When the Bank Comes to You:
Branch Network and Customer Omni-channel Banking Behavior

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Abstract

Banks today have been increasingly reducing their physical presence and redirecting customers to digital channels, and yet, the consequences of this strategy are not well studied. This paper investigates the effects of banks' branch network changes (i.e., branch openings and branch closures) on customer omni-channel banking behavior. Using approximately 0.85 million (33 months') anonymized individual-level banking transactions from a large commercial bank in the U.S., this paper shows the asymmetric effects of branch openings and branch closures on customer omni-channel banking behavior. In particular, we find that branch openings increase customers' branch transactions, however the first branch opening leads to a migration of complex transactions to the branches, which might result in a net decrease in online banking in the short term. As consumers interact more with the physical channel, there is a gradual synergistic increase in customers' transactions via online banking as well as alternative channels due to a learning spillover effect. The learning spillover effect goes from easy online inquiries to more complex online transactions as additional branches open. On the contrary, branch closures result in a favorable migration pattern from the branch channel to online banking. This pattern, however, could be reversed once the last branch closes within the customer's residential neighborhood. Our study teases out the underlying mechanisms that drive customer omni-channel banking behavior in the context of branch openings and branch closures, and discusses the managerial implications for branch network restructuring and banking channel management.

Keywords: Branch network, branch openings, branch closures, online banking, omni-channel, propensity score matching, difference-in-differences

1. INTRODUCTION

Branches, as the traditional banking channel, have played the essential role in interactions between banks and customers. However, the rapid adoption of technology in the financial services industry and the changing demands of customers have led to a dramatic rise in digital channels and a concomitantly sharp decline in branch traffic. Industry surveys show that the percentage of internet users adopting the practice of online banking grew from 58% in 2010 to 61% in 2013 (Pew Research 2013), while the percentage of customers preferring branches for routine transactions continuously declined, from 34% in 2011 to 23% in 2014 (Novantas 2014).

At the same time, the U.S. banking industry was hit tremendously by the 2008 financial crisis. It has since operated under strict regulatory restrictions that curtail most banks from growing rapidly. The average efficiency ratio[1] of U.S. banks is close to 60% (BankRegData 2016), which is much higher than the 40% – 50% ratio typical for Asian banks (The Asian Banker 2015). One reason for the high cost of retail banking is physical branches, the setting up and maintaining of which require substantial capital investments in physical operations and labor. According to the CEB Tower Group (2013), the average transaction cost of branches is approximately 40 times higher than that of online banking. Thus, due to the current shift of customer behavior in omni-channel[2] financial services, banks have great opportunities to reduce operational costs and improve efficiency ratios by transforming branch networks and redirecting transactions to digital channels (McKinsey 2014).

In fact, in response to shrinking customer traffic and the high-cost infrastructure of physical banking locations, leading banks in the U.S. have taken steps to scale down their branch networks in recent years. Figure 1 shows that in the wake of the substantial bank consolidation and merger activities consequent upon the U.S. financial crisis, large banks, including Wells Fargo Bank and Bank of America, began in 2010 to shut down their branches. This trend continued beyond 2012, as digital banking became more and

[1] Efficiency Ratio = Operating Expenses / Revenue; it measures how well a company uses its assets and liabilities to generate revenue. A lower percentage is better, as it represents a company's capability of producing equivalent earnings with lower expenses.
[2] We refer to Brynjolfsson et al. (2013) for a discussion on the concept of omni-channel interactions.

more popular. Bank of America closed about 300 branches in 2013, followed by another 148 in 2014. Overall, in 2014, banks in the U.S. shut down 2,599 branches and opened 1,137 new ones, for a net decline of 1,462 branches (1.5%) (CNBC 2014). Meanwhile, banks have been experimenting with new branch models. Specifically, they have further reduced operational costs by retaining flagship branches to showcase featured products and improve consultative services while setting up many more-compact stores that, by including more self-service kiosks for routine transactions, require fewer tellers.

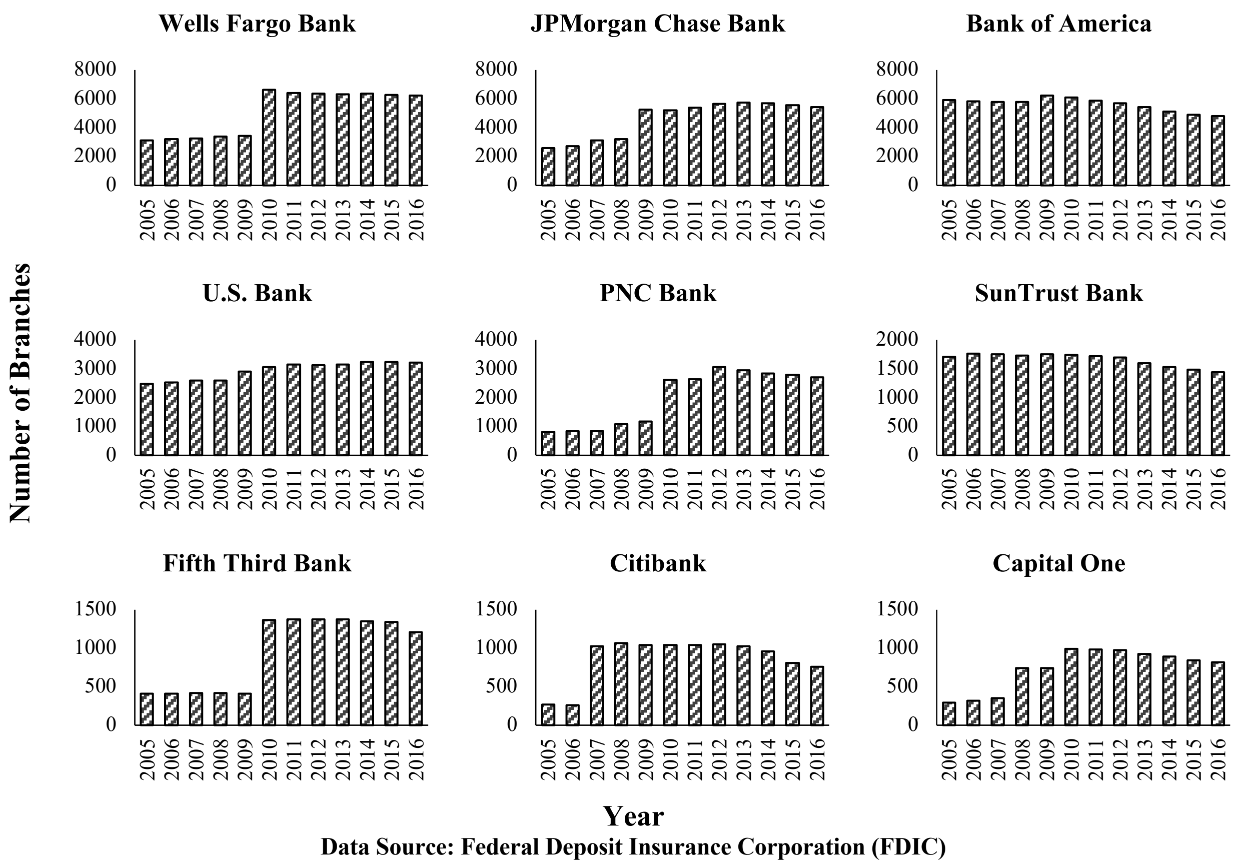


Figure 1. Branch Networks of Leading U.S. Commercial Banks

Notwithstanding financial institutions' attempt to reducing their physical presence, the effects of this strategy on consumer behavior are still not well understood, as we learned in our discussions with managers at several leading banks. In spite of the successful migration from physical to online transactions in many other industries (e.g., books, music, retail, etc.), online-only banking has not been particularly fruitful, due to service, security and relationship management issues (Investopedia 2017). Banks are especially wary of factors that can lead to adverse effects due to inappropriate channel management. For example, customers' channel preferences differ by transaction type (EY 2014). Although routine transactions such as balance checks are moving to digital channels, most customers still prefer face-to-face interactions at physical branches especially when seeking advice or purchasing complex products such as home mortgages and investments. This finding is supported by industry surveys, which show that about half of customers are likely to leave their banks due to inconveniences caused by closures of nearby branches (Accenture 2013). Bank branches may remain important for building and maintaining long-term customer relationships. As Paul Donofrio, CFO at Bank of America, said, "We still have one million people coming to our branches every day, and they need that channel. Some need it to transact, but a lot of them come in for advice and we want them to do that. So we need a certain footprint of financial centers (The Financial Brand 2017)."

These opposing opinions suggest that branch closure may successfully drive customers' migration to the digital channels, or it may actually hurt customer's relationship with the bank thus reducing their interaction with the bank eventually.[3] Hence, the effects of branch closures on customer omni-channel banking behaviors remain an unanswered question in the current literature, mainly due to the insufficiency of fine-grained individual-level data. Our paper aims to address this important gap by understanding customer behaviors in financial services with the development of financial technology. Moreover, there are several related papers investigating how the introduction of online channels affects customer behavior on existing physical channels (i.e., Campbell and Frei 2010, Xue et al. 2011), while the reverse effect is less studied. More recently, there are a few papers investigating how offline stores affect online sales for retailers (Pauwels and Neslin 2015, Bell et al. 2017, Wang and Goldfarb 2017, Kumar et al. 2018). However, all these studies have focused on understanding consumer behavior in the retail setting. Since consumer decision making in the banking context is quite different from that of retailing, as we point out below, we believe it requires a separate examination.

[3] We define branch closure to mean that the bank closes an existing branch, and branch opening to mean that the bank sets up a new branch.

Firstly, the extant omni-channel literature focuses on product-centric markets wherein factors such as product fit and look-and-feel are important considerations, whereas financial banking is a service-driven industry that is governed by interpersonal interactions that might be more tacit. Secondly, customer behavior is oftentimes more complex in the financial services context as compared to that of retailing. In the retail industry, there are often two types of channels for consumers to choose from – the online shopping website and the physical stores. In financial services, multiple channels (i.e., branch, online, call center, etc.) could co-exist and consumers have a lot more choices, complicating their decision-making process. Thirdly, due to the differences in the nature of transaction types in banking and retailing, the underlying mechanisms behind customers' omni-channel behaviors could be entirely different. For example, in the retailing context, offline stores may drive online sales due to a store return effect such that offline stores could provide the option of store returns which reduces customers' risk of online purchase (Kumar et al. 2018). Such a mechanism is unlikely to be at play in the banking context because of the differences in the inherent nature of financial services, and transactions such as banking inquires might be affected differently than bank transfers. As a consequence, one needs to practice caution when applying the findings in the retailing industry to the banking industry. In the sophisticated omni-channel setting, bank managers' informed decision-making regarding the restructuring of branch networks is thus critically dependent on a solid understanding of customers' multi-faceted behavior in the banking industry.

Therefore, in this study, we aim to address these gaps by empirically investigating how changes in the branch network affect customer omni-channel banking behavior. Using a unique, proprietary and large dataset (i.e., about 26,000 customers' banking transaction records during 33 months), we set out to complement the current omni-channel research by exploring the effects of branch network changes, including branch openings and branch closures, on customers' omni-channel banking behavior. In this paper, we address the following research questions: (1) What are the effects of branch openings and closures on customers' omni-channel banking transactions? (2) How do those effects change over time among customers? (3) What are the managerial implications given the consumer behavior? The presence of branch closures in our data greatly help in identification of mechanisms that could not be unraveled using only branch (or store) openings that the extant literature has focused on (i.e., Kumar et al. 2018, Bell et al. 2017).

We empirically answer these research questions by using a unique proprietary dataset from a large commercial bank in the U.S., which consists of customer profiles, anonymized individual-level banking transaction records, branch network data, zipcode-level aggregated characteristics, competition data of other banks' branches, and marketing efforts of the focal bank. Using difference-in-differences models coupled with propensity score matching, we find that customers' choice of different banking channels and transactions in these channels are affected by a *learning spillover effect*. In particular, branch openings tend to have a first-order effect on significantly increasing customers' visits to local branches for face-to-face transactions facilitated by bank employees. This is likely caused by the lower transportation costs of customers' traveling to the bank branches within their neighborhood as well as the increased awareness of the newly established local branch. For alternative channels (e.g., automated teller machine, voice response unit, call center), the impact of branch openings is insignificant. However, there is a small *substitution effect* on customers' transactions via online banking. This effect is especially strong for more complex online transaction types such as online money transfers and online services. On the contrary, when an additional branch opens, it shows a *synergistic effect* on increasing customers' omni-channel banking behaviors, including customers' usage of more complex transaction types via online banking. These seemingly contradictory effects between the two types of branch openings (i.e., first branch opening and additional branch opening) can be reconciled by a *learning spillover effect* caused by the more frequent interactions between customers and bank employees after branch openings.[4] Although the first branch openings may have the net result of consumers moving to the physical branch for the complex transactions, increasing number of transactions at the branches nudge the consumers to learn how they can perform more transactions online. Moreover, such customer learning goes from easy online inquiries to more complex online transactions as additional branches open over time.

[4] For example, as such increased face-to-face interactions with branch employees may translate into customers' better knowledge of online banking, it will gradually improve customers' perceived usefulness of online banking as well as their willingness to establish a relationship through this new channel, and, in the meantime, lower their perceived complexity and implicit fixed cost of using this new technology.

Interestingly, as branches close there is no simple reversal of the impacts of branch openings on customer omni-channel banking behavior. Firstly, after branch closures, we find that customers are not likely to abandon channels that they have already adopted, which again supports the underlying mechanism of a *learning spillover effect*. This is a consequence of customers already acquiring the requisite skills to use different channels from their interactions with branch employees, which they continue using even after branch closures. This also indicates that customers' adoption of omni-channel banking may help customers establish a long-term relationship with the bank. Secondly, customers tend to migrate to the online banking channel immediately after branch closures. However, once the last branch closes within the customers' residential neighborhood, consumers resort to human-service channels such as calling call centers to talk to a customer service representative, or even visiting branches outside of their residential neighborhood, in addition to online banking in the short to medium term. However, these effects are reversed in the long term and the overall volume of transactions go down across all channels. These findings highlight customers' complex reliance on human-service channels in today's omni-channel banking context and the need for human-mediated channels in banking services.

Our paper contributes to the literature on consumer behavior in financial services by empirically investigating the effects of branch network changes on customer omni-channel banking behavior and the underlying mechanisms. We also contribute to the empirical literature investigating physical store entries into the retailing context (i.e., Forman et al. 2009; Pauwels and Neslin 2015) and provide further insights into the effects of physical store closures in light of the recent demise of brick-and-mortar stores across many industries. We hope that this study will inform the store-closure strategies deployed by companies in various industries in today's digital world.

The remainder of this paper is organized as follows. In Section 2, we review the literature related to omni-channel studies in financial services and retailing industry. Section 3 describes the context, data and variables that we use in our empirical analysis. Section 4 specifies the econometric models and determines the estimation methods. Section 5 discusses our results. We perform the robustness checks in Section 6. The managerial implications are discussed in Section 7 and Section 8 draws conclusions.

2. THEORETICAL BACKGROUND

In this section, we review the relevant multi-channel studies that have investigated consumer behavior comparing online with offline channels in different contexts to build the theoretical background for this study. In particular, our paper is most closely related to three streams of research – the literature on the effects of online banking adoption on customers' offline banking behaviors, the literature on the effects of physical store entries on customers' online and offline purchase behaviors, and the literature on learning spillovers.

2.1. Online Banking Adoption and Offline Banking Behaviors in Omni-Channel Financial Services

The explosive evolution of online banking in the last decade has spurred researchers to examine customer channel preferences and banking behavior before and after adopting a new channel. Hitt and Frei (2002) explore the demographical differences between online banking users and traditional-channel users, finding that customers in the former group are more profitable and have higher retention. Xue et al. (2007) incorporate channel usage, determining that higher consumer efficiency in the online channel results in greater overall banking profitability. Xue et al. (2011) further investigate the drivers of online banking adoption, pointing to higher transaction demand, consumer efficiency, and local penetration as the primary motivations. They also find that customers significantly increase their banking activities, acquire more products and conduct more transactions after adopting online banking.

Campbell and Frei (2010) focus on customer channel preferences after online banking adoption, identifying the substitution effects of online banking on self-service channels including automated teller machines (ATMs) and voice response units (VRUs). They suggest that substitution is most likely to happen between channels offering a similar mix of services, such as online banking and self-service channels. On the other hand, strengthened financial controls after online banking adoption will improve customers' willingness to access all available service channels and increase transaction volumes via these channels. Hernando and Nieto (2007) support this finding through their firm-level analysis, finding that banks use online banking as a complement of, instead of a substitute for, physical branches.

All these studies have pointed out the important interactions between customers' online banking adoption and offline transaction behaviors. However, most of these studies have focused on the effect of customers' adoption of online banking on their transactions via other channels such as branches. It is still unclear how the changes of the physical branch channel would affect customers' transaction behaviors via online banking as well as other channels. If the relationship between online banking and physical branches is complementary rather than substitution (Hernando and Nieto 2007), then we should expect to see that branch openings and branch closures would increase or decrease customers' online banking transactions, respectively. Given there is a lack of empirical evidence on the impact of branch network changes on customer omni-channel banking behavior, our paper contributes to the literature by addressing this important gap using a unique and proprietary dataset to uncover the underlying mechanism behind the phenomena. We further delve deeper into this question by examining how self-serve versus human-assisted channels are affected by changes in the branch network.

2.2. Relationship between Online and Offline Channels in Omni-channel Retailing

The phenomenon of omni-channel retailing has received significant academic attention due to the availability of retail data and improved channel integration. Studies in this context focus on quantifying the pressure on physical stores exerted by the introduction of the online channel. Deleersnyder et al. (2002) explore newspaper data, and suggest that the general concerns about cannibalization with online channel implementation are overstated. Similarly, Biyalogorsky and Naik (2003) analyze data from Tower Records, and conclude that the addition of the online channel did not significantly take sales away from offline channels, but contributed to the amplification of the overall purchase share. Ansari et al. (2008) also argue for this positive effect of online channel usage on merchant sales. The underlying reasons for this effect involve the small overlap between online channel users and physical store visitors, as well as more active interactions between customers and retailers through the added online channel. Thus, transactions through physical stores are less likely to be reduced and more likely to synergistically contribute, with the introduced online channel, to growth. More recently, researchers have found significant channel complementarity across mobile, online and/or offline channels. For example, the adoption of mobile apps may lead customers to make more purchases (Xu et al. 2016, Sun et al. 2018), be more socially engaged (Jung et al. 2019) and consume more news (Xu et al. 2014). Moreover, Brynjolfsson et al. (2009) further analyze different product types, and show that internet retailers face significant competition from brick-and-mortar retailers when selling mainstream products, but are virtually immune from competition when selling niche products.

Several papers have treated the impact of physical store entries, attributing changes in customer channel usage to substitution, complementary, and awareness effects. For example, Forman et al. (2009) empirically examine the trade-off between the benefits of buying online and the benefits of buying in a local retail store. They find that when a physical store opens locally, customers substitute away from online purchasing. This is due to reduced transaction costs (e.g., transportation cost, time cost, uncertainty, etc.) and increased accessibility to physical facilities. Avery et al. (2012), however, suggest that channel substitutions occur only in certain scenarios where the capability of the added channel is superior or closely duplicates that of the existing one. Store entries can result in a complementary effect on the online channels if they provide supporting functionalities that encourage cross-channel purchasing. They can also strengthen brand awareness and customer loyalty, which might create a halo effect to other channels (Jacoby et al. 1978; Keller 1993; Kwon and Lennon. 2009). The complementary effect of physical stores is empirically identified by Kumar et al. (2018), who suggest that higher exposure to retail stores reduces customers' risks of purchasing online by providing them with a physical place for product evaluation and after-sale trouble resolution. Moreover, Bell et al. (2017) show that store opening increases both online and overall demand, and leads to operational efficiency. Wang and Goldfarb (2017) show the coexistence of substitution across online/offline channels and complementarity in demand. They suggest that whereas online and offline channels may be substitutes in distribution, they are complements in marketing communications.

Following this stream of research, we see that the interaction between the online channel and the offline channel could be either complementary or substitutive in the retailing context. One cannot easily predict what would happen on customers' omni-channel behavior after the physical network changes.

More importantly, although the channels studies in the retailing context could shed some light on the financial services industry, one should caution that consumer decision making in the banking context is quite different from that of retailing due to the many reasons discussed in introduction.

The relationship-centric nature of banking differs significantly from the product-centric nature of the retail industry. Hence, tacit factors might have a significant influence on consumers' banking decision as opposed to the fit and competition in the context of retail. Furthermore, while online and brick-and-mortar channels are coming closer in the retail industry, customer omni-channel banking behavior is oftentimes more complicated as consumers can only perform certain functions in certain channels. The multiplicity of these channels exacerbates the problem even further. Moreover, the fundamental difference in product-based versus service-driven markets can cause the underlying mechanisms behind customers' omni-channel behaviors to be entirely different. Thus, it is necessary to empirically examine how the physical branch network changes would affect customers' multi-faceted behavior in the banking context as well as the underlying mechanism that drives the phenomena. Interestingly, none of the prior research analyzes the effects of store/branch closures, which also is important, especially as banks and retailers have been closing physical stores more actively than opening new ones whereas the impact of such a strategy is still unknown to both managers and researchers. This also distinguishes our research from prior work as we aim to empirically explore the effects of branch network changes including both branch openings and branch closures on customers' omni-channel banking behavior.

2.3. Learning Spillovers in Retail

Our work is also related to a stream of literature from marketing on customer "spillover" learning of product. Prior studies have demonstrated theoretically and empirically that customers tend to perform "correlated learning" (e.g., Erdem 1998, Coscelli and Shum 2004, Sridhar et al. 2012, Chan et al. 2013, Ching et al. 2013), and "learning spillover" exists when customers learn the quality of a service (or product) from their previous experiences with similar yet not identical services (e.g., Musalem et al. 2017). For example, in the context of banking, we should expect customers to learn about a financial service in one channel (e.g., online banking) by using the same financial service in another channel (e.g., local branch), and/or learning about a new financial service provided by the online channel from an existing financial service provided by the local branch. Such learning spillover occurs mostly because customers' prior knowledge and/or information signals about the product or service can be correlated across different contexts. Previous literature has explored the learning spillover across multiple categories under the same brand (e.g., Erdem 1998) or type (e.g., Sridhar et al. 2012), or the learning spillover among attributes of a multi-attribute product (e.g., Coscelli and Shum 2004, Chan et al. 2013). Our study contributes to the existing literature by examining this learning spillover effect across digital and physical channels.

3. DATA

The data we use consist of anonymized individual transactions from a large commercial bank in the United States. The bank offers a variety of services in its branches, as well as through electronic channels such as ATMs and phone banking. It was also one of the first financial institutions to introduce online banking and mobile banking to its customers. With the rapid technology penetration into the financial services industry during the last decade, the bank has been making significant efforts to accommodate changing customer preferences. At the same time, the bank, after a huge expansion due to a series of merger and acquisition activities, has been actively restructuring its existing channel distribution over the last several years. The leading position of the bank in omni-channel financial services offers a unique and suitable research opportunity for our study. Also, the fact that the bank opened (inclusive of the merged bank branches) and closed a considerable number of branches between August 2010 and October 2013 ensures significant variation and efficient estimation with our data. This is another unique feature of our study, as the prior multi-channel literature typically observes only openings or closures (e.g., Forman et al. 2009; Pauwels and Neslin 2015) as noted in the previous section.

3.1. Raw Data and Panel Dataset Construction

Our raw data's anonymized customer transactions are summarized by month so that each observation describes a customer's monthly transaction volume and amount through each channel. We use subscript t to denote the month, i to denote an individual customer, and z to denote the zipcode throughout the paper.

We create a unique panel dataset by merging these data with monthly reports on branch information, customer demographics and account profiles, based on customer identifiers, dates, and their residential zipcodes. To control for the region-level differences in local economic environment changes and banking behaviors across different areas, we have also merged these data with the bank's advertising spending records, the presence of competitor branches of other banks, as well as region-level characteristics generated from a larger sample (more than 0.5 million customers) based on the dates and zipcodes. Using a propensity score matching method, we draw observations on a sample of customers by considering their experiences with nearby branch network changes. The matching process, described in detail in Section 4.1, yields a panel dataset that we use for econometric modeling and estimation.

Our original data covers 39 months from August 2010 to October 2013. The final panel data consist of 855,162 observations for 25,914 existing customers (denoted by i) during 33 months (denoted by t). After the matching procedure, the first six months' data were discarded in the main analysis because we use customers' banking transaction data from six months prior to the treatment for matching purpose. As a result, in the main analysis we use data during 33 months from February 2011 to October 2013. Besides the summary of monthly transactions, it contains the nearby branch network changes of each customer, including the number of branches opened and closed within the customer's residential zipcode during that month. Other information about customer banking profiles and characteristics, such as the number of accounts, the balance of each account type, age, and income level, are also included. We differentiate locations by zipcodes of customers. There are 1,798 distinct zipcodes overall (denoted by z), with the number of bank branches ranging from zero to seven in each area. Moreover, zipcode-level characteristics include the bank's advertising spending, the presence of competitor branches of other banks, as well as region-level variables generated from a larger customer sample (more than 0.5 million customers). In the next sub-sections, we will describe the dependent variables, main-effect variables and control variables that we use in our analysis. The summary statistics of these variables in the final panel data are provided in Table 1.

Table 1 Summary Statistics for Dependent, Main-Effect and Control Variables

VARIABLES	DEFINITIONS	MEAN	SD	MIN.	MAX.
DEPENDENT VARIABLES					
BRH	Number of transactions through branches	1.53	4.53	0	669
OLN	Number of transactions through online banking	36.98	80.55	0	10,724
ADC	Number of transactions through alternative delivery channels, which include ATM, VRU and CCT	5.47	10.58	0	2,061
ATM	Number of transactions through ATMs	3.66	5.67	0	151
VRU	Number of transactions through the VRU channel	1.30	6.91	0	368
CCT	Number of transactions through call centers	0.50	3.47	0	2,045
INQ	Number of inquiries through online banking	21.90	54.72	0	6094
SER	Number of services through online banking	2.45	16.03	0	8064
XFR	Number of transfers through online banking	0.93	4.09	0	1172
BRHoutzip	Number of transactions through branches outside the customer's residential zipcode	0.50	1.43	0	58
#Channels	Number of channels used	3.93	2.28	0	10
#NonBRHChls	Number of non-branch channels used (which does not include the branch channel)	3.42	2.11	0	9
MAIN-EFFECT VARIABLES					
FirstBranchOpening	Indicator of the first branch entry, inclusive of abandonment and re-entry	0.08	0.27	0	1
AdditionalBranchOpening	Count variables for the number of additional branches opened, excluding the first branch	0.35	0.65	0	5
NonLastBranchClosure	Count variables for the number of branches closed, excluding the last branch	0.16	0.40	0	3
LastBranchClosure	Indicator of the last branch exit	0.02	0.12	0	1
CONTROL VARIABLES					
(1) Individual-Level Variables:					
Age	Age of the customer	47.83	19.02	2	159
Tenure	Number of months that the customer has stayed with the bank	210.20	125.10	40	1,353
#DepositAccts	Number of deposit accounts in use	2.47	1.99	0	42
#LoanAccts	Number of loan accounts in use	0.64	1.31	0	20
#InvestmentAccts	Number of investment accounts in use	0.17	0.55	0	18
#OtherAccts	Number of other accounts in use	0.87	0.59	0	8
$DepositAccts	Balance of deposit accounts	21,944.00	70,450.91	-8,170	7,420,750
$LoanAccts	Balance of loan accounts	10,051.30	36,007.38	-170,942	1,097,283
$InvestmentAccts	Balance of investment accounts	7,643.00	60,275.38	-5,257	3,405,568
$OtherAccts	Balance of other accounts	2,310.00	23,207.23	0	1,600,000
LogTransaction$	Logarithm of the transaction amount	7.20	3.21	0	17
LowIncome	Indicator of the customer's income lev-	0.13	0.33	0	1

	el: 1 if he or she is from the low-income group and 0 otherwise				
(2) Zipcode-Level Aggregated Variables:					
Advertising	Bank's advertising spending for branches within the residential zipcode[5]	0.03	0.47	0	11.20
Competition	Number of competition branches of other banks within the residential zipcode	4.86	4.07	0	22
#Customers	Number of bank customers within the customer's residential zipcode	1,813	1,531.25	1	5,211
AverageAge	Average age of the customer	44.17	3.55	17	93
AverageTenure	Average number of months that the customer has stayed with the bank	149.55	30.49	25	511
Average#DepositAccts	Average number of deposit accounts in use	2.12	0.24	0	8
Average#LoanAccts	Average number of loan accounts in use	0.56	0.19	0	11
Average#InvestmentAccts	Average number of investment accounts in use	0.10	0.05	0	4
Average#OtherAccts	Average number of other accounts in use	0.76	0.11	0	2
Average$DepositAccts	Average balance of deposit accounts	18,507.00	10,509.21	-25,374	867,807
Average$LoanAccts	Average balance of loan accounts	8,321.30	5,908.28	-110	2,269,853
Average$InvestmentAccts	Average balance of investment accounts	4,724.90	5,849.56	-2.8	289,370
Average$OtherAccts	Average balance of other accounts	2475.00	3,058.56	0	187,078
AverageLowIncome	Average indicator of the customer's income level: 1 if he or she is from the low-income group	0.13	0.23	0	1
Note: The final panel dataset includes 855,162 observations for 25,914 existing customers during 33 months. Customers whose branch transaction locations cannot be detected are excluded from the *BRHoutzip* observations, resulting in 471,240 observations for this channel.					

3.2. Dependent Variables: Customer Omni-Channel Usages

We use the number of transactions to measure the channel usage by a customer in every month. There are ten transaction channels in the raw data: automated clearing house (ACH), automated teller machine (ATM), bank by phone (BBP), branch (BRH), call center (CCT), online banking (OLN), point of sale by check card (CC), point of sale by debit card (DC), telephone bill payment (TBP), and voice response unit (VRU). We focus on the five major channels in this paper — BRH, OLN, ATM, VRU and CCT — having eliminated those that have extremely low transaction volumes or that are used exclusively for certain types of services.[6]

Based on the omni-channel structure in retail banking, we look at branches as a traditional channel,

[5] For confidentiality reasons, we cannot disclose the actual unit of advertising spending of the bank.
[6] For example, automated clearing house is used only for debit and credit money, and point of sale by check card and point of sale by debit card are used only for payments with retailers.

online banking as a digital channel, and ATM, VRU and CCT are clubbed together as alternative delivery channels (ADC). Then, we examine the impact of branch network changes on customers' transactions via these three types of service-delivery channel (BRH, OLN and ADC) and investigate each separate channel as well. We also distinguish customers' online transactions into three major types based on the encoding scheme adopted by the focal bank, including online inquiry (INQ), online service (SER), and online money transfer (XFR). We also examine two additional variables, *#Channels* and *#NonBRHChls*, which count the total number of channels in use by customer, inclusive and exclusive of BRH, respectively, reflecting the variety of customer's adoption of different channels.

3.3. Branch Network Changes: Branch Openings and Closures

We observe branch network changes, including branch openings and closures, through access to the complete branch information of the bank. We create four main-effect variables. $FirstBranchOpening_{it}$ is an indicator for the first branch opening, whereas $AdditionalBranchOpening_{it}$ is a count variable for the number of additional branches that were opened after the first branch. Similarly, $LastBranchClosure_{it}$ is an indicator for the last branch closure, while $NonLastBranchClosure_{it}$ is a count variable for the number of branches that were closed excluding the last branch. Therefore, in this way, the coefficient for $FirstBranchOpening_{it}$ on its own would identify the effect of that first opening, and the coefficient for $LastBranchClosure_{it}$ would identify the effect of the last branch closure.

3.4. Control Variables

In our matching process, we use a variety of control variables in the logit model to account for customer heterogeneity in characteristics and transaction behavior as well as the region-level heterogeneity across different zipcodes. The customer-level control variables include the customer's age, tenure, and income level, as well as the number of channels used, the number of transactions through each channel, the transaction amount, the number of accounts, and the balance of each account type. We also consider region-level information to control for the region-level heterogeneity in local economic environment changes and banking behaviors across different areas. These zipcode-level variables include the bank's total number of customers for each zipcode, the bank's advertising spending for branches, the number of competition branches of other banks, as well as the average customer characteristics within each zipcode and their average banking behaviors across several different dimensions. These individual-level control variables and zipcode-level aggregated variables are summarized in Table 1. We discuss the detailed steps of matching in Section 4.2.

4. METHODOLOGY

In this section we describe our empirical strategy. First, we present the difference-in-differences model to examine the causal effects of branch network changes on customer channel usage. However, branch openings and closures are strategic, and can be endogenous. To resolve the potential endogeneity, we outline our identification strategy that uses propensity score matching. The matched dataset is used to estimate the difference-in-differences model.

4.1. The Difference-in-Differences Model

We examine the effects of branch network changes on customer omni-channel usage with a difference-in-differences model. We base the model on the counterfactual framework from the treatment effects literature (Imbens and Wooldridge 2007) and adjust the standard specification for our case.

First, while most zipcodes in our data have, at most, one occurrence of a branch opening or closure, several places have multiple ones. Thus, we use count variables — the number of branches opened and closed — in our base model to capture the repeated treatments. In particular, there are four main-effect variables as discussed in Section 3.3. In this way, we distinguish the effect of first branch opening from the effect of additional branch opening in our estimation. Similarly, for branch closures, we distinguish the effect of the last branch closure from the effect of other branch closures. Second, we collect the focal bank's promotional marketing spending for branches at each zipcode in each month to control for advertising effect. Third, we use the number of branches of other competing banks to incorporate the competition effect. Last but not least, as there are likely to be unobserved differences among customers with different characteristics, which can lead to different transaction patterns, we incorporate individual-fixed effects into our model to control for time-invariant individual heterogeneity. Since our outcome variables

— the number of transactions by each channel — have discrete values, we use Poisson models.[7] The difference-in-differences model is formulated as the following.

$$E(Y_{it}) = exp(C_i + \beta_1\ FirstBranchOpening_{it} + \beta_2\ AdditionalBranchOpening_{it} + \beta_3\ NonLastBranchClosure_{it} + \beta_4\ LastBranchClosure_{it} + \beta_5\ Advertising_{it} + \beta_6\ Competition_{it} + \delta_T\ Month_T + \varepsilon_{it})$$

where Y_{it} is the outcome variable for the number of transactions through each channel by customer *i* in month *t*. For example, we first estimate the model using customer transactions through the three channel types as the outcome variable, including branch (*BRH*), online (*OLN*) and alternative delivery channels (*ADC*), respectively. We also look at customers' transactions through branches outside of their residential zipcode, which is the *BRHoutzip* dependent variable. There are also several more different dependent variables as described in Section 3.2. Since we assume independent decision making for branch openings and branch closures by the bank, we can incorporate these types of treatments into one model. In the robustness checks, we also show that the results remain consistent if we estimate separate models without such an assumption. $Advertising_{it}$ is the log-transformation of advertising spending. $Competition_{it}$ is the demeaned number of competing branches of other banks within the same zipcode.[8] C_i captures individual-fixed effects, $Month_T$ captures time-fixed effects, and ε_{it} is the idiosyncratic error term.

4.2. Identification

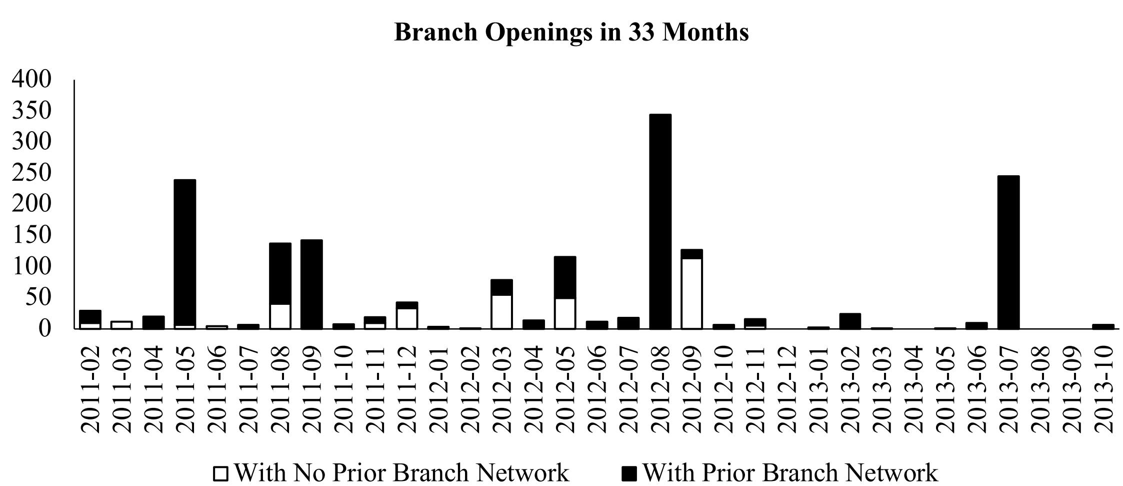
Banks' decisions related to branch openings and closures are endogenously motivated by regional customer profiles, such as the number of customers, their demographics, and their banking behavior. Competition and the economic environment of the local market also influence the service-channel management of banks. Therefore, we cannot simply treat branch openings or branch closures as exogenous variables in the difference-in-differences model discussed above. We use propensity score matching to resolve the potential endogeneity with branch network changes in the first stage of our analysis.

It should be noted that the treatment in our context is not applied to an individual customer but to all

[7] The Poisson model and the Negative Binomial model are both frequently used to model count variables. For individual-fixed effects in our analysis, we choose the Poisson model instead of the Negative Binomial model, because the latter is not a true fixed-effects method that controls for all stable covariates (Allison and Waterman 2002).
[8] We demean this variable so that the estimated average treatment effect is measured relative to average competition level.

the customers in the entire zipcode. Hence, a variety of control variables are used to account for customer-level heterogeneity, as well as the region-level heterogeneity across different zipcodes. While the customer-level features control for differences between consumers, the region-specific features control for the strategic decision of the bank to open or close branches in certain locations based on their attractiveness.

Another challenge in our setting is that different customers get exposed to the treatment at different times. Unlike prior studies in which customers get exposed to the treatment at the same time (e.g., Kumar et al. 2018), we want to utilize the entire panel to estimate the treatment effects, so that they are generalizable over time. As a result, we compute *time-dependent propensity scores* and match each treated customer with one control customer in each month. This allows us to accommodate the different timings for branch openings and closures and to balance the distributions of the observed covariates in the treated and control groups at each time point (Lu 2005). Since the matching is conducted at the individual level, we also consider the relative development of the local banking environment at the time of treatment. We start with a treated group, which is a random sample of 10,000 customers with experiences of branch openings or closures. Among them, 8,775 customers experienced openings and 5,382 experienced closures. There is an overlap of 4,157 customers who experienced both.



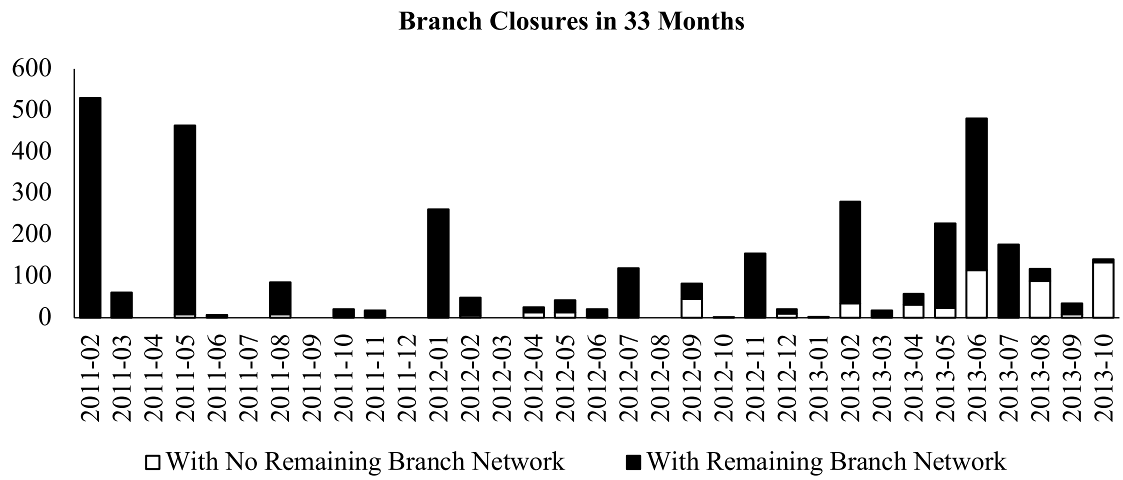


Figure 2. Branch Network Changes in 33 Months

For simplicity, we discuss the detailed steps of matching for branch openings and apply a similar method of matching for branch closures. Figure 2 illustrates the distribution of the treatments for branch openings and branch closures. Within each month, the treated customers are divided into two groups, based on whether there were previously established branch networks of the bank[9] within their residential zipcode, as pre-existing local branch would make a difference in the changes of customer banking behavior. We then randomly select a control group, in which the number of customers is five times that of the treated group. Customers in the control group are those who experienced no branch openings or closures throughout the study period but have similar local branch network condition as those in the treated group (e.g., they either have or do not have a pre-existing branch in their residential zipcode region). We acquire, for each customer, the average transaction and account data within six months prior to the treatment for the matching process. After the matching procedure, the first six months' data in the 39 months' observational period were discarded in the difference-in-differences analysis. Together with customer characteristics and other control variables described before, we estimate a logit model at the individual level as the following. A brief graphical illustration of the matching process is summarized in the Online Appendix.

Pr (Dummy factors: $BranchOpening_{it}$, $BranchClosure_{it} = 1 \mid \cdot\,) = f\,(Age_{it},\ LowIncome_{it}, Tenure_{it},$

[9] In the case of branch closures, we consider whether the local branch networks of the bank remain after the treatments.

ln(TransactionAmount$_{it}$), *#Channels$_{it}$*, *BRH$_{it}$*, *ATM$_{it}$*, *VRU$_{it}$*, *CCT$_{it}$*, *OLN$_{it}$*, *#DepositAccts$_{it}$*, *#LoanAccts$_{it}$*, *#InvestAccts$_{it}$*, *#OtherAccts$_{it}$*, *\$DepositAccts$_{it}$*, *\$LoanAccts$_{it}$*, *\$InvestAccts$_{it}$*, *\$OtherAccts$_{it}$*, *AvgAge$_{zt}$*, *AvgTenure$_{zt}$*, *Avg#DepositAccts$_{zt}$*, *Avg#LoanAccts$_{zt}$*, *Avg#InvestAccts$_{zt}$*, *Avg#OtherAccts$_{zt}$*, *\$DepositAccts$_{zt}$*, *\$LoanAccts$_{zt}$*, *\$InvestAccts$_{zt}$*, *\$OtherAccts$_{zt}$*, *Competition$_{zt}$*, *#Customers$_{zt}$*, *Month$_{T}$*)

An indicator of treatment is modeled as a function of the customer's age (*Age$_{it}$*), income level (*LowIncome$_{it}$*), tenure with the bank (*Tenure$_{it}$*), and average transaction behavior and account profile within six months prior to the treatment, including the transaction amount (*ln(TransactionAmount$_{it}$)*), number of channels used (*#Channels$_{it}$*), number of transactions through each channel (*BRH$_{it}$*, *ATM$_{it}$*, *VRU$_{it}$*, *CCT$_{it}$*, *OLN$_{it}$*), number of accounts held, and balances for each account type (*#DepositAccts$_{it}$*, *#LoanAccts$_{it}$*, *#InvestmentAccts$_{it}$*, *#OtherAccts$_{it}$*, *\$DepositAccts$_{it}$*, *\$LoanAccts$_{it}$*, *\$InvestmentAccts$_{it}$*, *\$OtherAccts$_{it}$*), as well as region-level customer characteristics and banking behaviors generated from a larger sample (more than 0.5 million customers) at zipcode *z* in month *t* (*AvgAge$_{zt}$*, *AvgTenure$_{zt}$*, *Avg#DepositAccts$_{zt}$*, *Avg#LoanAccts$_{zt}$*, *Avg#InvestAccts$_{zt}$*, *Avg#OtherAccts$_{zt}$*, *\$DepositAccts$_{zt}$*, *\$LoanAccts$_{zt}$*, *\$InvestAccts$_{zt}$*, *\$OtherAccts$_{zt}$*). Moreover, *Competition$_{zt}$* captures the number of competitor branches of other banks at zipcode *z* in month *t*. We use the number of customers in the local market (*#Customers$_{zt}$*) to control for the scale of the bank, as well as a monthly dummy (*Month$_{T}$*) to capture the time-fixed effects. Based on the predicted propensity scores, one treated customer is matched with one customer from the control group using the nearest neighbor (NN) algorithm with no replacement, and we create a final sample consisting of 25,914 customers for further analysis. The result of the propensity score matching is summarized in Table 2. The customers in the treated group and the control group are properly matched and there is no statistical difference between them before the treatment. This way, we need only include the main-effect variables in our difference-in-differences model using a balanced matched sample.

Table 2 Propensity Score Matching Results

	BRANCH OPENINGS	BRANCH CLOSURES

	With Existing Branches		*Without Existing Branches*		*With Remaining Branches*		*Without Remaining Branches*	
	Treated	**Matched**	**Treated**	**Matched**	**Treated**	**Matched**	**Treated**	**Matched**
Age	44.23	44.12	43.16	46.24	46.67	48.85	46.61	46.20
Tenure	179.27	179.08	171.17	181.53	200.78	205.09	208.48	203.72
LowIncome	0.14	0.14	0.14	0.13	0.10	0.11	0.18	0.15
#Channel	3.68	3.70	3.46	3.66	3.88	3.82	3.96	3.89
ATM	3.59	3.72	3.36	3.33	3.52	3.57	3.69	3.74
BRH	1.38	1.51	1.18	1.61	1.61	1.66	1.60	1.75
CCT	0.68	0.67	0.79	0.65	0.62	0.59	0.71	0.62
VRU	1.76	1.63	1.76	1.73	1.29	1.42	1.80	1.31
OLN	26.02	26.04	26.64	25.58	29.54	28.51	29.89	31.39
Ln(*Transac$*)	7.07	7.22	6.66	7.08	7.43	7.44	7.42	7.41
#DepoAccts	2.23	2.25	2.07	2.19	2.47	2.40	2.38	2.35
#LoanAccts	0.51	0.49	0.53	0.54	0.64	0.53	0.58	0.53
#InvesAccts	0.13	0.13	0.11	0.12	0.15	0.15	0.13	0.12
#OtheAccts	0.76	0.79	0.75	0.73	0.80	0.88	0.80	0.84
$DepoAccts	17.85	18.76	13.45	15.06	22.07	22.21	18.41	19.08
$LoanAccts	8.33	9.02	7.71	11.11	9.50	9.92	8.55	9.39
$InveAccts	6.48	5.81	4.85	4.27	8.16	7.54	3.76	3.49
$OtheAccts	0.28	0.58	0.36	0.46	0.94	0.97	2.89	1.43
#Customers	2355.11	1585.46	866.72	175.04	2404.60	1397.16	1021.51	699.57
Competition	7.22	5.27	2.75	2.32	8.43	5.73	1.58	2.18
AvgAge	43.35	42.98	44.11	44.13	44.62	44.09	45.98	45.13
AvgTenure	146.05	144.60	143.55	146.00	154.01	141.83	168.47	159.83
Avg#DepoAccts	2.17	2.17	2.13	2.07	2.12	2.07	2.12	2.10
Avg#LoanAccts	0.47	0.45	0.46	0.50	0.56	0.46	0.50	0.46
Avg#InveAccts	0.09	0.09	0.07	0.08	0.10	0.09	0.11	0.10
Avg#OtheAccts	0.68	0.71	0.65	0.67	0.71	0.80	0.69	0.73
Avg$DepoAccts	22.40	25.37	18.15	15.86	21.20	18.39	19.20	18.26
Avg$LoanAccts	8.76	8.13	6.94	11.17	8.93	8.05	8.55	7.81
Avg$InveAccts	4.47	4.28	3.27	3.31	4.66	4.64	4.44	4.13
Avg$OtheAccts	0.53	0.51	0.82	0.48	1.42	1.32	1.66	1.63
AvgLowIncome	0.14	0.13	0.16	0.13	0.11	0.12	0.20	0.17

Notes: Customers treated for branch openings and closures are matched separately. For branch-opening treatments, we look at whether there is an existing local branch around the customer before branch-opening treatments. For branch-closure treatments, we look at whether there is a remaining branch around the customer after branch-closure treatments. One control customer with a similar branch network condition (i.e., whether there is an existing branch around) is matched with the treated customer.

5. RESULTS AND DISCUSSIONS

In this section, we discuss the estimation results of the difference-in-differences models and the underlying mechanisms consistently revealed by different analyses. The main results that we have identified with model estimations include the effects of branch openings and closures on customer omni-channel transactions, which are summarized in Tables 3 - 7. In this section, we first discuss the effects of branch openings on customers' banking behaviors in different channels, followed by a discussion on the effects of branch closures, and time-varying effects of branch openings and closures.

5.1. The Effects of Branch Openings on Customer Omni-channel Banking

Table 3 summarizes our main results on the effects of branch network changes on customers' transactions through three different types of service channels: branch channel, online channel, and alternative channels. Firstly, for the branch channel, results in column (1) of Table 3 show that branch openings generally increased customers' visits to local branches (coefficients = 0.057, 0.033 for first branch opening and additional branch opening, respectively; $p < 0.001$, $p < 0.001$, respectively). This translates to a 5.8% increase in branch-related transactions when the first branch opens and a 3.3% increase when an additional branch opens. Moreover, the positive effects of branch openings are mainly restricted to local branches rather than remote branches as suggested by the insignificant coefficients in column (4) (coefficients = -0.020, -0.020 for first branch opening and additional branch opening, respectively; $p > 0.05$, $p > 0.05$, respectively). This suggests that when a local branch opens, customers tend to increase their visits to the local branch within their residential zipcode for banking transactions, due to the lowered transportation costs as well as the increased awareness of the newly established local branch.

Table 3 Effects on Branch, Online, and Alternative Channels

	(1) *BRH*	(2) *OLN*	(3) *ADC*	(4) *BRHoutzip*
First Branch Opening	0.057*** (0.013)	-0.007*** (0.002)	-0.004 (0.006)	-0.020 (0.031)
Additional Branch Opening	0.033*** (0.006)	0.020*** (0.001)	0.029*** (0.003)	-0.020 (0.014)
Non-Last Branch Closure	-0.012 (0.007)	0.021*** (0.001)	0.007* (0.003)	0.063*** (0.016)
Last Branch Closure	-0.041* (0.016)	0.060*** (0.003)	0.066*** (0.008)	0.304*** (0.029)
Advertising	0.010*** (0.002)	-0.005*** (0.000)	0.005*** (0.001)	0.000 (0.006)
Competition	0.001 (0.001)	-0.003*** (0.000)	-0.004*** (0.001)	-0.012*** (0.003)

Notes: 855,162 observations. Standard errors are in parentheses. Regressions include individual-fixed effects and time-fixed effects. *Significant at 5% level; **significant at 1% level; ***significant at 0.1% level. *BRH* refers to Branches, *OLN* to Online, *ADC* to Alternative Channels, and *BRHoutzip* to Remote Branches.

Second, for the online channel (column (2) of Table 3), we observe that the effect of branch openings differs between the first branch opening and additional branch opening. In particular, when the first branch opened in customers' residential neighborhood, this had a small *substitution effect* on customers' transactions via online banking (coefficient = -0.007; $p < 0.001$), and no significant effect on customers' transactions through alternative channels (column (3) of Table 3, coefficient = -0.004; $p > 0.05$). On the contrary, when an additional branch opened within customers' residential zipcode area, it significantly increased customers' transactions in the online channel (coefficient = 0.020; $p < 0.001$) as well as alternative channels (coefficient = 0.029; $p < 0.001$), which seems to point to a *synergistic effect* of additional branch opening on customers' omni-channel banking behaviors. Note that most of the customers in the data that see an increase in the number of branches, see either the first branch opens in their zipcode, or the count of existing branches goes up by one. Very few customers have a cascade of branch openings.

These seemingly contradictory effects between the two types of branch openings (e.g., first branch opening and additional branch opening) can be reconciled by a *learning spillover effect*. When a new branch opens, customers shift their online transactions to the branch, especially the more complex ones. However, increased face-to-face interactions with branch employees may translate into customers' better knowledge of online banking (or other alternative-channels). This translates into increased transactions online. As far as the first branch opening goes, the net effect is a decrease in online transactions. However, the substitution effect is not operative for additional branch openings, and therefore we see a net increase in the online banking activity whenever an additional branch opens. Later we show that this *learning spillover effect* is also consistently supported in several different analyses.

From a managerial perspective, online banking as a self-service channel is widely regarded as having the potential to lower the marginal cost of service interaction by substituting human labor in physical branches. From customers' perspective, online banking may also lower their marginal cost of service interaction through increased convenience, accessibility, and reductions in wait times (Curran et al. 2003, Bitner et al. 2000). However, even though online banking could serve as a desirable option for both parties, not every customer is willing to or able to adopt it. Because customers first need to learn about the usefulness and advantages of online banking so that they will be willing to adopt it (Pikkarainen et al. 2004, Tan and Teo 2000), and then, more importantly, they have to incur implicit fixed costs from adopting online banking including the costs of learning to use a new technology as well as the costs of establishing a relationship through a new channel (Klemperer 1987). Therefore, brick-and-mortar branches may serve as a tool to facilitate both of these two processes. As customers tend to increase their visits to branches in their neighborhood due to branch openings, such increased interactions with bank employees in local branches may translate into customers' better knowledge of online banking. This will gradually improve customers' perceived usefulness of online banking and also lower their perceived complexity of using this technology. Therefore, although branch openings may not immediately nudge customers to use online banking after the first branch opening, it plays an important role in facilitating customers' omni-channel banking behaviors via this *learning spillover effect* due to customers' increased branch interactions after both types of branch openings.

Further Analyses on Transaction Types: Analysis into customers' different transaction types also reveals this *learning spillover effect* brought by branch openings. To identify this effect, we divide customers' online transactions into different types to investigate the impact of branch openings on each specific transaction type. Due to the complexity of financial services, there are many different transaction types. Moreover, though some transactions could be performed in different channels, not all transactions can be performed in all channels (e.g., cash deposits and withdrawals cannot be performed via online banking). In our dataset, customers' transactions via online channel can be broadly categorized into three major types according to the encoding scheme adopted by the focal bank, including inquiry (INQ), service (SER), and transfer (XFR)[10]. Table 4 contains difference-in-differences models' estimation results for these three transaction types via online channel.

Table 4 Effects on Different Transaction Types via Online Channel

[10] There is also a fourth type termed as "others" in our data, which we do not have detailed information about what specific transactions are included in this type, thus is not included in our analysis.

	(1) *INQ*	(2) *SER*	(3) *XFR*
First Branch Opening	0.016*** (0.003)	-0.084*** (0.009)	-0.060*** (0.014)
Additional Branch Opening	0.006*** (0.003)	0.088*** (0.004)	0.041*** (0.007)
Non-Last Branch Closure	0.021*** (0.002)	0.075*** (0.005)	-0.004 (0.008)
Last Branch Closure	0.042*** (0.004)	0.202*** (0.010)	0.103*** (0.020)
Advertising	-0.005*** (0.001)	-0.006*** (0.002)	-0.006* (0.003)
Competition	-0.003*** (0.000)	-0.019*** (0.001)	-0.001 (0.001)
Notes: 855,162 observations. Standard errors are in parentheses. Regressions include individual-fixed effects and time-fixed effects. *Significant at 5% level; **significant at 1% level; ***significant at 0.1% level.			

From results presented in Table 4, we observe that when the first branch opened in customers' neighborhood, this significantly increased customers' inquiries via online banking (coefficient = 0.016; $p < 0.001$), while substituted away some more complex online transactions such as online services (coefficient = -0.084; $p < 0.001$) and online money transfers (coefficient = -0.060; $p < 0.001$). The increase in inquiries might be due to the increased awareness of the bank as has been reported in the existing literature, or a consequence of digital tracking of increased transactions in the branch (as shown in Table 3). On the other hand, consumers find it meaningful to move their complex transactions to the branch channel and for these types of transactions the two channels might be substitutes.

Therefore, the complementarity or substitutability of the online and branch channel depends on the nature of the transaction. To our best knowledge, this finding has been documented for the first time in the omni-channel literature. These results also demonstrate the richness of financial transactions with multiple facets as opposed to retail where the dominant transactions are purchases. The heterogeneous effect of branch network change on different transaction types is a novel contribution to the literature and pushes the literature further on developing an understanding of customers omni-channel behavior.

When an additional branch opens, we observe an increase in all types of transactions, but the increase is significantly higher for more complex transaction types via online banking (coefficients = 0.088, 0.041 for online services and online money transfers, respectively; $p < 0.001$, $p < 0.001$, respectively) as opposed to simple online inquiries (coefficient = 0.006; $p < 0.001$). When more branches open, customers have more opportunities to visit the nearby branch (due to reduced transaction costs) and have more face-to-face interactions with bank employees (as shown in previous discussion). Hence, in this case, they learn how to perform complex online transactions from branch employees. This significantly increases customers' usage of more complex transaction types via online banking. These results suggest that customer learning is required to mature from easy online inquiries to more complex online transactions. As customers increase their branch visits due to branch openings, their gradually increased interactions with bank employees can help them acquire more knowledge about online banking which makes it easier for them to learn how to use online banking to perform a variety of transaction types.

Therefore, banks who expect customers' more frequent visits to branches due to branch openings should take advantage of this *learning spillover effect.* Customers' increased interactions with bank employees in branches can facilitate their learning about self-service channels, which can not only lower banks' marginal cost of service interaction by substituting human labor in future, but also benefit customers through increased convenience and accessibility. Moreover, based on the nature of the transaction complexity, banks can better prepare for the expected service demand across channels as branch network changes. Branches can also better design the face-to-face interaction process with consumers to reduce the learning gap between different types of transaction services.

Note that the existence of consumer learning spillover points out another uniqueness of the banking context, as there is not much learning required when consumers purchase products on the internet. The main issue in online purchases is the product-level uncertainty, which might not translate as fast to other products. However, the learning effects are more salient for financial transactions.

Further Analyses on Channel Variety: Last but not least, this *learning spillover effect* is further supported by results presented in Table 5. As shown in Table 5, both types of branch openings significantly increased the total number of different channels used by customers (coefficients = 0.018, 0.017 for first branch opening and additional branch opening, respectively; $p < 0.01$, $p < 0.001$ for first branch opening and additional branch opening, respectively). If we only count the number of non-branch channels used by customers, then we observe that customers do not immediately increase the variety of channels they use after the first branch opening (coefficients = 0.012; $p > 0.05$) indicating the substitution effect, whereas we see that additional branch opening can significantly facilitate customers' omni-channel banking choices (coefficients = 0.014; $p < 0.001$). These results again indicate that customers do not immediately adopt different channels after the first branch opening, but as they experience further branch openings, they will be more likely to learn how to use and adopt other different channels when additional branch opens in their neighborhood.

Table 5 Effects on Number of Channels Used

	(1) ***Num. of Channels***	**(2)** ***Num. of Channels (excluding branch)***
First Branch Opening	0.018** (0.007)	0.012 (0.007)
Additional Branch Opening	0.017*** (0.003)	0.014*** (0.003)
Non-Last Branch Closure	0.003 (0.004)	0.003 (0.004)
Last Branch Closure	-0.002 (0.009)	0.002 (0.010)
Advertising	0.002 (0.001)	0.002 (0.001)
Competition	0.000 (0.001)	0.000 (0.001)

Notes: 855,162 observations. Standard errors are in parentheses. Regressions include individual-fixed effects and time-fixed effects. *Significant at 5% level; **significant at 1% level; ***significant at 0.1% level.

In addition to the effects of the main-effect variables on branch openings and branch closures, we also observe that the presence of competitor branches of other banks has a consistent negative effect on customers' omni-channel banking behavior. Moreover, the bank's advertising spending in general has positive effects on increasing customers transactions as expected. For example, in the main results shown in

Table 3, advertising has significant positive effects on customers' transactions through the branch channel and alternative channels (coefficients = 0.010, 0.005 for the branch channel and alternative channels, respectively; $p < 0.001$, $p < 0.001$, respectively), but has a negative effect on customers' transactions via online banking (coefficients = -0.005; $p < 0.001$). This is because the bank's marketing spending is mainly targeted for promoting transactions in traditional channels (e.g., loans), which could substitute away customers' transactions via online banking. Moreover, the zipcode-level advertising spending does not have significant impact on customers' branch transactions outside of their residential zipcode areas as expected (coefficients = 0.000; $p > 0.05$). We also observe that even though advertising spending may effectively increase customers' transactions with the bank, it does not necessarily help increase customers' adoption of different channels as reflected by the insignificant coefficients presented in Table 5 (coefficients = 0.002, 0.002 for the total number of channels used and the total number of non-branch channels used, respectively; $p > 0.05$, $p > 0.05$, respectively).

5.2. The Effects of Branch Closures on Customer Omni-channel Banking

The estimation results of branch closures indicate that the effects are not symmetric to branch openings. Results in Table 3 show that branch closures exhibit different effects on customers' omni-channel banking behavior depending on whether there is remaining branch within their residential zipcode area or not. In particular, for the branch channel, if there were still remaining branches nearby, branch closures did not significantly affect customers' branch transactions (coefficient = -0.012; $p > 0.05$), though it had a relatively small increase in customers' transactions in branches outside of their residential zipcode region (coefficient = 0.063; $p < 0.001$). This indicates that consumers reconfigure their usage patterns to confirm to the small changes in the branch network. However, if the closing branch was the last one within the customer's neighborhood, this significantly reduced customers' local branch transactions (coefficient = -0.041; $p < 0.05$), and had a much larger effect on increasing customers' transactions in branches outside of their residential zipcode area (coefficient = 0.304; $p < 0.001$), which highlighted the importance of the last branch within the customers' residential area.

For online channel and alternative channels, we observe that customers tended to significantly migrate to online banking (coefficient = 0.021; $p < 0.001$) and slightly increase transactions via alternative channels (coefficient = 0.007; $p < 0.001$) after non-last branch closure. If the closing branch was the last branch in their neighborhood, it significantly increased customers' transactions via both types of channels (coefficients = 0.060, 0.066 for online channel and alternative channels, respectively; $p < 0.001$, $p < 0.001$ for online channel and alternative channels, respectively). Note that the latter effects are much stronger than the former effects. These findings are also evident in Table 4 as all types of branch closures lead to a general increase in the different types of transactions in the online channels, however the increase is higher when all branches close in a zipcode. Overall, these results reflect customers' reliance on branches in the omni-channel context, especially when there is no remaining branch nearby after the last branch closure. Even though customers can choose other channels to perform transactions after branch closures, they still prefer face-to-face transactions in physical branches even at the increased transportation costs of visiting a branch outside of their neighborhood.

Furthermore, as shown in column (1) of Table 5, after both types of branch closures, customers do not abandon channels that they have adopted before (coefficients = 0.003, -0.002 for non-last branch closure and last branch closure, respectively; $p > 0.05$, $p > 0.05$, respectively). This result also holds if we only consider the number of non-branch channels used by customers (coefficients = 0.003, 0.002 for non-last branch closure and last branch closure, respectively; $p > 0.05$, $p > 0.05$, respectively). These results again support the mechanism of a *learning spillover effect*. This is because customers who are already familiar with the benefits of different channels and have incurred implicit fixed costs of adopting them are not likely to simply abandon these channels after branch closures. They can still enjoy the convenience and accessibility brought by different channels after branch closures. Therefore, customers will not immediately abandon adopted channels when facing branch closures as suggested by the insignificant coefficients presented in Table 5. This also indicates that customers' adoption of omni-channel banking may help customers establish a relatively long-term relationship with the bank and can act as a strategic lever while redesigning their branch networks.

5.3. Detailed Effects of Branch Changes on Alternative Channels

In order to further uncover the mechanisms behind customers' migration trend after branch closures, we conduct additional analysis by investigating the effects on each alternative channel respectively. Results are presented in Table 6 and yield two notable findings. First, as expected, first branch opening did not immediately increase customers' transactions via each alternative channel (coefficients = -0.003, -0.018, 0.031 for ATM, VRU, and CCT, respectively; $p > 0.05$, $p > 0.05$, $p > 0.05$, respectively). As customers increased their interactions with branch employees after branch openings, additional branch openings significantly increased customers' transactions through self-service alternative channels such as ATM and VRU (coefficients = 0.036, 0.033 for ATM and VRU, respectively; $p < 0.001$, $p < 0.001$, respectively). Meanwhile, it significantly reduced customers' CCT transactions (coefficient = -0.028; $p < 0.01$), which is the human-service call center. Second, when the last branch closed, this had a large positive effect on customers' transactions via the CCT channel (coefficient = 0.533; $p < 0.001$). These findings shed light on our earlier discussion about customers' reliance on human-service transactions after the last branch closure in their neighborhood. Because call centers as a human-service channel can assist the functionality of branches by providing similar services with the help of customer service representatives. It serves as the main substitute for the physical service channel of a bank providing human-based service.

Overall, when there are still remaining branches nearby, branch closures tend to mainly drive customers to migrate to online banking; but when facing the last branch closure in their neighborhood, customers tend to heavily resort to services provided by human beings, such as branch transactions outside their residential locations or calling the customer service center for transactions with the help of customer service representatives. This is consistent with survey-based research which has found that the importance attached to face-to-face contact (e.g., branches, call centers) actually increased significantly as the importance attached to remote interactions (e.g., online banking) increased. These results suggest that banking customers prefer increasing access to all available delivery channels and do not necessarily treat them as mutually exclusive or substitutable (Durkin et al. 2003).

Table 6 Effects on Alternative Channels

	(1) *ATM*	(2) *VRU*	(3) *CCT*
First Branch Opening	-0.003 (0.007)	-0.018 (0.013)	0.031 (0.018)
Additional Branch Opening	0.036*** (0.003)	0.033*** (0.007)	-0.028** (0.009)
Non-Last Branch Closure	0.006 (0.004)	0.017* (0.007)	-0.008 (0.011)
Last Branch Closure	0.025** (0.010)	-0.041* (0.016)	0.533*** (0.021)
Advertising	0.000 (0.001)	0.019*** (0.003)	0.001 (0.004)
Competition	-0.006*** (0.001)	0.003 (0.001)	0.006*** (0.002)
Notes: 855,162 observations. Standard errors are in parentheses. Regressions include individual-fixed effects and time-fixed effects. *Significant at 5% level; **significant at 1% level; ***significant at 0.1% level.			

5.4. Time-varying Effects of Branch Openings and Closures

To explore the time-varying effects of branch openings and closures on customer omni-channel banking behavior, we replace each of main-effect variables in the main model, namely $FirstBranchOpening_{it}$, $AdditionalBranchOpening_{it}$, $NonLastBranchClosure_{it}$, and $LastBranchClosure_{it}$, with three dummy variables that indicate the short-, medium-, and long-term post-treatments, respectively. These time durations are decided based on the focal bank's practice to look at the effects within three months of the branch network changes as their short-term impacts (within one quarter); at those between three months and one year as their medium-term impacts (within a year); and at those after one year as their long-term impacts (after a year). In the robustness checks, we also choose different timespans for the short-, medium-, and long-term definitions, which show qualitatively consistent results. Meanwhile, due to regulation requirements, when a bank was closing a branch, it was required by law to inform its customers three months in advance. Hence, for branch closures, there are two more variables, $CloseAdv_{it}$ and $LastCloseAdv_{it}$, which reflect the effects during the legal notification period before branch closures. Formally, we change our main model to the following.

$E(Y_{it}) = exp(C_i + \beta_1\ FirstOpenShort_{it} + \beta_2\ FirstOpenMedium_{it} + \beta_3\ FirstOpenLong_{it}\ + \beta_4\ AdditionalOpen$-

$Short_{it} + \beta_5\ AdditionalOpenMedium_{it} + \beta_6\ AdditionalOpenLong_{it} + \beta_7\ CloseAdv_{it} + \beta_8\ CloseShort_{it}$

$+ \beta_9\ CloseMedium_{it} + \beta_{10}\ CloseLong_{it} + \beta_{11}\ LastCloseAdv_{it} + \beta_{12}\ LastCloseShort_{it} + \beta_{13}\ LastCloseMedium_{it}$

$+ \beta_{14}\ LastCloseLong_{it} + \beta_{15}\ Advertising_{it} + \beta_{16}\ Competition_{it} + \delta_T\ Month_T + \varepsilon_{it})$

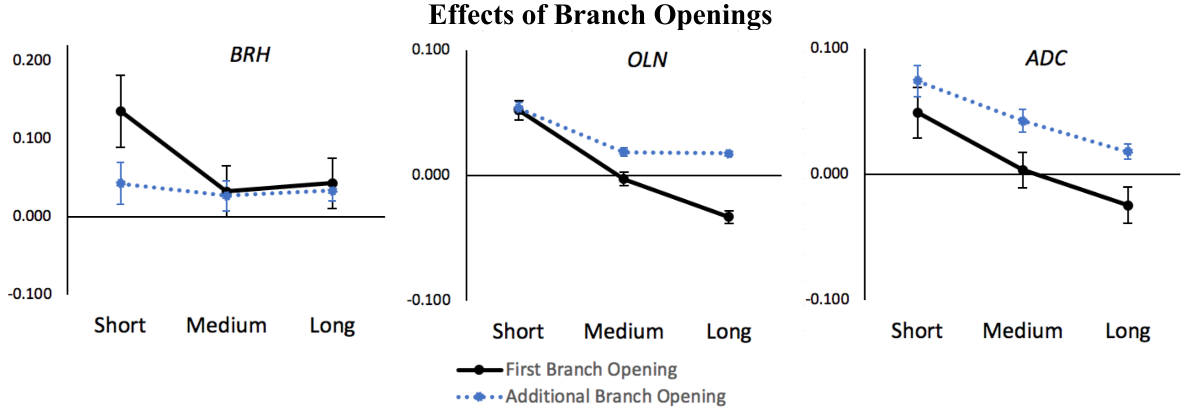
Table 7 Time-varying Effects of Branch Openings and Closures

		(1) *BRH*	(2) *OLN*	(3) *ADC*	(4) *BRHoutzip*
First Branch Opening	*Short*	0.136*** (0.024)	0.052*** (0.004)	0.049*** (0.010)	0.373*** (0.054)
	Medium	0.033 (0.017)	-0.003 (0.003)	0.004 (0.007)	0.055 (0.039)
	Long	0.043** (0.016)	-0.033*** (0.003)	-0.024*** (0.007)	-0.169*** (0.036)
Additional Branch Opening	*Short*	0.043** (0.014)	0.054*** (0.002)	0.074*** (0.006)	0.175*** (0.032)
	Medium	0.027** (0.010)	0.019*** (0.002)	0.043*** (0.005)	0.105*** (0.024)
	Long	0.034*** (0.007)	0.018*** (0.001)	0.018*** (0.003)	-0.052*** (0.015)
Non-Last Branch Closure	*Adv*	0.000 (0.010)	0.031*** (0.002)	-0.015** (0.005)	0.036 (0.024)
	Short	0.017 (0.009)	0.023*** (0.002)	0.016*** (0.005)	0.088*** (0.023)
	Medium	-0.016* (0.008)	0.018*** (0.002)	-0.007 (0.004)	0.022 (0.019)
	Long	-0.041*** (0.008)	0.013*** (0.002)	0.005 (0.004)	-0.002 (0.019)
Last Branch Closure	*Adv*	-0.036 (0.021)	0.044*** (0.004)	-0.002 (0.010)	-0.103* (0.046)
	Short	0.007 (0.022)	0.054*** (0.004)	-0.005 (0.011)	0.255*** (0.043)
	Medium	-0.082*** (0.022)	0.101*** (0.004)	0.164*** (0.010)	0.302*** (0.036)
	Long	-0.040 (0.029)	-0.029*** (0.005)	-0.027* (0.014)	0.188*** (0.051)

Notes: 855,162 observations. Standard errors are in parentheses. Regressions include individual-fixed effects and time-fixed effects. *Significant at 5% level; **significant at 1% level; ***significant at 0.1% level.

The estimation results are summarized in Table 7. We plot the coefficients of the short-, medium-, and long-term effects in Figure 3. The results generated from our main model estimations are generally supported in the time-varying treatment effects analysis, which, moreover, yields some interesting behavioral patterns of customers over time. First of all, we observe that in general the effects of branch openings in different channels usually peaked in the short term and then gradually diminished over time as shown in Figure 3. In contrast, the effects of branch closures tended to become more obvious in longer periods. For branch openings (the first three plots in Figure 3), the effects on customers' behavioral patterns over time also support our proposed *learning spillover effect*. For example, customers significantly increased their branch transactions in the short term after branch openings, indicating the short-term substitution effect in complex transactions and hence their frequent interactions with branch employees in this period. During the same time, we also observe significant positive effects on customers' transactions in the online channel as well as in the alternative channels. However, as the effects of branch openings on customers' branch transactions gradually decreased over time, indicating their reduced visits to branches and less frequent interactions with branch employees, the effects on customers' transactions in the other two types of channels also reduce in magnitude in the medium- and long-terms. These results suggest that with more frequent face-to-face interactions with branch employees due to branch openings, customers are more likely to gain better knowledge of and learn how to use different channels, which increases their omni-channel banking behaviors.

Effects of Branch Openings



Effects of Branch Closures

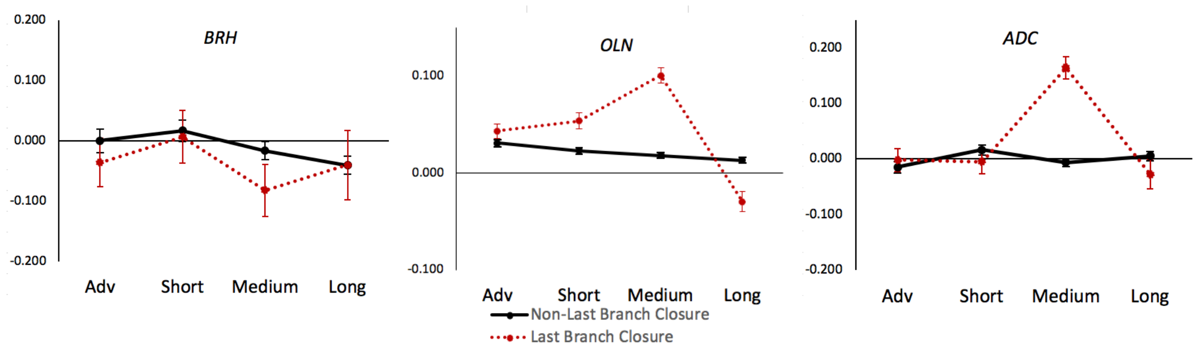


Figure 3. Long-term Treatment Effects on Branch, Online and Alternative Channels

For branch closures, the results also yield some interesting patterns of customer behaviors over time. In particular, if some branches existed in a zipcode after a branch closure, the closure mainly drove customers to migrate to the online channel as opposed to the alternative channels, suggesting that customers preferred to use online banking as a substitute after non-last branch closure. However, after the last branch closes, customers are likely to decrease their transactions through the branch especially in the medium to long-term. There is a temporary increase in transactions across online and alternative channels, however these effects also reverse in the long term, indicating that in the long term branch closures actually hurt transactions across all channels.

Overall, the time-varying treatment effects analysis shows that the bank's physical branches are still a vital part of customers' omni-channel banking behavior. Although we observe promising patterns in customers' increased transactions in the digital channels after branch network changes, we should caution that once customers lose access to the last branch in their neighborhood, this may reduce customer traffic in all the channels in the long run. These findings thus underscore customers' need for the local branch in their omni-channel experience rather than a digital-only banking world in future.

6. ROBUSTNESS CHECKS

We conduct an extensive set of robustness checks to further validate our main results. First of all, we estimate two separate models to test the potential correlation between the bank's branch opening and branch closure decisions. In the difference-in-differences model, we assume independent decision making for branch openings and branch closures by the bank. Because for the focal bank, which is ranked one of the top 5 largest bank by number of branches in the U.S., it is very rare to simultaneously open and close branches within the same zipcode area within a short period of time, as branch openings and closures are different important decisions which involve big changes on the bank's assets and employees. Therefore, we incorporate these two types of treatments into one difference-in-differences model. To test this assumption, we estimate two separate models for branch openings and branch closures, respectively. Ideally, the estimated coefficients from these two separate models should be similar as those in Table 3. However, if the bank's decision making for branch openings and branch closures are correlated or mutually dependent, then the estimation results from any of these two separate models would be quite different from the main results in Table 3 due to the removal of the other correlated variable. After running these two separate models for each channel, we find that the estimated coefficients for these two separate models shown in Table 8 and Table 9 remain qualitatively consistent with our main findings in Table 3, thereby affirming the specification of our difference-in-differences model and strengthening our confidence in the findings in this paper about customer omni-channel banking behavior in the context of branch network changes.

Table 8 Robustness Checks – Separate Models – Branch Openings

	(1) *BRH*	(2) *OLN*	(3) *ADC*	(4) *BRHoutzip*
First Branch Opening	0.058*** (0.013)	-0.009*** (0.002)	-0.001 (0.006)	-0.030 (0.031)
Additional Branch Opening	0.032*** (0.006)	0.024*** (0.001)	0.029*** (0.003)	-0.007 (0.014)
Advertising	0.010*** (0.002)	-0.005*** (0.000)	0.005*** (0.001)	0.001 (0.006)
Competition	0.001 (0.001)	-0.002*** (0.000)	-0.004*** (0.001)	-0.011*** (0.003)

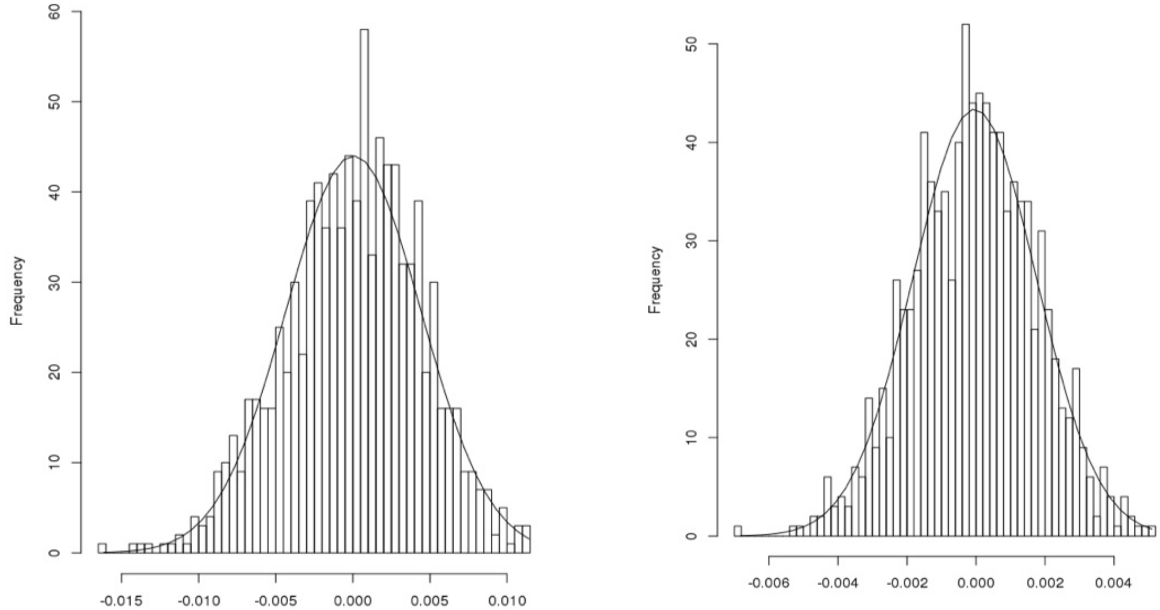
Notes: 855,162 observations. Standard errors are in parentheses. Regressions include individual-fixed effects and time-fixed effects. *Significant at 5% level; **significant at 1% level; ***significant at 0.1% level. *BRH* refers to Branches, *OLN* to Online, *ADC* to Alternative Channels, and *BRHoutzip* to Remote Branches.

Table 9 Robustness Checks – Separate Models – Branch Closures

	(1) *BRH*	(2) *OLN*	(3) *ADC*	(4) *BRHoutzip*
Non-Last Branch Closure	-0.006 (0.006)	0.027*** (0.001)	0.014*** (0.003)	0.058*** (0.015)
Last Branch Closure	-0.043** (0.016)	0.060*** (0.003)	0.064*** (0.008)	0.304*** (0.029)
Advertising	0.011*** (0.002)	-0.004*** (0.000)	0.006*** (0.001)	-0.000 (0.006)
Competition	0.002* (0.001)	-0.002*** (0.000)	-0.002*** (0.001)	-0.013*** (0.003)

Notes: 855,162 observations. Standard errors are in parentheses. Regressions include individual-fixed effects and time-fixed effects. *Significant at 5% level; **significant at 1% level; ***significant at 0.1% level. *BRH* refers to Branches, *OLN* to Online, *ADC* to Alternative Channels, and *BRHoutzip* to Remote Branches.

Second, we further implement a random (shuffled) treatment test to examine the possibility of false significance due to serial correlation in the dependent variable or spurious effects (Bertrand et al. 2004). Similar to Greenwood and Agarwal (2015) and Burtch et al. (2018), we first randomly shuffle the treatment variables (e.g., *FirstBranchOpening* and *AdditionalBranchOpening*), and then run the difference-in-differences model using the shuffled treatment variables and save the estimated coefficients. We repeat this procedure for 1,000 times (each time with a different set of random treatments). Results are shown in Figure 4. We observe that the distributions of the pseudo treatment effects are centered around zero as expected. Meanwhile, a t-test fails to reject the null hypothesis that the average estimated effect is equal to zero ($p > 0.1$). Moreover, comparing the distribution of the pseudo effects of random branch openings, we see that the real estimated coefficients of actual branch opening is at the right tail of the distribution (higher than the 99th percentile), suggesting that the probability of obtaining a similar estimate by random chance is extremely low.



(a) Distribution of Pseudo Effects of Random First Branch Opening

(b) Distribution of Pseudo Effects of Random Additional Branch Opening

Figure 4 Distribution of Coefficients Based on Random Treatments

Third, we have conducted two sets of robustness checks to corroborate our findings in the time-varying effects. In our main analysis, our choice of the relative timespans is based on the focal bank's practice to look at the effects within three months as the short-term impacts (within a quarter); at those between three months and one year as the medium-term impacts (within a year); and at those after one year as the long-term impacts (after a year). To demonstrate that our results on time-varying effects are not caused by arbitrary choice of relative timespans, we have added two sets of robustness checks with alternative timespans for each term. In particular, in the first set of robustness checks, we choose zero to four months, four to thirteen months, and after thirteen months as the timespans for short, medium, and long terms, respectively; in the second set of robustness checks, we choose zero to five months, five to fourteen months, and after fourteen months as the timespans for short, medium, and long terms, respectively. The results for these robustness checks are presented in Table 10 and Table 11 in the Online Appendix, which show qualitatively consistent time-varying effects. Moreover, we have also conducted a robustness check using the month-by-month impulse response function. The results are reported in Table

12 in the Online Appendix, which show qualitatively consistent trend in the short, medium, and long term.

7. MANAGERIAL IMPLICATIONS

Our study was motivated based on our discussion with the executives at our partner bank and has several managerial implications. The banking industry is under tremendous pressure to reduce their physical footprint to reduce the operational costs, however they find little guidance on the broader impact of such a change. Our study is the first one that focuses squarely on this question. Not surprisingly, we find that the interaction between the different channels in banking is complex and goes beyond the concept of complementarity and substitution as understood in the omni-channel retail literature. We summarize the managerial implications here and provide guidance to banking executives as they design their branch networks keeping the omni-channel behavior of consumers in mind.

Overall, when a bank adds more branches to a zipcode they not only increase the number of transactions in the branches, but also increase the transactions in the online and alternative channels, which occurs due to the learning spillover effect. Moreover, such customer learning spillover goes from easy inquiries to more complex transactions as additional branches open over time. When the first branch opens, facilitated with learning spillover customers start shifting simpler inquiries to the online channel, while preferring to move more complex transactions to the local branches due to habituation. Therefore, the total number of transactions in the online channel appears to go down first because the channel substitution effect associated with more complex transactions dominates in this condition. However, as additional branches open in the local neighborhood, customers' learning spillover gradually affects all transactions, both simple inquires and complex services (e.g., money transfer). Therefore, we observe the total number of transactions ultimately increases in the online channel.

When the bank closes branches, consumers increase the number of transactions in the online and alternative channels as well as branches in other zipcodes. Essentially, with learning spillover consumers adopt different channels to meet their needs over time, and such channel migration sustains when customers experience nearby branch closure. When the last local branch closes, there is a considerably higher increase in the usage of other channels, particularly human-centered service channels. Interestingly, we notice disturbing patterns with last branch closures indicating that the increase in other channel usage is short-lived and eventually the overall transactions reduce, suggesting that consumers might move away from the bank eventually after the last local branch closure. This is also indicated by a large amount of outgoing transfer from the focal bank after the last branch closes.

Our findings provide many directions that banking executives should keep in mind while changing their branch networks. Firstly, opening the first branch might result in a short-term reduction of online transactions, particularly the complex ones, but over time consumers will learn from the interactions in branches and move these transactions online. Hence, the banks should not only account for the increase in complex requests in the branches by hiring the right branch personnel, but also enable faster consumer learning that will intensify the spillover learning effect. Second, when the bank closes branches, they should anticipate the surge of consumers across other service channels, particularly human-centered channels and hire more call center agents. Finally, the banks should be careful in closing the last operating branch in a zipcode, as that might result in a short-term movement to other channels, but consumers might move away from the bank in the long term.

8. CONCLUSIONS

The reality and effects of disruptive technology in the financial services industry prompted us to rethink the distribution of physical bank branches. In this paper, we investigate branch network changes — a major strategy often deployed by leading banks in the retail banking industry today to accommodate changing customer preferences — and their impacts on customers' omni-channel banking behavior. Although a considerable number of papers have examined online banking adoption and explored customer channel preferences and banking behavior, there has been no empirical study focusing on the effects of branch network changes. We provide herein some first glimpses of consumer behavior in response to financial-services branch network changes. Some papers on the retailing industry have investigated the impact of physical store entries in local markets, but few of them have offered empirical evidence to quantify the effects of store closures. Our work thus also complements this stream of research by providing insights into consumer behavior from the perspective of physical store closures.

We identify a new omni-channel phenomenon in the context of banking. Opening more branches leads to more consumer visitation to the branches, which in turn results in consumer learning for complex transactions that we term the "learning spillover effect." This learning spillover effect shows how consumers initially move complex transactions offline when the first branch opens in a zipcode, but how these transactions are migrated to the online and alternative channels with the opening of additional branches (as the consumers are already aware of complex transactions). This effect also explains why consumers' transactions do not dramatically decrease once the bank closes branches (even if it is the last branch), and instead they shift their transactions to the online and alternative channels, as they already know how to perform these transactions in non-branch channels. Such a learning effect is unique to the banking industry given the complexity of banking transactions and the complex relationship between the different channels.

At the same time, this study shed a considerable amount of light on branch closures, an area that has not received much attention in the omni-channel literature. Our results suggest that branch closures lead to a reconfiguration of the consumers' channel usage and the consumers resort to more human-centered channels like call centers when their access to branches is reduced. However, the analysis of the time-varying effects of branch network changes suggests potential risks of customer churn in response to the last branch closures in the long term. Our research will hopefully help senior managers in commercial banks to develop more realistic views of consumer behavior in omni-channel financial services and to deploy branch network transformations in more effective ways.

The difficulty of generalizing our results in multiple contexts is one of the main limitations of this paper. Our empirical analysis has focused on the financial services industry given a unique proprietary dataset provided by a large commercial bank in the U.S., thus our insights will be especially pertinent to financial institutions. For external application, the differences in products and services offered by various firms would have to be considered. For example, our results are less likely to be informative for the retailing industry, in which the main products offered through multi-channels are physical goods. Instead, our results are likely to be more applicable in industries whose main products are virtual goods and/or services. This fact restricts the building of more-generalized knowledge of customer omni-channel behavior. Another limitation is that our data comes from a single U.S. bank; more-generalized insights into consumer behavior will require data from a variety of banks having different demographics and banking profiles. Nonetheless, since our data consist of a large sample of customers from a major U.S. commercial bank, which is one of the top 10 largest banks in the U.S. by assets, we are confident that our customer sample is representative of general customers of commercial banks in the U.S.; indeed, we believe that the conclusions drawn in our paper will shed light on branch network distributions more broadly given that the focal bank is ranked one of the top 5 largest bank by number of branches in the U.S.. Certainly, future research with data from a wider selection of sites or other behavioral and survey approaches will provide further insights into customers' omni-channel banking behavior in the context of physical branch network changes.

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