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The Value of Buy-Online-and-Pickup-in-Store in Omni-Channel: Evidence from Customer Usage Data

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The buy-online-and-pickup-in-store (BOPS) service has been widely treated by retailers as an important omni-channel initiative. However, few studies have attempted to quantify the impact of BOPS usage on subsequent purchase behaviors or examine the critical roles of offline stores in the value generation of BOPS. Thus, through 25,724 BOPS instances used by 16,202 unique customers via a hybrid retailer, this study investigated the impact of customers' BOPS usage on their online and offline purchase frequency and purchase amount. The moderating effect of offline store factors was investigated based on data from a focal retailer consisting of 110 stores in four cities. Using a combination of propensity score matching and difference-in-difference (DID) identification, our research found the significant positive effects of BOPS usage on offline purchase frequency and online purchase amount. We also found nuanced moderating effects of offline store characteristics (i.e., store density, product variety, and competition intensity) in the influence of BOPS usage on purchase behaviors. Our study thus generates important theoretical and practical implications for omni-channel operations.

Key words: omni-channel; offline store; buy-online-and-pickup-in-store; service value; difference-in-difference
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1. Introduction

With the continued growth of sales volumes in online channels, retailers are being pushed to operate omni-channel retailing—that is, the synergetic management of various channels and customer touchpoints—to enrich customer value and improve operational efficiency (Bell et al. 2015, Gao and Su 2017, Gu and Tayi 2017, Oh et al. 2012). For instance, Forrester (2014) reported that 71% of customers expect to view in-store inventory online, while 50% expect to buy-online-and-pickup-in-store (BOPS). Best Buy further announced that about 40% of its online customers opt to pick up in store. Moreover, in 2013, 64% of retailers implemented BOPS (Rosenblum and Kilcourse 2013). Accordingly, the BOPS service has been widely treated as an important omni-channel initiative by retailers (Gao and Su 2017, Gu and Tayi 2017).

Retailers benefit from BOPS because it can generate store traffic and increase sales (Gao and Su 2017). However, as one of many omni-channel initiatives, BOPS is still in its early stages and is becoming one of the top managerial challenges for retailers today (Gu and Tayi 2017, Tsay and Agrawal 2004). Retailers are thus eager to understand how to lead customers in actively responding to BOPS. So far, existing literature on the topic has applied retailer perspective or analytical models to investigate the value of BOPS. For example, Gallino and Moreno (2014) empirically tested the influence of stores' BOPS implementation on their online and store sales, while Gao and Su (2017) developed an analytical model to test the impact of BOPS initiatives on store operations. However, few operations management studies have used customer usage data to quantify the impact of BOPS usage on subsequent customer purchase behaviors, nor examined the critical role of offline stores in the value generation of BOPS services. Behavioral operations scholars have proposed that an operations management study utilizing customer-level data could enable more effective recommendations for supply chain design and improvement (Croson et al. 2013). As such, investigating customers' BOPS usage behaviors and interactions with operating systems (e.g., offline stores) can extend current understandings of BOPS' value.

This study thus aims to enter the discourse on omni-channel by examining the value of customers' BOPS usage. Specifically, we address the following research question: *What is the impact of BOPS usage on subsequent purchase behaviors*? To answer this question, we focus on two customer purchase behaviors in online and offline channels: purchase frequency and purchase amount. Purchase frequency refers to the number of purchase occurrences over a specific period of time, and purchase amount refers to the average amount of consumer purchases (i.e., basket value) per transaction. Since purchase frequency and amount are both important metrics for retailers, analyzing these two variables can provide direct insights on retailer performance.

Although it has been generally acknowledged that customers appreciate BOPS, BOPS services can yield different customer reactions. To this end, exploring store-level factors can help deepen our understandings of how retailers can benefit from omni-channel initiatives (Cao and Li 2015, Tsay and Agrawal 2004). Offline stores act as a contextual factor for BOPS, as they can substantially change customers' preferences, attitudes, and intentions toward the given BOPS service (Rabinovich and Bailey 2004, Simon and Usunier 2007, Tsay and Agrawal 2004). Customers may react differently to BOPS due to differences in the density, product variety, and competition intensity of a retailer's offline stores. However, no research has empirically investigated the interactive effects of BOPS usage and offline stores on customer purchase behaviors. This study thus aims to bridge this gap in the literature by addressing a second research question: *How do offline store characteristics relieve or magnify the impact of BOPS usage*?

Using 25,724 BOPS instances by 16,202 unique customers from a hybrid retailer spanning January 2015 to December 2015, the current study investigated the impact of customers' BOPS usage on their online and offline purchase frequency and amount. The focal retailer's data from 110 stores in four cities were used to evaluate how offline store factors (i.e., store density, product variety, and competition intensity) moderated customers' reactions to BOPS usage. Using the combination of propensity score matching and difference-in-difference (DID) identification, our research found that BOPS usage enhances customers' offline purchase frequency and online purchase amount. In addition, the role of BOPS usage in enhancing online purchase frequency and amount was strengthened with lower offline store density, larger product variety in pickup stores, and greater offline competition intensity. The enhancing effect of BOPS usage on offline purchase amount was found to be strengthened with a higher offline store density and lower offline competition intensity.

Given these results, this study contributes to extant literature by complementing and advancing current understandings of omni-channel in general and BOPS in particular. First, we focus on the value of customers' BOPS usage from a behavioral operations perspective, which complements literature on retailer perspective and analytical models when investigating the consequences of BOPS implementation. Second, we focus on the moderating effects of offline store factors on the influence of customers' BOPS usage, which contributes to our understanding of how and why BOPS service and offline store operations should be managed as a whole. Finally, our study provides practitioners with insights for improving retailing operation management when introducing BOPS initiatives.

2. Hypotheses Development

2.1. Impact of Customers' BOPS Usage on Purchase Frequency and Amount

Satisfactory experiences can positively influence customers' channel reengagement behavior due to stickiness effects (Barwitz and Maas 2018, Rego et al. 2013), and BOPS usage is one method for delivering this satisfaction. First, BOPS eliminates customers' information search friction, which facilitates their access to comprehensive information about product price and availability prior to purchase. Second, because customers can pick the product up in physical stores, they can experience immediate access to the purchased product (Bell et al. 2014). Third, BOPS offers customers the benefit of saving on delivery fees. Through such means of satisfaction, BOPS usage can enhance customers' stickiness to online channel, which can lead to more frequent online purchases.

BOPS also allows customers to learn about a retailer's pricing information in both online and offline channels (Huang et al. 2016). Depending on information asymmetry and profitability, retailers are incentivized to offer different prices to customers in different channels. BOPS enables customers to learn about pricing information in both online and offline channels, thereby reducing concerns regarding price discrepancies between online and offline channels. In this way, BOPS can facilitate the purchase of more items per basket in online channel and provide customers with an overall satisfactory experience. Such satisfactory experiences can, in turn, motivate them to allocate more time, effort, and money to shopping in online channel.

H1. *Customers' BOPS usage has a positive effect on their* (*a*) *online purchase frequency and* (*b*) *online purchase amount.*

Typically, after confirming the desired products are in stock and ordering them online, BOPS users go to offline stores for pickup. Importantly, offline stores provide the necessary context for fit and feel experiences (Bell et al. 2014). While picking up products, BOPS users have substantial opportunities to feel, smell, touch, and try the products displayed within stores. As such tactile interactions can be key to purchasing products like cosmetics and apparel, the experiential capabilities of offline stores can enhance brand equity and repeated purchases (Avery et al. 2012, Bell et al. 2014, Zhang et al. 2016).

Moreover, picking up products in-store leads to visibility and possible engagement with other products in offline, which can induce unplanned purchases and create more cross-selling opportunities (Gallino and Moreno 2014, Stilley et al. 2010). The offline store itself is a place of sensory stimuli. BOPS users are met with appealing product packages, colorful displays, and advertisements covering the walls and floor. Some customers enter with the intention to buy only a certain set of products and quickly change their minds as in-store stimuli inspire unintended purchases (Balakrishnan et al. 2014). Other customers use these in-store stimuli as cues to remind them of what products they need. In either case, in-store stimuli trigger memories of forgotten or unrecognized needs and desires, which can result in unplanned purchasing in offline stores (Hui et al. 2013, Inman et al. 2009).

H2. *Customers' BOPS usage has a positive effect on their* (*a*) *offline purchase frequency and* (*b*) *offline purchase amount.*

2.2. Moderating Effect of Offline Store Characteristics

2.2.1. Offline Store Density. A retailer's offline store density influences its desirability to customers (Tsay and Agrawal 2004). Customers favor the convenience of a nearby store over one that is more distant. As store numbers increase and create denser networks, customers find themselves closer to stores and thus not required to travel far to make purchases (Cachon 2014, Reynolds et al. 2002). In such cases, reductions in transportation costs can directly increase the utility of purchasing from offline channels and thereby decrease the likelihood that customers will buy from online channels (Forman et al. 2009).

In this way, higher store density can undermine the enhancing effect of BOPS on online purchase frequency and amount for two reasons. First, as previously mentioned, when store density increases, customers find they don't need to travel far to make purchases because they are closer to the stores. BOPS users can perceive and experience these decreasing transportation and time costs when picking up products in offline stores. In such situations, the value proposition of online channels offered by BOPS—such as full information delivered before purchase and immediate fulfillment after purchase—tend to be weakened. Second, BOPS users often visit offline stores to purchase products after checking product availability online, a behavior known as "research online, purchase offline" (Gallino and Moreno 2014). This channel-shift effect can be enhanced when store density increases due to the decreases in time and cost that can come from purchasing offline.

H3. *Offline store density weakens the positive influence of BOPS usage on* (*a*) *online purchase frequency and* (*b*) *online purchase amount.*

Higher offline store density strengthens the enhancing effect of BOPS usage on offline purchase frequency and amount for three reasons. First, as the density of offline stores increases, reductions in transportation costs directly increase the utility of purchasing from offline channels. As such, BOPS users can directly experience the increased utility of offline channels, which leads to higher offline purchase frequencies. Second, due to easier store access, store visits should increase customers' understandings of retailers' in-store products (Avery et al. 2012). Information from offline stores may incur BOPS users' interest in certain product categories, which can induce more unplanned purchases. Third, product returns are much easier to accomplish with access to offline stores (Ofek et al. 2011, Petersen and Kumar 2009). Given the decreasing risk of purchasing errors that result from the aforementioned points, BOPS can lead to more unplanned in-store purchases when the density of offline stores increases.

H4. *Offline store density enhances the positive influence of BOPS usage on* (*a*) *offline purchase frequency and* (*b*) *offline purchase amount.*

2.2.2. Product Variety in Pickup Stores. High product variety in pickup stores can strengthen the enhancing effect of BOPS usage on online purchase frequency and amount in several ways. First, high product variety in pickup stores can facilitate BOPS users' understandings of retailers' products and lead them to explore product alternatives. With the additional product knowledge provided by in-store showrooms, customers can have more confidence in their online purchases (Ton and Raman 2010). Second, when product variety in pickup stores is higher, pickup items are more likely to be in stock at offline stores. As a result, customers can experience immediate access to purchased products and, with less wait time, BOPS users tend to have higher levels of online purchase frequency and amount.

Higher product variety in pickup stores can also potentially generate countervailing effects on customers. For example, compared to offline channels, online channels carry a wide selection of products (Brynjolfsson et al. 2013). As product variety in pickup stores increases, the benefit of online channel —such as greater selection and availability—is weakened. Faced with the decreasing utility of purchasing from online channel, BOPS users might exhibit less repeated purchases and decide to buy fewer extra products during their visits to online channels. However, considering increases in product knowledge and the enhanced probability of immediate access to purchased products (as hypothesized above), we expect that the reinforcing effect caused by higher product variety in pickup stores will dominate the weakening effect.

H5. *Product variety in pickup stores enhances the positive influence of BOPS usage on* (*a*) *online purchase frequency and* (*b*) *online purchase amount.*

Higher product variety in pickup stores strengthens the enhancing effect of BOPS usage on offline purchase frequency and amount for two key reasons. First, when product variety is high, BOPS users are exposed to more product categories during pickup in physical stores. Customers thus have opportunities to feel, touch, and try more products displayed in stores (Balakrishnan et al. 2014). Facing greater selection and availability in pickup stores, BOPS users are likely to exhibit more repeated purchases and buy extra products during their visit (Gallino and Moreno 2014). Second, increasing the number of available products in pickup stores increases customers' choice sets and increases the probability that stores will have the products customers want (Ryzin and Mahajan 1999, Smith and Agrawal 2000). In other words, high product variety enables pickup stores to better match BOPS users' preferences and needs, as well as increases the likelihood that they will buy additional products (Ton and Raman 2010).

H6. *Product variety in pickup stores enhances the positive influence of BOPS usage on* (*a*) *offline purchase frequency and* (*b*) *offline purchase amount.*

2.2.3 Store Competition Intensity. Competition intensity influences the survival and growth of competitors in an industry (Auh and Menguc 2005). When the intensity of store competition is high, there are more competing stores in the same districts. Intensely competitive markets generate more choices for BOPS users, meaning they have more places to get accurate information about product prices and availability. Moreover, BOPS users have been shown to shift from online to offline fulfillment (Gallino and Moreno 2014). When store competition intensity increases, this channel-shift effect is often enhanced due to more purchase choices as well as greater product selection and availability in offline channels. As a result, the enhancing effect of BOPS usage on online purchase frequency and amount should be lower.

H7. *Store competition intensity weakens the positive influence of BOPS usage on* (*a*) *online purchase frequency and* (*b*) *online purchase amount.*

Higher offline competition intensity also tends to weaken the enhancing influence of BOPS on offline purchase frequency and amount, as intensely competitive environments are characterized by cut-throat rivalries that result in price and promotion wars, both of which increase the threat of customer loss (Jaworski and Kohli 1993). Indeed, BOPS usage can generate traffic (Gao and Su 2017); however, when competition intensity is high, BOPS users are exposed to more competitors' stores during in-store pickup. In such cases, these customers have more choices and may opt to purchase from competitors who offer more competitive pricing and promotions. The importance of BOPS usage in increasing offline purchase frequency and amount should thus be lower.

H8. *Store competition intensity weakens the positive influence of BOPS usage on* (*a*) *offline purchase frequency and* (*b*) *offline purchase amount.*

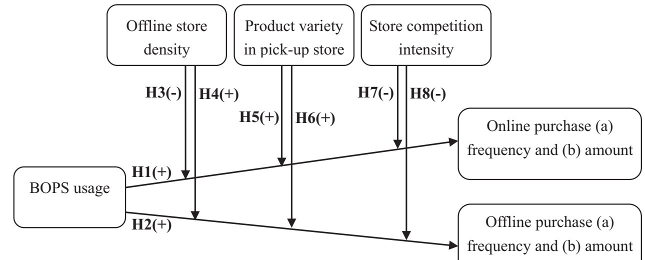
Figure 1 Illustrates our complete conceptual model.

3. Methodology

3.1. Research Context

The empirical setting of this study is a leading nationwide retailer in Asia. The company was founded in 1990 as a traditional brick-and-mortar retailer and, as of 2016, has more than 1000 offline stores in over 300 cities. In 2010, the company established its online

Figure 1 Research Model and Hypotheses



channel and became a hybrid retailer with both online and offline operations and infrastructures. It sells a diverse set of categories such as general merchandise, electronics, computers, and household appliances. In 2015, online sales represented 31.0% of total sales for this retailer. In 2016 and 2017, the percentage of online sales increased to 42.7% and 52.1%, respectively. In 2013, the retailer offered the option of BOPS. Their BOPS service allows customers to pay for products online and pick up from a nearby store of the customers' choice. Once products have been delivered from the distribution center to stores, the retailer notifies customers that their products are ready for pickup. The frequency of replenishment for offline stores is about once a day. If the pickup items are in stock at stores, customers can experience immediate access to the purchased products. In order to quantify the impact of BOPS usage on customer reactions to the service, we obtained longitudinal data from the retailer spanning January 2015 to December 2015. During this period, BOPS was available for each of the retailer's offline stores.

Due to limited availability, it was not feasible to obtain data from all of the cities in which the retailer has stores; thus, we chose four cities to focus on. These four cities were chosen for two reasons. First, two of them are located in the southern part of the country, whereas the other two cities are located in the north. This ensures sufficient variance in locations among the cities. Second, the total populations of these four cities are more than 30 million and, therefore, are representative of the retailer's potential spectrum of customers. In December 2015, the retailer had 110 offline stores in the four focal cities. The average size of these stores is 4494 m^2, with the largest store being 19,620 m^2 and the smallest store being only 419 m^2. Additionally, the stores' locations also vary widely. Some are located in downtown areas, whereas others are located in more suburban areas. Due to these variances in store size and location, these 110 offline stores can be considered representative for this retailer.

This hybrid retailer offers an ideal setting for empirical analysis for several reasons. First, the retailer takes detailed records on customers' transaction data in the omni-channel. This longitudinal transaction-level data was used to quantify the extent of customer purchase frequency and amount in both online and offline channels. Second, for each transaction, information was obtained regarding how the order was paid for and fulfilled. We were therefore able to clearly observe customers using the BOPS service. Since not all customers used BOPS, the observation of objective BOPS usage helped us understand the value of BOPS in detail. Obtaining objective data about the stores where BOPS users picked up their products allowed us to systematically analyze the moderating role of offline store factors and more accurately estimate the value of BOPS in this particular context.

We tested our hypotheses using data aggregated at the monthly level. Our data indicates that the transaction frequency for each customer was relatively low. When the data was collapsed at the weekly level, the short observation window did not entail sufficient variations; there were lots of zero values for customer purchase frequency and amount in the omni-channel. Similarly, the quarterly level data did not provide the granularity necessary to reveal ongoing patterns of customer purchase frequency and amount. Therefore, the observation window in the following research design was at the monthly level.

3.2. Research Design

To address potential endogeneity bias (Dhanorkar 2019, Gu et al. 2017), the ideal research design would be a field experiment. The ideal experiment would take a sample of customers who have never used BOPS before, and randomly assign some to use BOPS and others not to use BOPS. Then, the analysis would observe how customer behaviors change. However, in practice, opportunities for field experiments are very limited and random assignment could not be used. Our empirical analysis was instead built on the combination of propensity score matching and difference-in-difference (DID), a quasi-experimental approach that allowed us to approximate the ideal experiment.

Specifically, the main source of endogeneity in our context was the selection bias between users and non-users of BOPS because BOPS usage was a decision variable. Such bias may confound the influence of BOPS on subsequent purchase behaviors and prevent causality inference regarding the consequences of BOPS usage. To address this issue, we used propensity score matching to create treatment and control groups that were as similar as possible. Customers using BOPS comprised the treatment group, while customers who did not use BOPS comprised the control group. We aligned the data from matched treatment and control groups over identical time periods. Such matching allowed us to pair together customers that were as similar as possible, based on observables (as explained below), with the only exception being that one chose to use BOPS (treatment) and one chose not to (control). The matched control group enabled us to control for obvious sources of heterogeneity across groups, rule out most alternative explanations, and provide greater validity for addressing endogeneity concerns (Cook et al. 2002, Goldfarb and Tuck 2014).

In accordance with economics and operations management literature (Dhanorkar 2019, Gu et al. 2017, Ketokivi and McIntosh 2017), we combined DID with propensity score matching to address potential endogeneity biases in testing the hypotheses. The changes in BOPS usage implied two observation periods for customers: pre-period and post-period. Differences in purchase frequency and purchase amount in the treatment and control groups between these two periods were then compared. We chose 3 months as our observation window for the pre-period and post-period, respectively, for two reasons. First, it usually takes time for customers to perceive, experience, and respond to BOPS. Short observation windows run the risk of not capturing the full trajectory of purchase frequency and amount in omni-channels. Second, long observation windows run the risk of introducing other unobservable, confounding factors.

3.3. Data and Measurement

We tested our theoretical hypotheses using a longitudinal dataset shared by the hybrid retailer. This data comprised three key tables: a transaction table, a membership table, and a store table. The transaction table contained detailed transaction-level data for the four cities in both online and offline channels, such as customer ID, name of product, price, order time, channel for ordering, type of order fulfillment, and store names for offline transactions. The longitudinal data on customer transactions covered January 2015 to December 2015. The membership table contained membership information, such as customer ID, gender, date of birth, date of registration in the online channel, date of registration in the offline channel, and membership level. The membership data covered January 2006 to December 2015. Using customer IDs, we linked the transaction table with the membership table together to track different transactions to the same customer. The store table contained key data about offline stores for over four cities, such as store name and location, time of store opening, time of store closing, store size (measured by m^2), and store type. The store data covered March 2003 to December 2015. Using store name, the transaction table, and the store table were also linked together. Furthermore, we interviewed the retailer's top manager about competition with other retailers. In this interview, the manager identified three major competing retailers whose locations we obtained by searching online maps of the area.

In 2015, the hybrid retailer made approximately 5.7 million transactions, including 1 million online transactions across the four focal cities. Among the 1 million online transactions, 33,039 instances were fulfilled through BOPS service. We lacked sufficient data to examine the pre-period and post-period behaviors for some customers who made purchases in the first or last 3 months of 2015. We removed these BOPS usage behaviors accordingly, yielding 25,724 instances of BOPS usage behavior by 16,202 unique customers. The average number of BOPS usage behavior for these customers was 1.588. The transaction table further showed that the retailer sold 873 distinct product categories in total.

The key dependent variables in our empirical analysis were purchase frequency and purchase amount in both online and offline channels. Purchase frequency was operationalized as a monthly transaction count, whereas purchase amount was operationalized as average spending per transaction. Specifically, online and offline purchase frequencies were separately measured by the number of each customer's online and offline transactions in a given month. Online and offline purchase amounts were measured by the average amount of spending (i.e., basket value) per online and offline transaction in a given month. For customers with no transactions in a given month, the value of purchase amount was 0. To address the skew in distribution, we first added this value of purchase amount by 1 and then log-transformed the resulting value. Treatment and control groups were measured by a binary indicator with a value of 0 for the control group and a value of 1 for the treatment group.

Based on the time BOPS was used in the given month, both treatment and control groups can be observed within two time periods: pre-period and post-period. We used a dummy variable ($Post_{it}$) to distinguish between these two periods. $Post_{it}$ was defined as whether customer i, in both treatment and control groups, belongs to pre-period or post-period at time t. A value of 0 for $Post_{it}$ indicated the pre-period, in which customer i in the treatment group did not use BOPS. For the post-period, in which customer i in the treatment group had used BOPS, $Post_{it}$ had a value of 1. It is worth noting that the values of $Post_{it}$ were assigned to customers in the control group in the same way. For customers in the control group, $Post_{it} = 0$ for the pre-period, in which customer i's matched pair did not use BOPS before the end of t. $Post_{it} = 1$ for the post-period, in which customer i's matched pair used BOPS before the end of t. This is because, as a matched sample to the treatment group, customers in the control group also experienced these two different observation periods, though customers in the control group did not use BOPS. It is also worth mentioning that different customers in the treatment group used BOPS at different times, meaning the Post variable should change with both customer i and time t. Appendix A shows examples of our data for DID specification as well as illustrations of DID estimates.

To assess offline store density (*StoreDensity*), we used the number of the retailer's stores near the pickup store. Customers using the BOPS service did not have a designated pickup store and could voluntarily choose a nearby store for pickup. According to the transaction and store tables shared by the retailer, we had clear information regarding which store customers chose for pickup, as well as the characteristics of these pickup stores. In our calculation of store density, the threshold for the distance between pickup store and other nearby stores was 5 km. We used 10 km in the robustness check as the alternative threshold. In 2015, 10 stores closed and 16 new stores opened. The product variety in pickup stores (*StoreProductVariety*) was measured by the number of unique products sold in the offline pickup stores. According to the transaction and store tables shared by the retailer, we first observed offline stores that each customer chose for pickup. Then, we tracked the objective transaction data for each store and calculated the number of unique items selling in the pickup store within the given month. To address the skew in distribution, we log-transformed this value. To assess store competition intensity (*StoreCompetition*), we used the number of competing stores within 5 km as the measurement. A larger number of competing stores near the pickup store indicated a higher intensity of offline competition.

We controlled for several other factors. The first control was the individual BOPS experience, which was measured by the cumulated number of BOPS transactions in which customers had engaged. The second factor was the number of BOPS products, which was measured by the average number of products for BOPS users picked up. The value for the number of BOPS products was 0 for customers in the control group. The third factor was online product variety, which was measured by the number of different products sold in the online channel. We log-transformed this value to address the skew in distribution. The fourth factor was the number of distribution centers in each city, which may have influenced the value of BOPS. For each transaction, we observed the distribution center from where products were shipped and aggregated at the city level.

The fifth factor was customers' channel preference. Customers wanting to buy products through this retailer are required to register as a member of the retailer. If a customer registered in both online and offline channels, we treated them as a multi-channel customer. If a customer registered in only one channel, we treated them as a single-channel customer. Channel preference was measured using a dummy variable with a value of 0 for online-only customers and a value of 1 for multi-channel customers. The offline-only customers were excluded from both treatment and control groups. The sixth factor was the level of user membership, which was calculated by the retailer based on customers' cumulated spending in prior transactions. The membership has four different levels ranging from 1 to 4. Higher membership levels indicated higher spending in prior transaction histories. Customers whose cumulated spending was below approximately \$1500 had their membership treated as level 1. The range of cumulated spending for level 2 was \$1500 to \$7500. The range of cumulated spending for level 3 was \$7500 to \$15,000. Customers whose cumulated spending was above \$15,000 were assigned to level 4. Finally, to control for the influence of heterogeneity across cities, we also added three dummies with different cities as the control variables. Table 1 shows constructs and measures. For online and offline purchase frequency, the mean value was 0.271 and 0.096, respectively. For the value of online and offline purchase amount before log transformation, the mean was 295.600 and 367.970.

3.4. Propensity Score Matching between Treatment and Control Groups

In our matching, the propensity score was defined as the latent probability of using the retailer's BOPS service given the covariates (Rosenbaum and Rubin 1983). We built a matching model for the propensity score with covariates that included gender, age, level of user membership, channel preference, city, duration of registration in the online channel, and duration of registration in the offline channel. The matching was done with the values of these covariates that were

Table 1 Constructs and Measures

Variables	Measurement
OnlinePurchaseFrequency	Number of online purchase occurrences in a given month
OnlinePurchaseAmount	Average amount of online spending per transaction in a given month (log-transformed)
OfflinePurchaseFrequency	Number of offline purchase occurrences in a given month
OfflinePurchaseAmount	Average amount of offline spending per transaction in a given month (log-transformed)
Treatment	Dummy variable (=1 treatment group; =0 control group)
Post	Dummy variable (=1 the time belongs to post-period; =0 the time belongs to pre-period)
StoreDensity	Number of stores within 5 km of the pickup store
StoreProductVariety	Number of unique products selling in the pickup store (log-transformed)
StoreCompetition	Number of competing stores within 5 km
BOPSExperience	Number of BOPS services that customer has used before a given month
BOPSProduct	Average number of products for BOPS users to pick up before a given month
OnlineVariety	Number of unique products selling in the online channel (log-transformed)
DistributionCenter	Number of distribution centers in a given month
ChannelPreference	Dummy variable (=1 multi-channel customer; =0 online-only customer)
MembershipLevel	Four different levels based on customers' transaction history

measured 1 month before the time of treatment. To avoid upward bias in the treatment group during the post-period, for each customer in the treatment group, the matched customer in the control group had to complete a transaction in the same month. As there were many more observations in the control group than in the treatment group, we selected a match from the control group with the closest propensity score for each customer in the treatment group. We implemented the nearest neighbor matching technique to select the closest control for each treated case (Ho et al. 2011). The nearest neighbor matching was done without replacement; in other words, the control units could only be chosen once during matching.

Table 2 reports the absolute standardized difference in means for each covariate, which was used to measure the balance of covariate distribution between the two groups (Rosenbaum and Rubin 1983). It was defined as $|\overline{X}_{q,1} - \overline{X}_{q,0}|/D_{q,0}$, where $\overline{X}_{q,1}$ and $\overline{X}_{q,0}$ refer to the means of the covariate for the treatment and control groups, respectively. $D_{q,0}$ refers to the standard deviation for the control group. The subscript "q" refers to the ID of variables used for propensity score matching. After matching, the standard deviation between treatment group and control group were close to one another. Therefore, to calculate the absolute standardized difference in means, we chose the standard deviation of the control group as the denominator. The absolute standardized difference in means usually suggests 0.25 as the balance criteria (Rubin 2001, Stuart 2010). As Table 2 indicates, the absolute standardized differences in means on all of the measured dimensions were markedly reduced and were all below the threshold of 0.25 after matching the data. Such a difference between the two groups thus satisfied the balance requirement.

To ensure that we obtained high-quality matching, the logit model results, which tracked propensity generation, are also shown in Table B1 of Appendix B. We checked the overall balancing properties of the matching by comparing the joint significance of all matching variables in the logit models before and after matching. The last row shows that the pseudo-R^2 was much lower for the matched sample than for the raw sample. The matching covariates were jointly significant before matching, but were found to be non-significant with a p-value of 0.301 after matching, indicating that matching improved the overall balance. Table 3 shows the descriptive statistics and correlation matrix for all variables.

3.5. Model Specification

The basic assumption for DID analysis is that time trends in dependent variables from treatment and control groups are the same without treatment. To demonstrate this, we generated a figure to visually inspect whether two lines shared the same trend prior to treatment. As shown in Figure 2, the four dependent variables in our analysis exhibited constant difference between treatment and control groups prior to treatment. In addition, we adopted the relative time model (Angrist and Pischke 2008) to conduct another common trend analysis. As summarized in Appendix C, the two groups closely resembled each other in terms of online purchase frequency, online purchase amount, offline purchase frequency, and offline purchase amount before the treatment. Significant trend differences appeared only after the treatment. This suggests that the treatment and control groups in our DID analysis met the parallel trend assumption.

Specifically, we first estimated the following model:

$$\begin{aligned} DependentVar_{it} = {} & \beta_0 + \beta_1 Treatment_i + \beta_2 Post_{it} \\ & + \beta_3 Treatment_i \times Post_{it} \\ & + ControlVars_{it} + \mu_i + v_t + \varepsilon_{it} \end{aligned} \tag{1}$$

where $DependentVar$ = {$OnlinePurchaseFrequency$, $OnlinePurchaseAmount$, $OfflinePurchaseFrequency$, $OfflinePurchaseAmount$}; i indexed the customer; and t indexed the month. μ_i was the individual-level fixed effect and v_t was the time-period fixed effect. The key focus of the DID specification was on the coefficient of $Treatment_i \times Post_{it}$, that is, β_3. It gave us the DID estimate of the treatment effect and reflected the effect of BOPS on the treatment group relative to the control group (Goldfarb and Tuck 2014, Gu and Tayi 2017). Since both treatment and

Table 2 Descriptive Statistics of Covariates Before and After Matching

		Original control group		Matched control group	
Covariate	Treatment group Mean (SD)	Mean (SD)	SDiff	Mean (SD)	SDiff
Gender	0.435 (0.496)	0.450 (0.497)	0.030	0.439 (0.496)	0.011
Age	31.001 (9.557)	37.204 (10.496)	0.649	31.213 (7.185)	0.377
Membership level	2.567 (0.754)	1.943 (0.893)	0.828	2.557 (0.759)	0.041
Duration of online registration	67.074 (15.511)	62.268 (13.915)	4.992	67.260 (15.190)	0.186
Duration of offline registration	51.114 (27.668)	59.240 (33.876)	5.452	53.788 (29.365)	2.674
Channel preference	0.450 (0.497)	0.569 (0.495)	0.074	0.495 (0.500)	0.045

Note. The city where a customer lived was also matched in the treatment group and control group.

Table 3 Correlation Matrix and Descriptive Statistics

Variable	Mean	SD	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
			Correlation matrix														
(1) *OnlinePurchaseFrequency*	0.271	0.352	1.000														
(2) *OnlinePurchaseAmount*	5.689	2.275	0.033	1.000													
(3) *OfflinePurchaseFrequency*	0.096	0.255	0.070	0.002	1.000												
(4) *OfflinePurchaseAmount*	5.908	1.674	0.029	0.001	0.387	1.000											
(5) *Treatment*	0.500	0.500	0.009	−0.004	0.001	−0.012	1.000										
(6) *Post*	0.500	0.500	0.038	0.002	−0.050	−0.050	0.000	1.000									
(7) *StoreDensity*	2.138	2.493	−0.001	0.005	−0.025	−0.005	0.000	0.000	1.000								
(8) *StoreProductVariety*	6.786	3.619	−0.015	0.003	−0.026	−0.002	0.000	−0.006	−0.293	1.000							
(9) *StoreCompetition*	2.387	2.128	−0.016	0.001	−0.007	0.009	0.000	0.000	0.531	−0.256	1.000						
(10) *BOPSExperience*	0.266	1.001	0.303	0.008	0.069	0.011	0.266	0.000	0.001	0.033	0.024	1.000					
(11) *BOPSProduct*	1.353	2.326	0.018	0.176	−0.005	−0.005	0.000	0.000	0.002	0.003	−0.227	0.015	1.000				
(12) *OnlineVariety*	9.634	2.556	0.020	−0.007	0.010	−0.014	0.000	0.000	0.028	−0.078	0.005	0.024	−0.002	1.000			
(13) *DistributionCenter*	32.486	11.059	0.032	0.009	−0.020	−0.027	0.000	0.302	−0.216	0.201	−0.097	0.076	−0.006	0.193	1.000		
(14) *ChannelPreference*	0.472	0.499	0.010	−0.002	0.234	0.146	0.000	−0.045	0.042	0.074	0.022	0.048	−0.004	−0.008	0.014	1.000	
(15) *MembershipLevel*	2.536	0.772	0.147	0.008	0.138	0.085	0.000	−0.026	0.102	0.074	−0.012	0.126	0.007	−0.024	0.056	0.325	1.000

Note. |Correlation| > 0.09 are all significant at the $p < 0.05$ level.

control groups existed, and pre-and post-periods were 3 months long, this analysis contained 308,688 (25,724 × 2 × 6) observations.

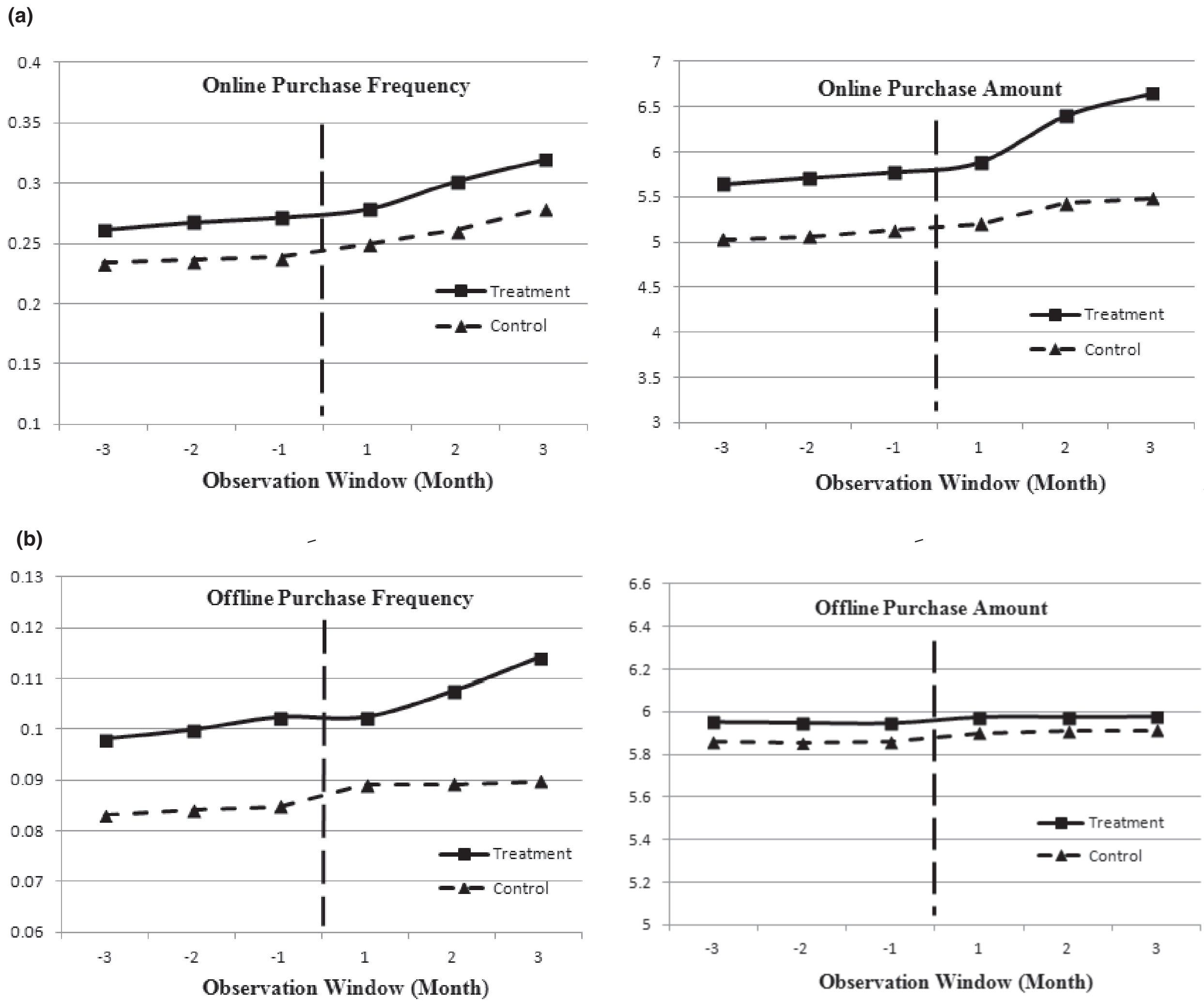
Given the influence of BOPS usage identified in Model 1, we further examined how the impact of BOPS was moderated by offline store characteristics. For customers who had never used BOPS, the variables of *StoreDensity*, *StoreProductVariety*, and *StoreCompetition* had no value. As a result, the moderating effect analysis was not built on the DID approach. Only the treatment group (i.e., customers using BOPS) was focused on in the following analysis. Although these moderating effect tests were not causal, they were merely associative in nature. Since there is no control group in the sample, this analysis contained 154,344 (25,724×6) observations. We added the following three factors to our specifications as the moderators: {*StoreDensity*, *StoreProductVariety*, *StoreCompetition*}. To avoid the concern of multi-collinearity, we centered these three moderators and then multiplied the mean-centered moderators by the Post. The specification, then, was as follows:

$$\begin{aligned} DependentVar_{it} = {} & \beta_0 + \beta_1 Post_{it} + \beta_2 StoreDensity_{it} \\ & + \beta_3 StoreProductVariety_{it} \\ & + \beta_4 StoreCompetition_{it} + \beta_5 Post_{it} \\ & \times StoreDensity_{it} + \beta_6 Post_{it} \\ & \times StoreProductVariety_{it} + \beta_7 Post_{it} \\ & \times StoreCompetition_{it} + ControlVars_{it} \\ & + \mu_i + v_t + \varepsilon_{it} \end{aligned}, \tag{2}$$

where μ_i was the individual-level fixed effect and v_t was the time-period fixed effect. For each model, the standard errors were clustered at the individual customer level. We used panel data with the fixed effects method to estimate coefficients in both Model 1 and Model 2, and included both individual-level fixed effects and time-period fixed effects. Adding individual-level fixed effect allowed us to control for individual-level heterogeneity, whereas adding time-period fixed effect allowed us to control for all time-period specific heterogeneity. As a result, the fixed effects estimation made the results more robust.

Variance inflation factors (VIF) were also checked to assess the extent of multi-collinearity. Large VIF values indicated a high degree of collinearity or multi-collinearity among the independent variables. Test outcomes showed that the VIFs of all independent variables for Model 1 and Model 2 were between 1.229 and 5.171, which suggested no potential problems with regard to multi-collinearity (Hair et al.

Figure 2 Time Trends for Treatment and Control Groups (a) Online channel; (b) Offline channel



1998). It was possible that the serial correlation in the error term would undermine the accuracy of the DID specification, so we used the Durbin–Watson test to assess the extent of autocorrelation. The test outcomes showed that the Durbin–Watson statistics for Model 1 and Model 2 were between 1.670 and 2.074. As these values were above the upper bound for the 5% critical value (Greene 2012), they suggested no potential problems in regards to autocorrelation issues. Table 4 shows the summary statistics for the key dependent variables.

4. Results

4.1. Hypotheses Testing

Tables 5 and 6 represent our estimation results. We first assessed the effect of BOPS usage on purchase frequency and amount in both online and offline channels. As columns (1) and (2) in Table 5 indicate, the coefficient of the interaction between *Treatment* and *Post* in the models was significantly positive for online purchase amount (β = 0.031, p < 0.001) and non-significant for online purchase frequency (β = 0.022, n.s.). When compared to the control group, BOPS usage led to 3.15% (=$e^{0.031}$ − 1) greater increases in online purchase amount for the treatment group. Given this, H1 was partially supported. Columns (3) and (4) in Table 5 show that the coefficient of the interaction between *Treatment* and *Post* in the models was significantly positive for offline purchase frequency (β = 0.072, p < 0.01) and non-significant for offline purchase amount (β = 0.011, n.s.). In other words, compared to the control group, the treatment group exhibited a 7.2% greater increase in purchase frequency in the offline channel after using BOPS. Accordingly, H2 was partially supported.

Given the influence of BOPS usage on purchase behaviors, we further examined how the impact of BOPS was moderated. In terms of the moderating effect of offline store density, columns (1) and (2) in Table 6 show a negative and significant coefficient for the two-way interaction (*Post* × *StoreDensity*) in the model for

Table 4 Summary Statistics for Dependent Variables

	(1) Treatment group (Pre-BOPS)	(2) Treatment group (Post-BOPS)	(3) Control group (After matched)	(4) Control group (Overall/Before matched)
Online purchase frequency	0.267 (0.005)	0.300 (0.020)	0.250 (0.007)	0.183 (0.381)
Online purchase amount	5.714 (0.068)	6.313 (0.387)	5.227 (0.191)	4.530 (1.463)
Offline purchase frequency	0.100 (0.002)	0.108 (0.005)	0.087 (0.003)	0.112 (0.253)
Offline purchase amount	5.948 (0.003)	5.975 (0.002)	5.883 (0.028)	5.580 (1.070)

Note. Standard deviations reported in parentheses.

online purchase frequency ($\beta = -0.088$, $p < 0.001$) and amount ($\beta = -0.076$, $p < 0.001$). These results suggest that, with a larger offline store density, the effect of BOPS usage becomes less prominent in enhancing online purchase frequency and amount. Hence, H3 was supported. A simple slope analysis provided further insights. When store density was low (one standard deviation below the mean), BOPS usage resulted in greater increases in online purchase frequency ($\beta = 0.429$, $p < 0.001$) and online purchase amount ($\beta = 0.336$, $p < 0.001$). When store density was high (one standard deviation above the mean), these two positive effects became weaker and insignificant ($\beta = 0.009$, n.s.; $\beta = -0.042$, n.s.).

Columns (3) and (4) in Table 6 indicate that the coefficient of the two-way interaction (*Post* × *StoreDensity*) was positive and significant in the model for offline purchase amount ($\beta = 0.038$ $p < 0.05$) and non-significant for offline purchase frequency ($\beta = 0.011$, n.s.). This suggests that, with a larger offline store density, the enhancing effect of BOPS usage on offline purchase amounts was stronger. According to a simple slope analysis, at low levels of store density, BOPS usage resulted in non-significant increases in offline purchase amount ($\beta = -0.085$, n.s.). At high levels of store density, the effect became significant and positive ($\beta = 0.104$, $p < 0.05$). Therefore, H4 was partially supported.

In regard to product variety in pickup stores, columns (1) and (2) in Table 6 show that the coefficient of the two-way interaction (*Post* × *StoreProductVariety*) was positive and significant in the model for online purchase frequency ($\beta = 0.056$, $p < 0.001$) and online purchase amount ($\beta = 0.053$, $p < 0.001$). This suggests that the enhancing effect of BOPS usage on online purchase frequency and purchase amount was strengthened by product variety in the pickup stores. Therefore, H5 was supported. A simple slope analysis showed that, when product variety in pickup stores was low, BOPS usage exerted a non-significant influence on online purchase frequency ($\beta = 0.007$, n.s.) and online purchase amount ($\beta = -0.045$, n.s.). When product variety was high, this effect became significant and positive ($\beta = 0.413$, $p < 0.001$; $\beta = 0.339$, $p < 0.001$).

Columns (3) and (4) in Table 6 show that the coefficient of the two-way interaction (*Post* × *StoreProductVariety*) was non-significant in the model for offline purchase frequency ($\beta = 0.018$, n.s.) and offline purchase amount ($\beta = -0.001$, n.s.). In other words, the enhancing effect of BOPS usage on offline

Table 5 Analysis Results on the Main Effect

	Online channel		Offline channel	
	Online purchase frequency	Online purchase amount	Offline purchase frequency	Offline purchase amount
Post	0.170*** (0.021)	0.025** (0.009)	0.175** (0.059)	0.013 (0.009)
Treatment × *Post*	0.022 (0.019)	0.031*** (0.008)	0.072** (0.026)	0.011 (0.007)
BOPSExperience	1.061*** (0.017)	0.579*** (0.013)	0.546*** (0.032)	0.149*** (0.011)
BOPSProduct	0.630*** (0.047)	0.020*** (0.002)	0.217** (0.080)	−0.008*** (0.002)
OnlineVariety	2.093*** (0.127)	0.731*** (0.051)	1.196*** (0.154)	0.295*** (0.050)
DistributionCenter	0.006 (0.029)	−0.021 (0.012)	0.068 (0.047)	−0.027* (0.012)
ChannelPreference	−0.285*** (0.015)	−0.115*** (0.006)	2.163*** (0.037)	0.515*** (0.006)
MembershipLevel	0.717*** (0.010)	0.191*** (0.003)	1.075*** (0.031)	0.101*** (0.002)
CityDummies	Included	Included	Included	Included
Individual FE	Included	Included	Included	Included
Time FE	Included	Included	Included	Included
N	308,688	308,688	308,688	308,688
Adjusted R^2	0.108	0.065	0.105	0.090

Note. The main effect of *Treatment* was dropout because it only varied with customer *i*, not time *t*. It was collinear with the fixed effects. $^{*}p < 0.05$; $^{**}p < 0.01$; $^{***}p < 0.001$; standard errors reported in parentheses.

Table 6 Analysis Results on Moderating Effects

	Online channel		Offline channel	
	Online purchase frequency	Online purchase amount	Offline purchase frequency	Offline purchase amount
Post	0.210* (0.107)	0.147* (0.066)	0.126 (0.172)	0.009 (0.042)
StoreDensity	0.105*** (0.025)	0.026 (0.021)	−0.080 (0.054)	−0.085*** (0.022)
StoreProductVariety	−0.023 (0.017)	−0.044*** (0.014)	0.159*** (0.035)	0.052*** (0.013)
StoreCompetition	−0.155*** (0.032)	−0.090*** (0.026)	−0.179*** (0.064)	−0.046 (0.028)
Post × *StoreDensity*	−0.088*** (0.025)	−0.076*** (0.023)	0.011 (0.036)	0.038* (0.019)
Post × *StoreProductVariety*	0.056*** (0.018)	0.053*** (0.016)	0.018 (0.028)	−0.001 (0.012)
Post × *StoreCompetition*	0.099*** (0.031)	0.093*** (0.027)	0.001 (0.040)	−0.034** (0.012)
BOPSExperience	0.972*** (0.017)	1.498*** (0.027)	0.525*** (0.038)	0.464*** (0.028)
BOPSProduct	0.631*** (0.050)	0.015*** (0.004)	0.171 (0.105)	−0.014*** (0.004)
OnlineVariety	2.233*** (0.212)	1.908*** (0.182)	0.733 (0.278)	0.217 (0.135)
DistributionCenter	−0.268*** (0.048)	−0.317*** (0.040)	0.090 (0.083)	−0.016 (0.035)
ChannelPreference	0.026 (0.021)	−0.086*** (0.019)	2.658*** (0.079)	0.973*** (0.018)
MembershipLevel	1.018*** (0.020)	0.487*** (0.009)	1.651*** (0.064)	0.156*** (0.007)
CityDummies	Included	Included	Included	Included
Individual FE	Included	Included	Included	Included
Time FE	Included	Included	Included	Included
N	154,344	154,344	154,344	154,344
Adjusted R^2	0.143	0.128	0.139	0.097

Note. $^*p < 0.05$; $^{**}p < 0.01$; $^{***}p < 0.001$; standard errors reported in parentheses.

purchase frequency and purchase amount was not influenced by product variety in pickup stores. Therefore, H6 was not supported. A potential explanation for this is that product variety online is much larger than that of pickup stores. The BOPS service can help customers obtain rich product information when conducting online purchases. Such information might limit the attractiveness of product variety in pickup stores. Therefore, although higher product variety in pickup stores tends to lead to greater selection and availability, these advantages may not be strong enough to attract BOPS users to spend a lot of time in physical stores, thereby resulting in a non-significant moderating effect of product variety in pickup stores.

Regarding offline store competition, columns (1) and (2) in Table 6 show that the coefficients of the two-way interaction term (*Post* × *StoreCompetition*) were positive and significant in the model for online purchase frequency ($\beta = 0.099$, $p < 0.001$) and online purchase amount ($\beta = 0.093$, $p < 0.001$). Contrasting with our prediction, this result suggests that the effect of BOPS usage in enhancing online purchase frequency and purchase amount was stronger in stores facing greater competition. A potential explanation for this is that, as offline stores face growing numbers of competing stores, retaining customers in online channel becomes more important for retailers. BOPS usage can facilitate satisfactory shopping experiences and can help customers deepen their relationships with retailers' online channel. Thus, when store competition intensity increased in the context of this study, the effect of BOPS usage in enhancing online purchase frequency and purchase amount was stronger.

Columns (3) and (4) in Table 6 show that the coefficient of the two-way interaction term (*Post* × *StoreCompetition*) was negative and significant in the model for offline purchase amount ($\beta = -0.034$, $p < 0.01$) and non-significant for offline purchase frequency ($\beta = 0.001$, n.s.). In other words, store competition weakened the enhancing effect of BOPS usage on offline purchase amount, partially supporting H8. A simple slope analysis showed that, when the level of store competition was low, BOPS usage exerted a significant influence on offline purchase amount ($\beta = 0.082$, $p < 0.05$). When the level of store competition was high, the effect became weaker and non-significant ($\beta = -0.063$, n.s.).

4.2. Robustness Check

We conducted several additional analyses to verify the robustness of our results. First, our main analysis used a 3-month window for pre- and post-periods to examine the impact of BOPS usage on subsequent purchase behaviors. To verify the insights of our analysis, we shortened the window to 2 months and reran the models. The sample size in the estimation was reduced accordingly. The results, as summarized in Appendix D, were consistent with the main results.

Second, when assessing offline store density, our main analysis used 5 km as the threshold for density calculation. To verify the robustness of this analysis, we chose 10 km as an alternative threshold for density calculation. The results, as summarized in Appendix E, were qualitatively consistent with the main results. Third, when assessing product variety in pickup stores, our main analysis used the number of unique products selling as the measurement. For further verification of our results, we also chose a number of product categories as an alternative measurement for product variety. The results, as summarized in Appendix F, were qualitatively consistent with the main results.

Fourth, we included pre-period purchase frequency and amount in the propensity score matching covariates and reran the model with the new matching results. The results, as summarized in Appendix G, are qualitatively consistent with the main results. Fifth, we chose customers who had only used BOPS once as the alternative treatment group. The results, as summarized in Appendix H, were qualitatively consistent with the main results. Sixth, to mitigate concerns about between-store variation, we used store type data to conduct a robustness check. The retailer categorized the stores into different types according to store size that ranged from level 1 to level 6. Higher levels indicated lower store sizes. For customers in the treatment group, the value of store type was measured by the level of pickup stores. For multi-channel customers in the control group, the value of store type was measured by the level for offline stores from which they had recently purchased products. For online-only customers in the control group, the value of store type was 7. The variable of store type did not usually change over time for specific customers. As a result, we only included the individual-level fixed effect in the analysis. The results, as summarized in Appendix I, are qualitatively consistent with the main results.

Seventh, we used a 3-month window before and after the treatment (i.e., BOPS usage) to observe customer purchase frequency and amount. As it was possible for new instances of BOPS usage may overlap with previous instances of BOPS usage within the 3-month window, multiple treatments may influence subsequent purchase behaviors with overlap. To better address these potential chain effects, we performed a robustness analysis by including a binary control variable (Overlap). This variable had a value of 1 if the corresponding customer in a treatment group had exhibited any new BOPS usage in the 3 months prior to treatment, and a value of 0 otherwise. The results of this robustness analysis are summarized in Appendix J and are, as well, consistent with the main results.

Finally, we created a false BOPS variable and conducted a falsification test. For the treatment group, we selected the treated customers without BOPS usage from January 2015 to June 2015 and yielded 2749 instances of BOPS usage. We treated January to March as the pre-false period and April to June as the post-false period. Using the same matched control customers, we compared the pre-false and post-false periods. This analysis contained 32,988 (2749 × 2 × 6) observations. The results, as summarized in Appendix K, indicate no significant differences in dependent variables between these two groups. This placebo test provided additional supportive evidence that the event affecting customers' purchase behaviors was actually the treatment (i.e., BOPS usage).

4.3. Additional Insights

We conducted several additional analyses to develop insights that complemented our main findings. First, we conducted an additional analysis to explore the moderating effect of customer characteristics. To do so, we added channel preference and BOPS experience in the moderating analysis. The results, as summarized in Table 7, show that, compared to online-only customers, the enhancing effect of BOPS usage on online purchase amount was stronger for multi-channel customers ($\beta = 0.127$, $p < 0.001$). The effect on offline purchase amount was weaker for multi-channel customers than for online-only customers ($\beta = -0.056$, $p < 0.01$). Compared with inexperienced BOPS users, the enhancing effects of BOPS usage on online purchase frequency and purchase amount were found to be weaker for experienced BOPS users ($\beta = -0.550$, $p < 0.001$; $\beta = -0.996$, $p < 0.001$). Such effects on offline purchase frequency and purchase amount were also found to be relatively weaker for experienced BOPS users ($\beta = -0.084$, $p < 0.01$; $\beta = -0.105$, $p < 0.001$).

Second, we quantified the economic impact of increasing the purchase frequency and purchase amount associated with BOPS usage. For each transaction, the average customer spending (i.e., purchase amount) was about \$295.600 and \$367.970 in the online and offline channel, respectively. Based on the coefficients shown in Table 5, we estimated that enhancing online purchase amount through BOPS usage would approximately lead to a \$2.523 ($(e^{0.031} - 1) \times \$295.600 \times 0.271$) increase in monthly online spending. Enhancing offline purchase frequency through BOPS usage lead to about a \$2.543 ($0.072 \times 0.096 \times \$367.970$) increase in monthly offline spending. In total, the increasing monthly spending in omni-channel after using the BOPS service was about \$5.066. Given the 25,724 instances of BOPS usage behavior in our data, the yearly increasing sales for the hybrid retailer over the four selected cities was approximately 1.564 million (25,724 × \$5.066 × 12). Increases in online sales approximately equaled the changes in offline sales.

Finally, given the nuanced moderating effect of store characteristics in the influence of BOPS usage on customer purchase behaviors in online and offline channels, we combined the purchase frequency and

Table 7 Additional Analysis on the Moderating Effects of Customer Characteristics

	Online channel		Offline channel	
	Online purchase frequency	Online purchase amount	Offline purchase frequency	Offline purchase amount
Post	0.499*** (0.036)	0.383*** (0.027)	−0.044 (0.102)	0.058** (0.020)
ChannelPreference	0.003 (0.025)	0.020 (0.022)	2.603*** (0.091)	1.001*** (0.021)
BOPSExperience	1.265*** (0.019)	1.958*** (0.029)	0.568*** (0.040)	0.517*** (0.031)
ChannelPreference × *Post*	0.034 (0.028)	0.127*** (0.027)	0.103 (0.088)	−0.056** (0.021)
BOPSExperience × *Post*	−0.550*** (0.023)	−0.996*** (0.035)	−0.084** (0.030)	−0.105*** (0.027)
StoreDensity	0.055* (0.022)	−0.013 (0.018)	−0.075 (0.052)	−0.061** (0.020)
StoreProductVariety	0.006 (0.014)	−0.015 (0.012)	0.167*** (0.030)	0.048*** (0.011)
StoreCompetition	−0.099*** (0.028)	−0.044^{+} (0.023)	−0.178** (0.061)	−0.070** (0.026)
BOPSProduct	0.630*** (0.050)	0.679*** (0.069)	0.172 (0.105)	0.134** (0.043)
OnlineVariety	2.006*** (0.209)	1.664*** (0.181)	0.705* (0.278)	0.205 (0.135)
DistributionCenter	−0.214*** (0.049)	−0.280*** (0.040)	0.093 (0.083)	−0.016 (0.035)
MembershipLevel	1.018*** (0.020)	0.479*** (0.009)	1.651*** (0.064)	0.154*** (0.007)
CityDummies	Included	Included	Included	Included
Individual FE	Included	Included	Included	Included
Time FE	Included	Included	Included	Included
N	154,344	154,344	154,344	154,344
Adjusted R^2	0.187	0.140	0.212	0.194

Note: $^{*}p < 0.05$; $^{**}p < 0.01$; $^{***}p < 0.001$; standard errors reported in parentheses.

purchase amount in two channels and reran the model. The results, as summarized in Appendix L, indicate the significant effect of BOPS usage on enhancing total purchase frequency and total purchase amount in omni-channel. The effect of BOPS usage on total purchase frequency was stronger with lower levels of store density, higher levels of product variety in pickup stores, and greater offline store competition. The effect of BOPS usage on total purchase amount was stronger with higher levels of product variety in pickup stores and greater offline store competition.

5. Discussion

5.1. Theoretical Implications

This study provides several theoretical implications for existing literature on BOPS. First, our study is among the first to attempt to empirically investigate BOPS using individual level transaction data. Prior BOPS literature has applied either retailer perspective or analytical models to investigate the value of BOPS (Gao and Su 2017, Gu and Tayi 2017), marking a need for individual-level investigation in the literature. As such, our study provides empirical evidence for the online and offline values of BOPS usage. The findings strongly support the claim that customers' BOPS usage can promote their spending in omni-channel (Bell et al. 2015, Gu and Tayi 2017, Oh et al. 2012). The current study thus addresses the above research gap.

Second, our study sheds new light on the role of offline stores in omni-channel retailing. In extant operations management literature, few studies have analyzed how offline store factors can affect customer purchase behaviors (Cachon 2014, Forman et al. 2009, Simon and Usunier 2007). By combining individual level transaction data with offline store data, the current study finds that offline store factors can be contingent on the relationships between BOPS usage and customers' online and offline purchase behaviors. Our findings thus provide preliminary understandings of the roles of offline stores in the value generation of BOPS, a new and necessary avenue for research in regard to how offline store factors can interact with omni-channel initiatives.

Finally, our study extends previous findings in omni-channel research through the application of a behavioral operations perspective. Given the current limitation of such an approach (Gallino and Moreno 2014, Gao and Su 2017), scholars have widely urged researchers to examine operations management issues from this lens, and the current study is in part a response to such a call (Croson et al. 2013, Gino and Pisano 2008). Our findings indicate that this perspective can extend our current understandings of individual customers' reactions to retailers' omni-channel initiatives, especially considering offline stores as the contextual factors.

5.2. Managerial Implications

The findings of the current study also offer guidelines for practitioners managing omni-channel initiatives. First, based on the longitudinal transaction-level data, our findings directly respond to concerns over the economic value of BOPS. Our findings indicate that BOPS usage can increase customers' monthly spending in omni-channel by \$5.066. The enhancing effects of BOPS usage on online and offline purchase behaviors were weaker for experienced BOPS users compared to those of inexperienced BOPS users. For this hybrid retailer, the yearly increasing sales over the four selected cities was approximately 1.564 million. A similar study can be leveraged by retailers to unveil the economic value of their own BOPS initiatives.

Second, our findings provide retail managers with actionable guidelines for BOPS implementation. While many managers have instinctively attempted to reap the benefits of BOPS, we found that BOPS usage can simultaneously enhance customers' online and offline spending. The enhancement in online spending was found to be approximately equal to increases in offline spending. Thus, managers should pay equal attention to increases in online and offline sales associated with BOPS usage. Our results inform benefit analyses for retailers and help retail managers design strategies to promote BOPS usage.

Moreover, operations managers are encouraged to understand the importance of offline stores in leveraging the value of omni-channel initiatives. More and more retailers are favoring BOPS implementation. However, managers should realize that omni-channel retailing has integrated online and offline channels, and certain offline factors have been shown to exert influence over customers' online and offline reactions to BOPS. For example, we found that offline store density can weaken the effect of BOPS usage on online purchase amount, while strengthening the influence of BOPS usage on offline purchase amount. As implementing an omni-channel strategy like BOPS requires substantial investments, managers should pay attention to the nuanced influence of offline store factors in the value of omni-channel initiatives.

5.3. Limitations and Future Research

Our findings provide unique insights into the value of BOPS in an omni-channel context. However, the current study has limitations that should be carefully considered by future researchers. First, the results of this study account for only one hybrid retailer. Extensions of this work should consider investigating whether such findings can be generalized to other hybrid retailers. Additionally, the BOPS service was offered by the focal retailer in 2013, yet our findings are specific to longitudinal transaction data from January 2015 to December 2015. A more comprehensive understanding of the benefits of BOPS requires analyses using data covering the time when the BOPS service was first launched. Second, although we investigated customers' reactions to BOPS usage, the scope of this study did not allow for examinations of how BOPS usage leads to such reactions. An in-depth investigation of the relationship between customers' BOPS usage and their online and offline reactions to it can provide further insights into such phenomenon. Finally, the secondary data was restricting in that it forced us to consider the moderating role of offline store factors in our framework. Alternately, it would be interesting to apply other theoretical lenses and data sources toward developing a more comprehensive contingency model for furthering investigations into the value of BOPS.

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Supporting Information

Additional supporting information may be found online in the Supporting Information section at the end of the article.

Appendix A: Difference-in-Difference Specification.
Appendix B: Balancing Tests from Matching.
Appendix C: Common Trend Analysis.
Appendix D: Using Two Months as Alternative Observation Window.
Appendix E: Using 10 Kilometers as Alternative Threshold for Store Density.
Appendix F: Using Number of Product Categories as Alternative Measurement for Store Product Variety.
Appendix G: Including the Pre-Period Purchase Frequency and Amount in the Matching Covariates.
Appendix H: Using Customers Who Only Used BOPS Once as Alternative Treatment Group.
Appendix I: Adding Store Type as Additional Control Variable.
Appendix J: Analysis Considering Overlap of Treatment Effects.
Appendix K: Placebo Test.
Appendix L: Using Total Purchase Frequency and Total Purchase Amount as Dependent Variables.