study whether changes in online traffic can be attributed to the BOPS implementation. To do this, we consider the number of unique visitors ($NUMVISITORS_{it}$) from a DMA i in a day t as our dependent variable. Our independent variables include a dummy variable that indicates whether or not the DMA i is within the area of influence of a store ($CLOSE_i$), a dummy variable that indicates if the observation corresponds to the period after the pickup implementation ($AFTER_t$), and the interaction between these two terms ($CLOSE_i * AFTER_t$), which is our variable of interest.

In addition to defining our treatment and control groups and the independent variables described in the previous paragraph, we include an exhaustive number of control variables, taking advantage of the panel structure in our data. Our model includes fixed effect for each DMA i , week and day of the week in our sample. Our model specification is the following:

$$NUMVISITORS_{it} = \mu_i + \alpha_1 CLOSE_i + \alpha_2 AFTER_t + \alpha_3 CLOSE_i * AFTER_t + \alpha_4 CONTROLS_{it} + \epsilon_{it} \quad (1)$$

Since we have DMA fixed effects μ_i , it is not possible to identify α_1 separately from μ_i , because there is no variation in $CLOSE_i$ for a given store in the period of analysis. This is not problematic, because we are interested in the value of the coefficient α_3 in this specification, which is identified⁵.

⁴ We defined a DMA as being within the area of influence of a store if a 50 miles radius circle centered at a store overlaps with the DMA area. We consider a distance of 50 miles as this is the distance that the retailer's management team estimates as the area of influence of their stores in their business analysis. We tested other distance specifications (e.g., 40 and 60 miles) and our results were robust to these alternatives.

⁵ This also happens in equations 2, 3, 4, 6 and 7. We leave the unidentified variables in the model specification for clarity, but we focus our analysis on the interaction terms that are identified.

The results of the estimation of this model are presented on the first column of Table 3. We can observe that after the BOPS implementation, for those DMAs that are in the area of influence of a store (i.e., $CLOSE_i * AFTER_t = 1$), there was a positive and significant effect on the number of unique website visitors, relative to those DMAs that were not within the area of influence of a store ($CLOSE_i * AFTER_t = 0$). In other words, visits from DMAs that were in the catchment area of a B&M store increased more than visits from DMAs that were not close to a B&M store.

The next step is to study the impact on online sales, before and after the implementation. For this analysis we implement a similar model to the one described above, but now our dependent variable, $SALES_{it}$, corresponds to the total dollar sales from online visits from DMA i on day t . In addition, we also tested the specification including the number of unique visitors ($NUMVISITORS_{it}$) as an additional control in our model.

$$SALES_{it} = \mu_i + \beta_1 CLOSE_i + \beta_2 AFTER_t + \beta_3 CLOSE_i * AFTER_t + \beta_4 * CONTROLS + \epsilon_{it} \quad (2)$$

The results of this analysis are presented on the second and third columns of Table 3. The third columns presents the results when the online traffic is included as an additional control variable. After the BOPS implementation, for those DMAs in the area of influence of a store (i.e., $CLOSE_i * AFTER_t = 1$), we observe a negative and significant effect on sales, relative to DMAs that are not within the area of influence of a store ($CLOSE_i * AFTER_t = 0$). That is, BOPS implementation reduces online sales.

Although the brick and mortar store locations are decided endogenously, we do not believe that this poses a serious concern for the validity of our results. During the period of analysis, no stores were opened or closed, and the store locations were determined many years before the BOPS implementation. The BOPS implementation was executed at the same time at every location. In addition, the panel structure of the data gives us the ability to add fixed effects that fully control for all the invariant characteristics across the DMAs. For further robustness of our analysis we include the results obtained when a previous sample matching is used. For this analysis, we consider DMAs that have a comparable traffic pattern (less than 900 daily visits to the online store), to make sure that our results are not driven by fundamental differences between the treatment and control groups. These results are presented on Table 8, where the second column includes the online traffic as an additional control.

The results presented in this section go against intuition and conventional wisdom, which suggest that online sales should increase after the BOPS implementation, because customers are given more options to order online. We find that, although online traffic *increases* at the DMAs affected by the BOPS implementation, sales *decrease* at those DMAs, relative to the DMAs that were unaffected by the change. Section 5 gives a holistic interpretation of this unexpected phenomenon.

4.2. Impact on the Brick and Mortar Channel

We now tackle the analysis of the impact of BOPS on the B&M stores. In particular, we want to understand how the implementation of the store pickup option impacts traffic and sales at the B&M stores.

Again, we face the challenge that an appropriate answer cannot be obtained simply by observing what happened with store sales before and after the pickup implementation. To answer this question properly, we propose a difference-in-differences approach with new treatment and control groups.

In this case, the key variation that allows us to identify the effect of BOPS comes from the fact that while the retailer owns B&M stores both in the US and Canada, the BOPS option was not deployed for stores in Canada. This situation allows us to use the B&M stores in Canada as a control group for our analysis. The treatment group includes all the B&M stores in the US. The reasoning behind this definition is that customers visiting the stores in Canada were not influenced by the BOPS pickup implementation while customers in the U.S. were exposed to this new alternative and could benefit from it.

After BOPS implementation, the retailer had a total of 79 stores in the US that offered the pickup option and 4 stores in Canada that did not offer this alternative.

As before, we want to focus first on the impact on customer traffic at the B&M stores. To do this, we consider the traffic count at a store i on day t ($TRAFFIC_{it}$) as our dependent variable. Our independent variables in the model include a dummy variable that indicates if store i is located in the U.S. or not (US_i); a dummy variable that indicates if the observation corresponds to the period after the pickup in the store implementation ($AFTER_t$); and the interaction between these two terms ($US_i * AFTER_t$), which is our main variable of interest. Our model also includes also fixed effects for each store i , week and day of the week in our sample. The model specification is the following:

$$TRAFFIC_{it} = \mu_i + \alpha_1 US_i + \alpha_2 AFTER_t + \alpha_3 US_i * AFTER_t + \alpha_4 CONTROLS + \epsilon_{it} \quad (3)$$

The results for the estimation of this model are presented in the first column of Table 4. We observe that there was a positive and significant effect on the traffic of the US stores (i.e., $US_i * AFTER_t = 1$) compared to the traffic in the Canada stores, after the store pickup implementation. In other words, stores that were affected by the BOPS implementation saw a higher increase in their store traffic.

The next step is to study the impact on store sales. To do this, we define the following model:

$$SALES_{it} = \mu_i + \beta_1 US_i + \beta_2 AFTER_t + \beta_3 US_i * AFTER_t + \beta_4 CONTROLS + \epsilon_{it} \quad (4)$$

where $SALES_{it}$, the dependent variable, corresponds to the total dollar sales at store i during day t . In addition, some of our specifications include the total traffic at store i on day t ($TRAFFIC_{it}$) as a control variable (recent work in retail operations has considered how store traffic affects conversion rates, see (Perdikaki et al. 2012)). The results of this analysis are presented on the second and third column of Table 4. We observe a positive and significant effect on sales for the US stores after the pickup implementation (i.e., $US_i * AFTER_t = 1$) compared to the stores in Canada. This result suggests that the B&M stores that were affected by the BOPS implementation (i.e., stores in the US) saw an increase in sales compared to the control group (i.e., stores in Canada).

It is important to notice that our analysis includes, as an additional control, a daily measure for currency exchange rate between the US and Canada. This variable can capture changes in the economic situation between the two countries during the period of analysis that could potentially affect our results.

For additional robustness checks of our results, we restrict our attention to different subsamples of the data, such as a shorter period before and after the implementation of BOPS (e.g., considering only one month before and after). The results do not qualitatively change.

The analysis of the impact of BOPS on the B&M stores indicates that B&M stores received *more traffic* and *increased their sales* as a consequence of the BOPS implementation.

4.3. Positive Externality of Store Pickup

There is an additional mechanism by which B&M sales can benefit from the pickup in the store implementation. Customers who visit the B&M stores to pick up an item they bought online might decide to buy extra items during their visit. Also, some customers may go to pick up the items with someone else who may make additional purchases while visiting the store. In any case, we are interested in testing whether there is evidence about this positive externality effect in our data.

Our data does not allow us to uniquely identify purchases made by customers when visiting the store to pick up an item they have ordered online. If this were possible, we could evaluate whether BOPS customers add extra items to their purchase while at the store. The main limitation here is that the pickup transactions are done; hence, if the customer makes a purchase while at the store, the retailer records this as a different transaction. We do not have access to the data that could potentially enable the link between these two transactions.

To overcome this challenge, we test whether the total number of customers that picked up items at a store on a particular day ($NUMPICKUPTX_{it}$) is correlated with an increase in store sales on that day. By doing this analysis we can observe if more pickup customers at the stores generate more store sales. We propose the following model:

$$SALES_{it} = \mu_i + \beta_1 NUMPICKUPTX_{it} + \beta_2 TRAFFIC_{it} + \\ + CONTROLS + \epsilon_{it} \quad (5)$$

where $SALES_{it}$ corresponds to the total dollar sales at store i during day t . The independent variables in the model include total traffic at each store ($TRAFFIC_{it}$), store fixed effects, and week and day of the week dummies. Controlling for traffic mitigates the potential bias that we would have if people choose to pick up items on days that have particular characteristics that might be correlated with sales. Obviously, this analysis only applies to the period that follows the BOPS implementation, since no customers were picking up items before that.

The results of this analysis are presented on Table 5. In the first column we observe that the number of pick up transactions has a positive and significant effect on the number of transactions. The second and third columns on Table 5 present the analysis for the impact of the pickup transactions on the store sales. This result is consistent with the hypothesis that there are positive externalities on store sales due to those customers that visit a store to pick up their online order.

5. Interpretation of Results: The Role of Verifiability

The results presented on the previous section are somewhat perplexing. Conventional wisdom suggests that when the retailer decides to offer a new service to online customers (the store pickup option), if anything, this service should benefit the retailer's online sales. However, the results presented on Section 4.1 tell us the opposite: online sales decrease after the pickup implementation⁶. On the other hand, as presented on Section 4.2, B&M sales benefit from this new online service. This is also surprising since, a priori, we could have assumed that a service level increase on the online store could have hurt B&M sales.

As discussed in Section 4.3, part of the increase in B&M sales can be explained by the positive externality generated by customers picking up their online orders at the stores. However, this does not give the entire picture. For example, this does not explain why online sales go down in areas close to a store or why traffic increases online and at the stores subject to the BOPS implementation. Section 5.1 proposes an explanation based on how the implementation of BOPS provides a shock to the credibility of the inventory information shown online. Based on this explanation, two additional hypotheses are developed and tested in Sections 5.2 and 5.3.

5.1. Credibility of Inventory Information

Our explanation draws from recent models proposed by the operations management literature to study how strategic consumers react to inventory information. Following Su and Zhang (2009), there is a cost for customers to visit a store. Customers form rational expectations of product availability

⁶ To make our exposition more clear we will refer to our results in absolute terms. However, it is important to note that the results obtained on section 4.1 should be interpreted in relative terms, since we are always comparing a treatment and a control group and their relative differences. For example, it is possible that both the treatment and the control group sales increased during the period under analysis, but at different rates.

and make patronage decisions based on their expectations. Our retailer was sharing inventory availability online during the entire period of analysis. However, customers do not necessarily perceive inventory information shown to them as reliable. For example, in Su and Zhang (2009) the seller has an incentive to convince customers that inventory will be available, because that increases the probability that they visit the store. Accordingly, buyers should ignore the seller's claims. Similarly, Allon and Bassamboo (2011) provide a model in which a retailer shares unverifiable inventory information with strategic consumers. In equilibrium, the information becomes cheap talk and consumers ignore it. Furthermore, DeHoratius and Raman (2008) report a considerable amount of inventory record inaccuracy, and it is possible that some consumers consider any inventory information as unreliable.

Su and Zhang (2009) show that committing to an inventory level is valuable. In our case, offering "buy-online, pick up at store" provides an exogenous shock to the credibility of inventory information and works as a commitment device. Offering an online customer the option to pick up her online purchase at a nearby store can be beneficial to the customer for several reasons. For example, she can get the item in a couple of hours (not a couple of days) or avoid the payment of shipping costs. However, there is an additional benefit to the customer that might not be evident right away: She now knows that the item she wants is available in a nearby store. Hence, the customer can decide to check the availability online and drive to the store to pick up the item without closing the transaction online. This behavior will allow her the benefit of getting the item fast with no shipping cost, and additionally, let her evaluate the item at the store before actually paying for it (while avoiding the risk of making a trip to the store and not finding the item she is looking for).

We want to emphasize that the customer is facing reliable availability information. Everyone has suffered the unpleasant experience of cheap talk regarding inventory information; car dealers are a good example of this type of cheap talk. However, the information released by the retailer under the BOPS alternative is different. After BOPS implementation, online customers do not observe a vague promise of availability; they can actually buy the item online and pick it up at the store two hours later. They know that the item is actually there. Furthermore, customers can anticipate that offering the BOPS functionality requires increased accuracy in the retailer's internal inventory records, lending even more credibility to the inventory information.

In addition, some customers will obtain additional information by touching the fabric, seeing the color, or evaluating the actual size of the product they want to purchase. There is a benefit to seeing and touching the type of items that this retailer sells before committing to the purchase. This first-hand experience is less relevant for customers when buying other types of products that are more standardized (e.g. books or electronics).

Hence, our results can be explained by the following behavior: After implementing BOPS, some customers (more than before) visit the online store to browse the catalog, find the item they want to buy, check its availability and travel to their local store to close the sale knowing the item is there. The customers, after observing reliable availability information, decide to visit the store without closing the sale online.

We predict that a shock to the credibility of inventory information would reduce the cost of visiting the stores and would result in:

1. *Increase in store visits* to stores that share credible inventory information, relative to those that do not.
2. *Increase in store sales* in stores that share credible inventory information, relative to those that do not.
3. *Decrease in online sales* in DMAs that are within the area of influence of the stores, relative to those DMAs that not.

These are precisely the results that we found in Section 4. In order to confirm that our explanation is indeed valid, we develop two additional tests in Sections 5.2 and 5.3.

5.2. Cart Abandonment

In order to validate that the aforementioned mechanism is in place, we have established a hypothesis that would be supported if the described mechanism occurs. This hypothesis is related to shopping cart abandonment. A number of customers *abandon* their online shopping carts before finishing the transaction. After BOPS was deployed, customers could place an order for an item in their shopping cart and pick it up from the store. The fact that a product is available in a local store can prompt some customers to abandon their shopping carts and buy the items directly from the store without closing the transaction online. If, as our explanation suggests, the inventory availability information is perceived as more reliable after the BOPS project has been implemented, we can hypothesize that the rate of shopping cart abandonment will increase after BOPS is implemented.

Once again, we follow a DiD approach. We want to compare what happened before and after the BOPS implementation. To do this we consider the group of DMAs that were affected by the BOPS implementation (our treatment group) and the group of DMAs that were not affected (our control group). These groups are the same as those described on Section 4.1.

Our dependent variable ($ABANDON_{it}$) corresponds to the fraction of customers that, after placing an item in their cart, did not close the sale⁷. As described before, if our inventory credibility story holds, we would expect a higher increase in cart abandonment rate after BOPS implementation for those DMAs that are in the area of influence of a store (some customers in those DMAs

⁷ The abandonment rate in our sample has a mean of 51% with a standard deviation of 24%.

may decide to rely on the inventory availability information and visit the store to make a purchase), relative to those DMAs that are not. This is captured by the $CLOSE_i * AFTER_t$ variable in the following model:

$$ABANDON_{it} = \mu_i + \beta_1 CLOSE_i + \beta_2 AFTER_t + \beta_3 CLOSE_i * AFTER_t + \beta_4 CONTROLS + \epsilon_{it} \quad (6)$$

The results of this analysis are presented in Table 6. Our hypothesis is validated. Shopping cart abandonment rate increased after BOPS was deployed for those DMAs where the BOPS was available compared to those DMAs where customers could not take advantage of this new feature.

5.3. Online Sales in the Area of Influence of a Store

In this subsection we present an additional analysis that attempts to further validate the explanation presented on Section 5.1. If our explanation is correct, we expect that, for those DMAs that are within the area of influence of one or more stores, online sales will decrease compared to the B&M store sales in those DMAs. In other words, we expect that in DMAs within driving distance to the store, the sales share of B&M stores will increase after the pickup implementation.

Note that this analysis is different but complementary to the analysis shown in Section 4. The model developed in Section 4.1 compares the lift in online sales that occur in *DMAs far from stores* with the lift in online sales that occur in *DMAs that are close to stores*. The model developed in Section 4.2 compares the lift in *store sales in the US* with the lift in *store sales in Canada*. Although consistent with a shift from the online to the brick and mortar channel, the models in Section 4 do not provide a direct test. The present analysis looks at the area of influence of a store, and compares the lift in *online sales in the area of influence of a store* to the lift in *sales of the store*. Combined with the previous evidence, finding that sales in a store increase more than online sales in the area of influence of the store would suggest that there is a shift of customers from the online channel to the brick and mortar channel.

To implement this analysis, we consider daily online and B&M sales ($SALES_{it}$) aggregated at the DMA level as our dependent variable. Our independent variables consist of a dummy that indicates whether the daily sales observation corresponds to an online or B&M sales ($ONLINE_i$), a dummy variable that indicates whether the observation corresponds to the period after the pickup implementation ($AFTER_t$), and the interaction of these two terms ($ONLINE_i * AFTER_t$), our variable of interest. :

$$SALES_{it} = \mu_i + \beta_1 ONLINE_i + \beta_2 AFTER_t + \beta_3 ONLINE_i * AFTER_t + CONTROLS + \epsilon_{it} \quad (7)$$

The results of this analysis are presented on Table 7. As expected, the coefficient for our variable of interest ($ONLINE_i * AFTER_t$) has a negative and significant effect. This tells us that, after the pickup implementation, the share of online sales decreases with respect to the share of B&M sales.

6. Conclusions

Our analysis of the impact of an online-offline integration strategy offering the option of buying items online and picking them up in a physical store shows that, contrary to conventional wisdom, online sales do not increase with the implementation of the BOPS functionality. We find that the BOPS implementation results in lower online sales, higher store sales and higher store traffic. We explain these results in light of recent models from the operations management community that study sharing inventory information with strategic consumers. The implementation of BOPS provides a natural experiment that gives a positive shock to the credibility of the inventory information shared with the customers. As this information becomes more credible, more customers use the online channel to browse store inventory availability but make their purchases online.

One question unaddressed so far is whether the increase in store sales compensates for the decrease in online sales. It turns out that, in our particular case, it does. Based on our results, we can give an estimation of the net effect of the BOPS implementation. Using representative values from our sample, the decrease in online sales that can be attributed to the BOPS implementation is approximately 1.8% of the total retailer sales, while the increase in the store sales amounts to around 3.6% of the total retailer sales, giving a net increase of 1.8% of the total sales. Interestingly, without the holistic interpretation of online and store sales, an evaluation of the effects on the online channel might have suggested that BOPS was not a good idea.

One of the consequences of the increase in online activity in retail is the availability of richer data that can be used to evaluate the impact of operational interventions and to discover relationships between different operational aspects of the business. However, the available data is often channel dependent. Incentives for managers are also often channel dependent, and making decisions based on own-channel data is often tempting. Our results show that decisions affecting one channel should be evaluated holistically. A partial analysis of this project based on online sales might give the wrong conclusions, as illustrated in Section 4.1. For example, in online settings it is customary to evaluate potential changes by conducting A/B testing (which consists of showing one condition to a fraction of the visitors and a different condition to the rest of the visitors) and monitor how conversion rates differ across conditions. Typically, interventions that A/B testing identifies as negatively affecting the channel conversion rate are ruled out. Evaluating the impact of online-offline integration strategies requires a holistic view of company operations, since an intervention

that might be detrimental in one channel can yield substantial benefits in the other one. Our results show that when evaluating actions that perform integration between channels, it is very important to close the loop and evaluate their impact on all channels.

To our knowledge, this is the first academic study of the impact of implementing a buy-online-pickup-at-store channel. Contrary to the a priori expectation that a BOPS intervention would result in an increase of transactions closed online, we find that the additional reliability of the inventory information prompts some customers to actually visit the stores, which in turn increases the relative importance of the brick and mortar stores in terms of share of sales. Our explanation of the observed results is related to the credibility of the inventory information that retailers share. When retailers share reliable inventory information, the perceived risk that customers experience in visiting the stores is reduced; they visit stores more frequently and stores sell more.

Our results raise questions about where the value of BOPS for customers comes from. The value proposition for the customer was originally to increase the speed of the delivery for online customers and to allow them to save shipping costs. Interestingly, if we examine the time that it takes BOPS customers to pick up their items, we see that speed does not seem such an important concern for the average customer (see Figure 3). Besides saving shipping costs, the BOPS project seems to offer a positive externality to customers in the form of more reliable inventory information that can be used before going to the store. For the company, BOPS results in additional traffic and sales in the stores and cross-selling of products for customers that visit stores to pick up their orders.

Our results might depend substantially on the type of products transacted. In our empirical setting, most of the products have an experiential component and shopping in the store is a pleasant experience. For highly standardized products, or for products which lead to a less pleasant store experience, it is possible that BOPS implementation does not result in such a substantial shift from the online channel to the store channel.

Randomized field experiments are an ideal way to cleanly identify the impact of retail online-offline strategies implementations. In situations where randomized field experiments are not feasible, we believe that the framework we have presented, consisting of identifying natural experiments and performing DiD estimation of the effect of the treatment, can help retailers achieve a more precise estimation of the effect of their online-offline integration strategies.

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7. Appendix: Tables and Figures

Table 1 Summary Statistics

| B&M Stores - Daily Parameters per Store | | | | | |
|---|-------|--------------|-------|---------|---------|
| Traffic | | Transactions | | Sales | |
| Mean | StDev | Mean | StDev | Mean | StDev |
| 1018.1 | 801.8 | 285.5 | 205.9 | 27424.2 | 20716.1 |

| Online Store - Daily Parameters per DMA | | | | | |
|---|--------|--------|-------|--------|---------|
| Visitors | | Orders | | Sales | |
| Mean | StDev | Mean | StDev | Mean | StDev |
| 912.4 | 2485.2 | 24.7 | 71.2 | 3722.7 | 12907.7 |

Table 2 Variable Definitions

| Analysis of the Impact on the Online Channel | |
|--|--|
| Variable Name | Definition |
| $NUMVISITORS_{it}$ | Total number of unique visitor to the CB website coming from DMA i on day t . |
| $CLOSE_i$ | Dummy variable that is 1 if the DMA i has a BM store within its geographic area. |
| $AFTER_t$ | Dummy variable that is 1 if on date t the BOPS option was offered. |
| $SALES_{it}$ | Total dollar sales at the online store coming from DMA i on day t . |

| Analysis of the Impact on the Brick and Mortar Channel | |
|--|--|
| Variable Name | Definition |
| $TRAFFIC_{it}$ | Total number visitors to BM store i on day t . |
| US_i | Dummy variable that is 1 if the BM store i is located in the US. |
| $AFTER_t$ | Dummy variable that is 1 if on date t the BOPS option was being offered. |
| $SALES_{it}$ | Total dollar sales at the BM store i on day t . |

| Analysis of Channel Marketshare | |
|---------------------------------|--|
| Variable Name | Definition |
| $ONLINE_i$ | Dummy variable that is 1 if the observation refers to the online store. |
| $AFTER_t$ | Dummy variable that is 1 if on date t the BOPS option was being offered. |
| $SALES_{it}$ | Total dollar sales from the BM or the online store i on day t . |

| Analysis of BOPS Positive Externality | |
|---------------------------------------|---|
| Variable Name | Definition |
| $NUMPICKUPTX_{it}$ | Total number of customers that visit the BM store i on day t to pick up their BOPS order. |
| $TRAFFIC_{it}$ | Total number visitors to BM store i on day t . |
| $SALES_{it}$ | Total dollar sales at the BM store i on day t . |

| Analysis of Cart Abandonment | |
|------------------------------|---|
| Variable Name | Definition |
| $ABANDONMENT_{it}$ | Percentage of customers that place at least one item in their shopping cart and left without closing the sale at DMA i on day t . |

Table 3 DMA's Online Store

| | TRAFFIC | SALES | SALES |
|-----------------------|----------------------|----------------------|-------------------------|
| AFTER | -50.30*** (13.05) | 366.48** (111.80) | 686.99 (173.91) |
| CLOSE* AFTER | 135.56** (42.39) | -410.72* (188.81) | -1274.55*** (355.15) |
| ONLINE TRAFFIC | | | 6.37*** (0.36) |
| Fixed Effects | YES | YES | YES |
| Week | YES | YES | YES |
| Day of the Week | YES | YES | YES |
| <i>N</i> | 76903 | 76903 | 76903 |
| DMA | 210 | 210 | 210 |
| <i>R</i> ² | 0.96 | 0.77 | 0.83 |

Robust standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 4 BM Stores

| | TRAFFIC | SALES | SALES |
|------------------------|-----------------------|-------------------------|--------------------------|
| AFTER | -375.00*** (53.63) | 7995.71*** (1598.99) | 12486.33*** (1526.24) |
| US* AFTER | 246.71*** (39.33) | 4857.41*** (754.02) | 2210.21** (711.54) |
| TRAFFIC | | | 10.93*** (0.17) |
| Fixed Effects | YES | YES | YES |
| Macroeconomic controls | YES | YES | YES |
| Week | YES | YES | YES |
| Day of the Week | YES | YES | YES |
| <i>N</i> | 28138 | 28133 | 28133 |
| Stores | 83 | 83 | 83 |
| <i>R</i> ² | 0.75 | 0.66 | 0.70 |

Robust standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 5 Pickup Visits in the Stores

| | TRANSACTIONS | SALES | SALES |
|-----------------------|-------------------|----------------------|---------------------|
| PICKUP VISITS | 5.13*** (0.91) | 318.03*** (61.95) | 139.68** (46.20) |
| TRAFFIC | 0.22*** (0.02) | | 10.83*** (1.28) |
| Fixed Effects | YES | YES | YES |
| Week | YES | YES | YES |
| Day of the Week | YES | YES | YES |
| <i>N</i> | 12093 | 12547 | 12088 |
| Stores | 79 | 79 | 79 |
| <i>R</i> ² | 0.92 | 0.61 | 0.68 |

Robust standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 6 Cart Abandonment

| ABANDONMENT | |
|-----------------------|---------------------|
| AFTER | 0.004 (0.013) |
| CLOSE*AFTER | 0.009*** (0.007) |
| Fixed Effects | YES |
| Week | YES |
| Day of the Week | YES |
| <i>N</i> | 73500 |
| DMA | 210 |
| <i>R</i> ² | 0.136 |

Robust standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$ **Table 7** Store sales vs online sales in the area of influence of a store

| SALES | |
|-----------------------|--------------------------|
| AFTER | 21759.35*** (1862.40) |
| ONLINE*AFTER | -3685.37*** (572.74) |
| Fixed Effects | YES |
| Week | YES |
| Day of the Week | YES |
| <i>N</i> | 55412 |
| DMA | 161 |
| <i>R</i> ² | 0.41 |

Robust standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$ **Table 8** DMA's Online Store with Average Traffic less than 900 daily visits

| | SALES | SALES |
|-----------------------|--------------------|--------------------|
| AFTER | 34.54 (27.58) | 24.02 (28.29) |
| CLOSE*AFTER | -65.20* (25.45) | -51.08* (24.49) |
| ONLINE TRAFFIC | | 4.03*** (0.21) |
| Fixed Effects | YES | YES |
| Week | YES | YES |
| Day of the Week | YES | YES |
| <i>N</i> | 42405 | 42405 |
| DMA | 116 | 116 |
| <i>R</i> ² | 0.18 | 0.22 |

Robust standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

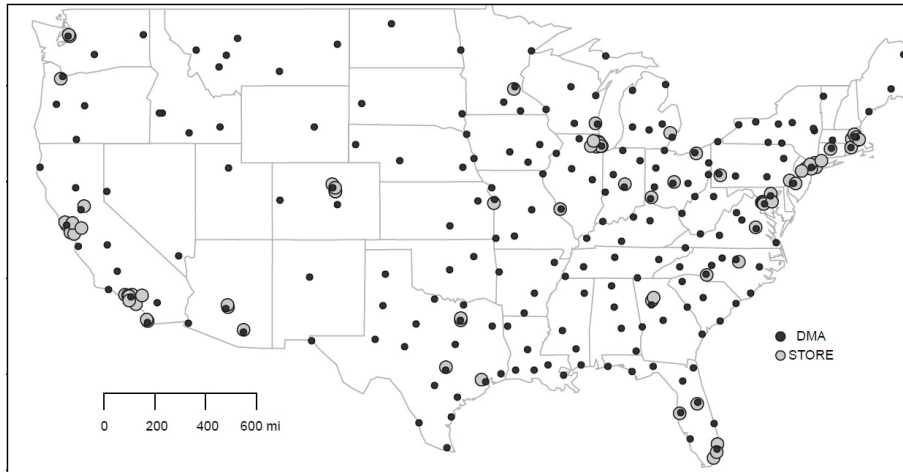


Figure 1 Brick and mortar stores and DMAs

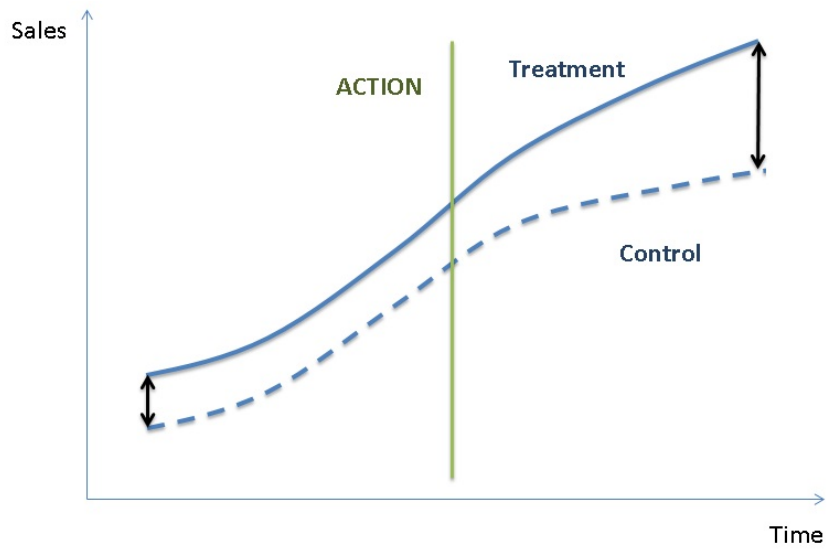


Figure 2 Natural Experiment

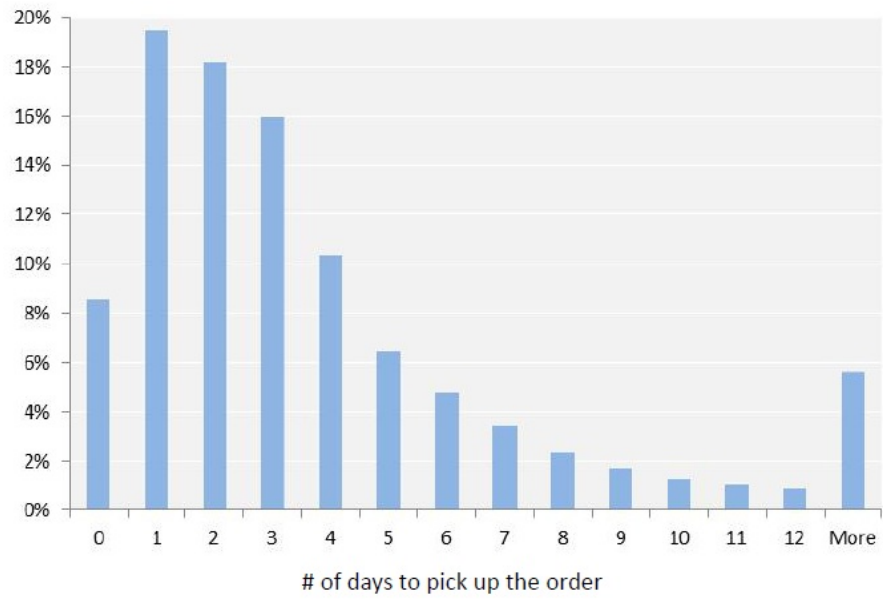


Figure 3 Pickup Delay