7-2017

How technology Is reshaping financial services: Essays on consumer behavior in card, channel and cryptocurrency services

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SINGAPORE MANAGEMENT UNIVERSITY
2017

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by

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Submitted to School of Information Systems in partial fulfillment of the requirements for the Degree of Doctor of Philosophy in Information Systems

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Singapore Management University
2017

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Abstract

The financial services sector has seen dramatic technological innovations in the last several years associated with the "fintech revolution." Major changes have taken place in channel management, credit card rewards marketing, cryptocurrency, and wealth management, and have influenced consumers' banking behavior in different ways. As a consequence, there has been a growing demand for banks to rethink their business models and operations to adapt to changing consumer behavior and counter the competitive pressure from other banks and non-bank players. In this dissertation, I study consumer behavior related to different aspects of financial innovation by addressing research questions that are motivated by theory-focused research literature and managerial considerations in business practice. I seek to understand how technology is reshaping financial services, and how financial institutions can leverage big data analytics to create deep insights about consumer behavior for decision support.

The first essay studies credit card-based partnerships between banks and retailers. I test a number of hypotheses that assess the indirect effects related to the impacts of credit card programs in my research setting. I use publicly-available data, together with proprietary data from a large financial institution, to examine the impact of card-based promotions on consumer behavior and merchant performance. The results show that such promotions create positive indirect effects, leading to increased purchases from customers of other banks, in addition to the bank running the promotion. This research creates insights that banks can leverage

to optimize their card-based reward programs, and paves the way forward for strengthening credit card merchant partnerships.

The second essay emphasizes the importance of investigating bank branch network changes, including branch openings and closures, and their impacts on customers' omni-channel banking behavior. I find that branch openings create customer awareness and lead to synergetic increases in transactions across channels, and branch closures result in a migration pattern from alternative channels to online banking due to the joint effects of negative perceptions and substitution. This essay contributes to our knowledge of multi-channel services in the IS and Management literature, and provides strategic implications on branch network restructuring in omni-channel financial services.

In the third essay, I draw on social contagion theory and a spatiotemporal perspective to explore the global penetration of bitcoin, and how security events have been influential in this process. This essay uses transaction data from Mt.Gox, one of the largest bitcoin exchange platforms in the world before its bankruptcy in 2014, and other publicly-available data sources for county-level information. The results suggest that the global penetration of bitcoin is jointly influenced by the economy, technology and regulatory situation of a country. And news about the occurrence of security incidents related to the cryptocurrency has a negative impact on its cross-country diffusion. This study contributes to the literature on the diffusion of emerging financial technologies, as well as business practices at the early stage of the development of a digital currency.

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Acknowledgments

The last five years I spent in Singapore Management University has been the most challenging and rewarding time of my life thus far. I would like to first thank Prof. Robert Kauffman, for his patient guidance through the PhD program. I have learned many things beyond research from him. I am extremely fortunate to be blessed with an advisor who is supportive and accessible all the time when I need his help. I would also like to thank Profs. Zhiling Guo, Qiuhong Wang, and Dr. Yinping Yang for being in my committee and giving valuable advice on my work. I especially thank Profs. Vibhanshu Abhishek and Beibei Li for being excellent mentors during my visit to Carnegie Mellon University, and having an enormous influence on my research path. I appreciate insightful discussions and general support from Profs. Dan Ma, Qian Tang, Mei Lin, Youngsoo Kim, and my Ph.D. colleagues Jianhui Huang, Jun Liu, Kustini Lim-Wavde, Emmy Hoang, Yuzhou Hu, Zhiyuan Gao, Deserina Sulaeman, LARC Research Fellow Zhuolun Li, and Prof Eric Clemons, Thomas Weber and all participants at the HICSS and ICIS conference seminars.

I would like to thank the Living Analytics Research Centre at SMU and the PNC Center for Financial Services Innovation at CMU for generous financial and data support. Many thanks go to Profs. Ee-Peng Lim, Baihua Zheng, Stephen Fienberg, Alan Montgomery, and Ms. Pei Huan Seow, Chew Hong Ong and Phoebe Yeo for all the administrative help.

Last but not the least, I would like to say a special thanks to my parents for providing me with the best opportunities to pursue my dreams. I am forever grateful for their unconditional understanding, unflinching support and unlimited sacrifice.

To my parents, Xiaolan Pu and Guosen Geng,

who have offered tremendous support in my life.

Chapter 1. Introduction

Advances in information technology (IT) have fueled waves of financial innovations that have revolutionized the "Bank 1.0" traditional bank branch services-based financial services industry. In the "Bank 2.0" era, the popularity of online and mobile banking, mobile payments and social networks have changed the way that consumers make transactions and interact with their banks (King 2010). At the same time, the gap between consumers and banks has been widening due to the emergence of peer-to-peer (P2P) lending, crowdfunding and cryptocurrency services, bringing financial services rapidly to the "Bank 3.0" stage (King 2012). This has resulted in big challenges for banks, and forced them to rethink their organizational structures to adapt to changing consumer behavior. It has also spurred new business models and encouraged non-bank players to challenge the banking sector's traditional competitive advantage, including lower cost of funds and privileged access to customers, and digitally disrupt the industry.

In the credit card market, card products are increasingly bundled with a series of benefits, including rewards, instant cash rebates, and price promotions involving retail merchants, to attract customers and drive new levels of retail banking profitability. The digital transformation of the card market, including mobile payments, real-time technologies, and online and mobile card marketing, have enabled banking systems to become new *mandatory participation third-party payer* (MP3PP) *markets*, in which credit card-issuing banks and associations serve as intermediaries and provide customers with free access to merchants, while merchants are charged for the services as third parties. This is likely to create enormous business value for banks, yet currently there are several challenges that prevent the credit card programs from growing rapidly. To calibrate the revenue production capabilities of the programs, banks must figure out whether the benefits bundled with credit cards can drive increasing revenue from the merchant partner based on using consumer preferences in a way that creates customer centricity.

Channel management is another major area of business strategy that banks are actively pursuing. Today, bank customers have become omni-channel users, and over 90% of banking transactions are executed electronically through automated teller machines (ATMs), call centers, the Internet and mobile devices (McKinsey 2014). The changing demand of customers has led to the dramatic rise of digital channels and a sharp decline in customer traffic in branches. Considering continuing cost inefficiency, banks have been scaling down their physical branch networks and experimenting with new branch models. But the effects of this strategy are not well understood yet, and banks are trying to avoid customer churn due to branch closures. Hence, it is critical for banks to become more deeply aware of sophisticated consumer behavior in an omni-channel banking environment for informed decision-making related to branch network restructuring.

Bitcoin, as an emerging digital cryptocurrency, has generated intense interest in the financial services industry. The trade volume, the number of blockchain wallet users, the online and offline retailers that have accepted bitcoin as a payment option, and the amount of venture capital invested have all increased in recent years. Although the price of bitcoin has fluctuated a lot, its main features and the underlying blockchain technology have convinced many academic researchers and industry pioneers of their potential to disrupt business practices, such as trade finance, financial transactions and payments, and beyond. Since bitcoin is in an early stage of development, it is important to understand which markets and consumer segments may prove to be the most fertile for its adoption and use. Framing an answer to this question will also help governments and regulators to understand the economic opportunities and the potential risks presented by bitcoin.

Many more financial innovations are underway, opening up the financial services market to fierce competition. For example, payment companies PayPal, Swiff, and Square, and Apple Pay and Google Wallet services have been making inroads into the traditional payment services domain of banks. Such competition is likely to shrink the revenue pool available to banks, expose their inefficiencies, and undermine the banking value chain (Deloitte 2014). Misapplication and poor management of these innovations can also result in potential threats, including consumer service problems, the insolvency of some financial institutions, systemic risk, and loss of market quality (World Economic Forum 2012). So it is critical for financial institutions to create financial innovations to harness the benefits and avoid the negative outcomes to achieve sustainable success.

My dissertation research has been made possible through the sponsorship of financial services firms. They have made available large amounts of customer and transaction data, and have expressed an interest in university research collaboration due to the emergence of advanced data analytics. Advances in financial technologies have boosted the capabilities of banks to have intimate and valuable interactions with individual customers and retailers. At the same time, they are taking advantage of big data, characterized by volume, variety, velocity and veracity – the "4 V's." We have also seen the introduction of Teradata and Hadoop data processing and querying technologies. More transactional data are being generated and collected than ever before, and the innovations now extend into the realm of mobile banking, while mobile payments allow for the acquisition of spatiotemporal and geospatial information.

These abundant digital data enable banks to detect complex consumer behavior patterns, and implement information-based strategies to influence consumer decision-making, improve product and service designs, and optimize marketing and business operations. One of the earliest and most successful examples in the card marketing area is Capital One: its business model has been instrumental to its success. During the 2000s, the company conducted more than 30,000 experiments per year to identify differences in customer receptiveness to card product adoption in the presence of data mining and differential pricing, and to earn higher profit by targeting the most profitable accounts (Clemons and Thatcher 2005). Econometric modeling has also been widely used to reveal the relationships, influences and marginal effects, based on the detection of different consumer behavior.

The techniques for data analysis have been improving too. The availability of R Statistics analytics, Python programming, and Hadoop data queries have enabled new and faster ways of processing large data stores and streaming data. Using the computing power of these advanced tools, companies have been able to go beyond descriptive analytics and traditional econometrics to conduct sophisticated experiments. Today, they are building predictive models based on machine learning algorithms and datasets from sources that are available from both inside and outside the organization. The new methods provide more predictive information besides the explanatory information delivered by traditional econometric modelling.

Recently, new modes of discovery have become available with fusion analytics, which combines machine learning, statistics, econometrics, and predictive analytics to assess causal influences. The related approaches have been increasingly applied in marketing, operations, and e-commerce research. They support pattern recognition from machine-based algorithms, and insights on the impacts of business policies through econometric analysis. Advanced data analytics also go beyond the limitations of machine learning and econometric methods when they are applied separately, and improve the effectiveness of an analyst to discover causal relationships. This helps to create insights on the full product and service portfolio of financial institutions, identify profitable customers, and then suggest how to tailor their key business strategies in appropriate ways.

Based on these new data analytics techniques and my research questions, I have looked closely into interesting issues and have contributed new knowledge on consumer insights related to the inner workings of financial services and technology. My thesis work explores consumer behavior in omni-channel retail banking operations, credit card-based partnerships, and for cross-country penetration of bitcoin in the presence of security concerns. I aim to contribute new knowledge by answering: (1) How can banks leverage big data analytics to influence consumer decision-making and improve the performance of card-based partnerships with retailers? (2) How will omni-channel retail banking shift due to technology, and how should banks restructure their physical branch networks in response to such a shift? (3) How can cross-country adoption and diffusion of cryptocurrency be understood in spatial and temporal terms, when security issues are recognized to be major threats?

The remainder of this dissertation is laid out as follows. Chapter 2 examines the impact of credit card-based promotions and tests the indirect effects on consumer behavior and merchant performance. Chapter 3 investigates the physical branch channel and the effects of related branch network changes on consumer omni-channel banking behavior. Chapter 4 presents an empirical analysis of the spatiotemporal penetration of Bitcoin. Chapter 5 summarizes my experience as a doctoral research intern in the corporate trenches. And Chapter 6 concludes with contributions, limitations and future research.

Chapter 2. Indirect Effects in Credit Card Rewards Marketing: The Impacts of Cards in Bank-Merchant Partnerships

2.1. Introduction

Card products in financial institutions, especially credit cards, are getting ever more sophisticated in the ways in which they create value for consumers. They now offer a mix of hard and soft benefits, including rewards and cash rebates, co-branded loyalty programs, and long-term promotions for purchases from participating retail merchants. To attract customers and drive new levels of retail banking profitability, banks have created new card-based programs, and increased their shares of marketing-related spending from 30% in 2002 to over 70% in 2015 (Consumer Financial Protection Bureau 2015). Customers have been using more credit cards and have become more engaged in card-based programs as well. For example, in 2014, about 72% of U.S. consumers held at least one credit card (Federal Reserve Bank of Boston 2014), with total credit card spending during the last decade rising to over USD 2.6 trillion by 2015 (The Nilson Report 2015). This has provided a foundation for growth in card-based reward programs in financial services, as firms have struggled to lock in their market shares.

2.1.1. Evolution of Card and Loyalty Programs

Modern reward programs were introduced in the airline industry, when American Airlines launched its frequent-flyer program, AAdvantage, in 1981 (American Airlines 2011). This allowed customers to earn free flights based on the number of trips they made or distance they flew with American Airlines. By 1995, the hotel and retail sectors began to adopt a similar model. Firms including Marriott, Starwood, and Tesco started implementing loyalty programs to build stronger customer relationships (Kumar 2008). Card-based reward programs reached the financial services industry in the mid-1980s. Discover, Diners Club, and Citibank were among the first financial institutions that introduced purchase reward and cash-rebate products (Salik and Henry 2007). These early credit card programs gave cash to customers based on their spending at the end of the year, and are still in place and remain popular today.

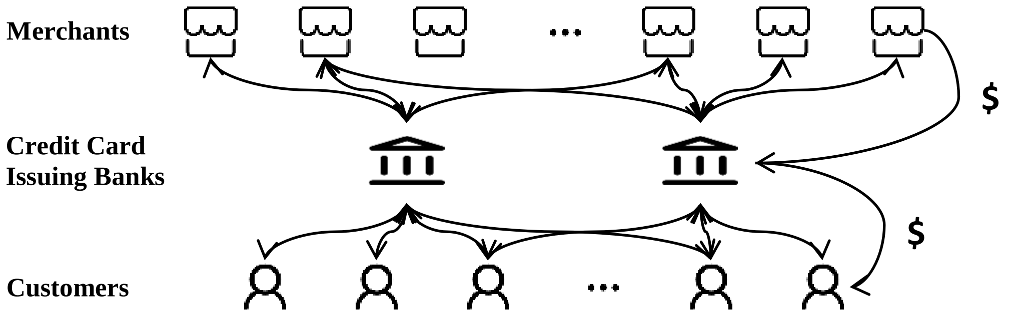
Card-based reward programs began to flourish in the 1990s, and leading banks and credit card companies created a broad array of card products (McEachern 2014). By the end of 2000s, about half of all Visa and MasterCard credit cards provided an associated reward component (Capgemini 2012). The total number of memberships in loyalty programs reached 3.3 billion people in 2014, with each household in the U.S. involved in about 29 different reward programs on average (Colloquy 2015). Moreover, a variety of reward types of loyalty programs appeared, as financial institutions fought to innovate and differentiate themselves in an increasingly saturated market for card-based rewards (Capgemini 2012). The new innovations included points, cash back, discounts, or a combination of these and other elements. Among them were Citibank's Thank You Rewards and Points Programs, and Barclays Bank's Freedom Reward Program (Cook et al. 2015). These programs were recognized by industry observers in the late 1990s and early 2000s as integrating card and banking rewards, while offering rewarding cash bonuses directly to their customers. In particular, card-based partnerships emerged and became an industry-wide phenomenon, as many business segments started to tie up with banks and financial institutions, and offer co-branded credit cards (MarketResearch.com 2013). Today, such bank-merchant partnerships based on credit cards exist in almost every industry, with the airlines and hotels the most popular (Capgemini 2014).

2.1.2. Digital Transformation of the Card Market and the MP3PP Banking Systems

Industry reports have shown that advances in information technology (IT), especially innovations in products and payments, have fueled the growth of loyalty programs in the financial services industry (Bain 2014, Capgemini 2015, McKinsey 2013). For example, the development of point-of-sale (POS) services, mobile payments, and communication technologies, such as radio frequency identification (RFID) and near field communication (NFC), have made card-based purchase transactions easier to implement in different service environments, and have accelerated consumer spending and rewards redemption, yielding additional revenue-generation opportunities for the leading financial service providers (Bain 2014). It has become possible to deliver time- and location-based offers and coupons instantly to customers (PricewaterhouseCoopers 2015a). In addition, the popularity of the Internet and the growth of social networks give customers easy access to bank-based card programs, and created increased brand awareness through online card marketing (Eldridge 2017).

This has made it so the related banking systems have become firmly entrenched digital utilities that support merchant and customer interactions. A new system-based geometry of credit card markets, known as *mandatory participation third-party payer* (MP3PP) *markets*, has also been put forward (Clemons 2011, Clemons and Madhani 2011). An MP3PP market is one in which credit card-issuing banks and associations act as intermediaries and give users free access to merchants, while merchants as third parties are charged for providing services. (See Figure 2.1.) The figure suggests that MP3PP markets in financial services allow merchants to reach potential users through platforms operated by banks.

Figure 2.1. Mandatory Participation Third-Party Payer Structure in the Credit Card Market



Source: Adapted from Clemons and Wilson (2016)

Well-designed MP3PPs have the potential to create enormous business value where they are used. Examples include Orbitz in hospitality and travel booking services (Granados et al. 2007), Uber and Lyft in transportation services (PricewaterhouseCoopers 2015b) and Airbnb for accommodation (Weber 2016). As user bases grow, these platforms enroll more service providers, and become the strongest competitors among traditional providers (House of Lords 2016). Moreover, competition among operators in an MP3PP often leads to a *reverse price war*, which allows them to charge higher prices for services provided over time, instead of reaching a low-price market regime, as suggested by economic theory (Clemons and Wilson 2016). As a result, credit card programs have the potential to enhance the relatively low margins of card products, and drive better retail banking profitability.

On the other hand, technological innovations have made the processing and management of credit card reward program-related transactions increasingly sophisticated. This is because customers now can accumulate and redeem reward points in multiple channels, such as via POS, the online channel, and mobile phones. Banks also provide a variety of customer-centric features and options that supports the redemption, transfer, sharing, and gifting of reward points. Merchants have become more concerned about their eventual business revenues due to the costs incurred to fund the card programs. This has made many merchants reluctant to partner with banks, which has been a challenge for the development of more effective credit card reward programs. To calibrate the performance of their programs, banks have been making efforts to become more deeply aware of consumer behavior and figure out whether the bundled benefits with credit cards can drive increasing revenue from their merchant partners based on becoming more informed about consumer preferences in ways that create customer centricity (Carbó-Valverde 2011).

This has been made possible based on the new availability of historically large amounts of customer and transaction data, as well as the emergence of tools and infrastructures for complex data analytics. They have supported more advanced research on card and loyalty programs, and have been building on prior theory and modeling work (Kopalle et al. 2012, Caillaud and Nijs 2014) toward quantitative analysis that enables the acquisition of causal inference-driven insights on consumer behavior (Wang et al. 2016). Recently, new approaches to Computational Social Science have been applied in Marketing, IS, Operations, and Environmental Sustainability research that combine machine learning, statistics and econometrics to assess causal relationships and make more accurate predictions (Hoang and Kauffman 2016, Kauffman et al. 2017). Such methods now are creating the capability to acquire deeper insights into the full spectrum of products and services offered by financial institutions, identify customers who are likely to be profitable, and suggest appropriately tailored offers.

2.1.3. Research Questions

Research on card programs has been on the rise, showcasing the new perspectives of academic strategists and data analytics specialists. The card and loyalty program literature has explored issues including preferences, redemption, and customer behavior (Liu and Brock 2009, Ching and Hayashi 2010, Kopalle et al. 2012). This research tests their *effects in credit card marketing* and examines the impacts of card-based promotions on consumer behavior and merchant performance. We answer these questions: (1) What are the direct effects of card promotions? (2) Do card-based promotions create positive indirect effects, which benefit merchant partners by attracting customers who are not card holders at the partnering bank? And (3) how should banks leverage insights on customer behavior to design the bundled loyalty program with a credit card including the funding and redemption options?

We focus on the market of Singapore, an Asian country that is relatively prosperous, and whose credit card economy has been growing rapidly. The number of cards issued in the country has increased by 52% from 5.4 million in 2009 to 8.2 million in 2014 (Data.gov.sg 2017), while the average number of credit cards held per person is 3.9, exceeding that in U.S. (2.6), U.K. (1.5) and China (0.29) (Financial Conduct Authority 2015). We study a popular business segment: the hotel, shopping and dining services sectors. The transparency in this business sector enabled us to collect merchant data from an online aggregator.

We acquired other data, such as credit card offers from the websites of various banks, and anonymized data on transactions and customers from a financial institution. By consolidating the data with a fuzzy matching algorithm, we were able to construct a panel dataset for econometric analysis. Our results suggest an interesting indirect effect of card promotions, which increases consumer purchases beyond the partnering bank. The indirect effect is stronger with merchants that have lower sales. We also find positive effects of card-based promotions on customer traffic and transaction volume for the merchant partner through credit card transactions with bank customers. The effects are moderated by competitive credit cards offered by rival banks though. However, it is unclear that card promotions increase merchant sales from the bank.

We contribute to the foundational theoretical knowledge in the prior literature on loyalty programs and price promotions by empirically testing the indirect effects in credit card marketing. We also examine actual customer behavior in response to card-based partnerships in the context of financial services. Our unique access to merchant and customer information allow us to include a broad set of relevant variables, and compare the effectiveness of credit card programs based on different segments. Our research also offers new knowledge about credit card programs and paves the way forward for decision support in banks to more deeply probe credit card customer rewards and loyalty program behavior.

This chapter is structured as follows. We review related literature in Section 2, and develop hypotheses related to direct and indirect effects of credit card promotions based on Economics and IS theories in Section 3. In Section 4, we describe the data that were collected, and how we consolidated and constructed a unique panel data set for our empirical analysis. Model development and estimation methods are shown in Section 5. We discuss the results of model estimations in Section 6. Then we conclude with contributions, limitations and future research directions in Section 7.

2.2. Theoretical Background

We draw on several streams of literature, including: (1) card rewards and loyalty programs, (2) price discounts and sales promotions, and (3) advertising effects of promotions.

2.2.1. Card Rewards and Loyalty Programs

Existing research related to card rewards in financial services has studied a variety of issues, including biased consumer preferences, redemption behavior, and customer loyalty (Bolton et al. 2000, Keh and Lee 2006, Meier and Sprenger 2010, Liu and Brock 2009). Research that is relevant to our work has looked into the impact of credit card programs on consumer buying behavior.

Wirtz et al. (2007) used consumer survey data to examine the impact of credit card loyalty programs on wallet share, and suggested that attractive reward programs are likely to increase credit card usage. Using a unique research design for empirical falsification, Ching and Hayashi (2010) found that consumers were willing to switch to cash and checks for in-store payments if card rewards were removed. However, few prior works have systematically examined the effects of such programs, due to mostly inaccessible data in a strictly-regulated industry.

Loyalty program studies have been conducted in other contexts such as airlines, hotels, and supermarkets. It is widely accepted in Marketing that loyalty programs are profitable for firms (Agustin and Singh 2005, Fornell et al. 1996, Reichheld and Teal 1996). An example of such profitability is Kopalle et al. (2012), who used data from a major hotel chain and found that the reward frequency and the different customer-tier components of a loyalty program contributed to incremental sales. In a similar context, Wang et al. (2016) launched a large-scale field experiment and identified increases in buying behavior by consumers due to loyalty promotions.

Some research suggests otherwise though: that loyalty programs are not always producing the benefits that the firms offering them hope to reap. For example, Gupta and Lehmann (2005) demonstrated that a number of companies invested large amounts of money in loyalty management but received few tangible profits. Villenueva et al. (2007) argue that increased price competition may cause lower profits when firms focus on long-term profit maximization in loyalty programs. Another stream of research has applied game theory to analyze business strategies for higher profitability through loyalty programs (Kim et al. 2001, Singh et al. 2008, Caillaud and Nijs 2014). The implications of these earlier works for the present research include the necessity for firms to have a strategic view, and to take the market competition and their rivals' actions into consideration when designing their loyalty programs. Moreover, the size, preferences, and relative price sensitivity of customer segments need to be thoroughly understood to ensure that the marketing tactics used will result in higher profits through reward programs that are implemented.

2.2.2. Price Discounts and Sales Promotions

There are numerous studies on coupons, price discounts, and other types of promotions that use econometrics for data analysis, and a theoretical basis for the authors' investigations. These studies have explored the market responses and dynamics of different promotion sizes and types, and discussed some optimal competitive strategies for retailers. For example, Neslin (1990) estimated a market response model using retailer scanner data, and revealed some of the effects of couponing on market shares. Subramanian and Rao (2016) developed a theoretical model, which showed that displaying sales on websites can transform the cannibalization of merchant revenues into an advantage and improve customer acquisition.

In contrast, Simonson et al. (1994) and Anderson and Simester (2001) suggested that sales promotions sometimes serve as adverse signals of product quality, resulting in negative impacts on consumer purchase decisions. Others studied the long-term effects of price promotions and reported mixed results on merchant profitability and consumer brand choices, based on time trends, promotion strength and other factors (Jedidi et al. 1999, Kopalle et al. 1999). More recent research has studied new promotion types, such as embedded premiums and probabilistic free-price promotions. In addition, Arora and Henderson (2007) and Mazar et al. (2016) have discussed their effectiveness compared to traditional price promotions.

Research on loyalty programs and promotions has been conducted for different business settings. Loyalty programs in financial services, especially credit card-based programs, differs from those in other industries. First, classic loyalty programs in retailing are usually created for a single company, but card promotions in retail banking often involve multiple stakeholders in the same market. Second, unlike firms in hospitality, air travel and retailing areas, banks usually have larger and more long-lived customer bases that exhibit greater heterogeneity in their preferences. Third, rather than a single type of reward, as with traditional loyalty programs, credit card programs may offer several types of promotions, including rewards, cash rebates, and price discounts simultaneously. So loyalty programs have more sophisticated design elements. The research gap in promotion-related research between financial services and other industries encourages our exploratory research with unique data.

2.2.3. Advertising Effects of Promotions

Beyond the promotional effects due to price reduction, the catalog and coupon literature have suggested that there is an advertising exposure effect associated with coupon promotions (Ansari et al. 2008, Bawa and Shoemaker 1989). Coupons, as a special type of sales promotion, usually contain brand name, image, and other relevant descriptions, so they provide both savings value and addition information about a brand or a product (Ward and Davis 1978). Consumers who receive the promotions are expected to mentally assimilate information that is shared about the advertised brand into their mental model of the brand over time. Such accumulated information is likely to create a heightened awareness of a brand, strengthen the relationship between the customers and the brand, and improve customer perceptions of the brand's key characteristics (Venkatesan and Farris 2012). Thus, consumers acquire monetary value through the usage of the coupon, but also informational value from mere exposure to the brand or product promotion (Chandon et al. 2000). The acquired information increases the possibility that consumers will make a purchase in the future, and will result in the growth of the promoted merchant's business, even if the customers do not directly respond to the promotions they have received (Srinivasan et al. 1995).

Several research articles have identified the advertising exposure effects of coupon promotions, and have sought to build theoretical foundations for the mechanism that is at work when a targeted promotion may also increase purchases from non-targeted customers. Sahni et al. (2016) conducted an experiment that involved experimental offers given to targeted customers on a large online ticket resale platform. Their results suggested that about 90% of incremental sales increases were achieved without the use of discounts in an extensive research design in which the authors conducted 70 field experiments.

They concluded that targeted discount offers can go beyond tools for price discrimination, and may serve as an advertising message for the promoted product or merchant. Prior to their work, Venkatesan and Farris (2012) identified a similar effect with retailer-customized coupon campaigns from grocery chains on consumer purchases. They reported that this effect results in the contribution of more value than just coupon redemption to the campaign returns. In a similar vein, Bawa and Shoemaker (1989) found that coupon promotions sometimes have the effect of increasing sales by attracting consumers to make an incremental purchase, even if the coupons are not redeemed. They suggested that coupons may act like an email advertisement and a reminder about the brand to influence consumer choices.

2.3. Theory Development for Hypotheses

We conceptualize the market response to card-based partnerships and other related factors based on economic and psychological theories. We also develop hypotheses that relate to the direct and indirect promotional effects of credit card offers with merchant performance and customer behavior in mind.

2.3.1. Promotional Effects of Credit Card Promotions on the Business of the Partnering Bank

The sales promotion literature has extensively studied the short-, middle- and long-term impacts of sales promotion on brand sales (Blattberg et. al. 1995). For example, using scanner data at both the household level and market level, they demonstrated that retail price reductions increase merchant sales dramatically (Moriarty 1985, Krishnamurthi and Raj 1988, Blattberg and Wisniewski 1989). This positive effect may come from merchant switching, accelerate consumer purchases, and encourage wider category consumption (Blattberg and Neslin 1990), among which brand switching appears to be a major outcome according to several studies (Gupta 1988, Totten and Block 1987). By providing monetary incentives, these promotions increase consumer utility, reduce search cost, and mitigate uncertainty regarding the price and quality of the promoted merchant, leading to a higher likelihood for selecting that merchant.

Credit card promotions in our study are helpful for increasing the volume of purchases in several other ways. First, cardholders are provided with recognition by merchants through the privileges and distinction offered by card-based programs. The sense consumers have of being targeted for special services satisfies their basic need for self-actualization and increases their willingness to buy (Maslow 1954). Second, credit card partnerships are helpful for large-scale, word-of-mouth (WOM) marketing, which increases referrals from among customer networks of the bank. Third, multiple authors have identified the occurrence of stockpiling behaviors during periods of promotions (Litvack et al. 1985, Chakravarthi et al. 1996, Sun 2005). Thus, card-based promotions are also likely to encourage repeated purchases from existing customers. As a result, card-based programs tend to increase the purchase transaction volume of the promoted merchant from customers of the bank:

- **Hypothesis 1 (The Promotional Effects of Card Offers Hypothesis).** *Credit card promotions increase merchant sales from customers of the partnering bank.*

2.3.2. Indirect Effects of Rival Banks' Card Offers

Credit card promotions in the financial services research setting involve the display of price discounts and other descriptions of a merchant, which may advertise and register the merchant in consumers' mental shopping lists. These promotions may be more attractive to customers than general advertisements that do not contain promotions (Bowman 1980). The easy access to the bank websites, together with additional offline marketing efforts that the card issuing bank made, has ensured wide readership of the credit card offer advertisements, and enhanced the possibility of an exposure effect (Srinivasan et al. 1995).

At the same time, the banks also allocate a portion of their marketing budget to inform their own customers about merchant promotions through electronic direct mailers (EDMs) and short message services (SMSs), leading to dramatic increases in customer traffic of the partnering merchant. The initial popularity of the merchant may then attract other customers who are not from the bank and are not aware of the promotions. This way, the exposure effect is strengthened through social interaction. So we propose:[1]

- **Hypothesis 2a (The Indirect Effects of Card Promotions Hypothesis).** *Exclusive credit card promotions increase the transactions of the partnering merchant from customers beyond those of the partnering bank.*

While the exposure effect has been demonstrated to be a highly pervasive and robust phenomenon in various industries ranging from advertising to art (Crisp et. al. 2009), its effectiveness weakens as exposure increases beyond a threshold (Zajonc et. al. 1972). Stang and O'Connell (1974) found that the effect peaks with a relatively small number of exposures. Since merchants with higher customer traffic and sales are initially more exposed to the public, the curiosity of customers about the merchant is reduced when they already have received such advertising information embedded in the credit card offers (Pracejus 1995). Therefore, the exposure effect decreases with partnering merchants that are sufficiently well

[1] Although credit card promotions may also have an advertising exposure effect on targeted customers, we focus on non-targeted customers as it would be very difficult to separate the incremental transactions due to the exposure effect from those due to price discounts and other benefits among the targeted bank customers. Also, we limit our analysis to exclusive credit card offers from rival banks because: (1) we have customer transaction data only from the bank that we are working with; and (2) it is very difficult to distinguish the changes in customer purchases attributable to offers given by the partnering bank and that are attributable to offers given by rival banks for competing promotions.

known by customers. Another stream of the Marketing literature has also noted that merchants with higher market shares do not benefit from the utility gains that consumers may perceive due to promotion-driven price elasticity (Bolton 1989, Bemmaor and Mouchoux 1991, Vilcassim and Jain 1991). Based on these theoretical arguments, we propose that:

- **Hypothesis 2b (The Strength of the Indirect Effects Hypothesis).** *Partnering merchants that have lower sales benefits obtain a higher incremental volume of purchase transactions from customers of banks that are not running the promotions*.

2.3.3. The Moderating Effects of Countervailing Offers

In the complexity of our research context, a merchant can partner with multiple banks for credit card promotions. Although we suggest there is an advertising exposure effect from exclusive offers by competing banks, competitive offers are likely to moderate the promotional effect of offers that may develop out of the partnering bank's actions. This is because the customer bases of different banks may overlap to some extent, even if the banks strategically target somewhat different customer profiles. Thus, a portion of customers who hold credit cards from multiple banks may be convinced to switch their card services by competitors when parallel promotions with the same merchant exist, and the competitors' offers are better. The moderating effect of competitive promotions has been considered by existing marketing research, and has been included when the analyst models the responses to sales promotions (Gupta 1988). Gelb et al. (2007) also did an empirical study to investigate this kind of effect with the case of discount marketing competition between General Motors Corp. and its rivals. Hence, our third hypothesis is:

- **Hypothesis 3 (The Moderating Effects of Competitive Offers Hypothesis).** *Competitive offers of rival banks will moderate the promotional effect of the credit card promotions of the partnering bank.*

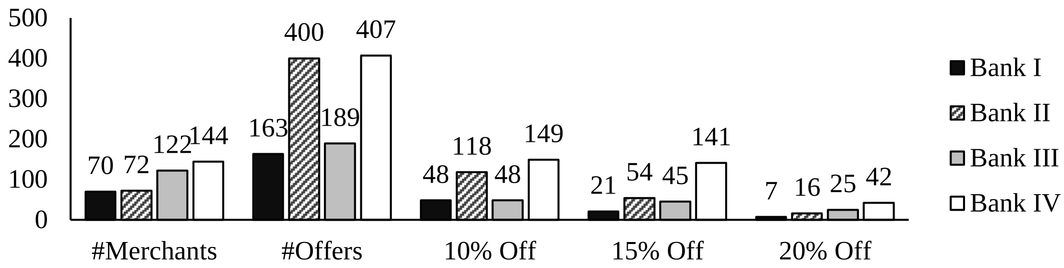
2.4. Research Context and Data

The research site for this work involves the credit card market of an Asian country, where the retail banking industry has dominant local banks and other highly active foreign banks. The credit card rewards business has been thriving and is highly competitive. We focus on the food and dining sector, which is one of the most popular and highly transparent business in the credit card economy and enables the acquisition of rich merchant data to support the study of our *indirect effect of credit card promotions hypothesis*. Our raw data are drawn from multiple sources, including: (1) card offer data from the websites of various banks; (2) merchant data from an online aggregator for the targeted business sector; and (3) anonymized transaction and customer data from a financial institution. We next explain how we constructed the dataset for empirical analysis.

2.4.1. Credit Card Offers from Banks

We acquired credit card offers from 4 leading banks, which we will refer to as 'Banks I, II, III and IV,' so their identities will be protected. Each bank typically displays such offers on its webpage, a major channel that incurs low cost, and creates notifications on promotions that are sent to its customers. The banks have invested lots of effort to develop their websites to broadcast these card-related promotions. At the same time, they have invested in offline advertisements at popular public locations, including municipal rail transit stations, bus stops, upscale shopping districts, and at the partnering merchants as well. In addition, the banks send EDMs and SMSs to their targeted customers based on their analytics. This way, the promotional information is shared broadly throughout the country, including with the customers of many banks. We acquired monthly observations for September to December 2015, including the names of the merchant partners and descriptions of the offers for the banks. Summary statistics for the card offers are shown in Figure 2.2.

Figure 2.2. Credit Card Offers of the 4 Banks



The figure shows that banks enrolled a number of merchant partners each: Bank I (70), Bank II (72), Bank III (122), and Bank IV (144). The banks arranged different deals for the various outlets that the merchants operate, leading to numerous card-based offers: I (163), II (400), III (189), and IV (407). This reveals that the business strategies for the credit card campaigns that the banks implemented were different from one another, to ensure that their card market activities maximally supported their value propositions. For example, Banks II and IV preferred to partner with popular local merchants with many chain stores, and Banks I and III were identified to have preferred certain merchant types. In addition, it appears that most merchants gave a 10% discount by default, while others offered 15% to 20% price reductions, and still other types of deals that they offered included one-paid-one-free, special instant rebates, and complementary goods.

2.4.2. Merchants in the Local Market

We collected merchant data from a popular online dining aggregator with a special focus on the business sector that we investigated in the local market. It provides an online platform for users to acquire merchant information as well as to contribute to the completeness of the data by voting for scores, writing reviews, and giving comments. The aggregator covers 100,000+ merchants, from which we acquired details on 20,766 of the most popular ones. Useful attributes in the dataset include merchant name, zipcode location, perceived quality score, number of votes, price levels, service type, and other information about the merchants' operations.

We further obtained review data on 9,811 merchants from the online users of the aggregator. As shown in Figure 2.3, the average review scores and votes were 69.58 and 11.73, respectively. The scores reported by the reviewers tended to be anchored, with a relatively high proportion of merchants scoring 0, 50, 70, 75 or 100. The votes also had a right-skewed distribution: some exceptional merchants were very popular, for example. While most merchants chose lower service prices (average USD 23.44), more upscale merchants that charged higher prices also were present in the marketplace. For the user base that is involved in this research setting, the data represent the characteristics of the merchants and consumer preferences very well.

Figure 2.3. Distribution of Merchant Quality Levels

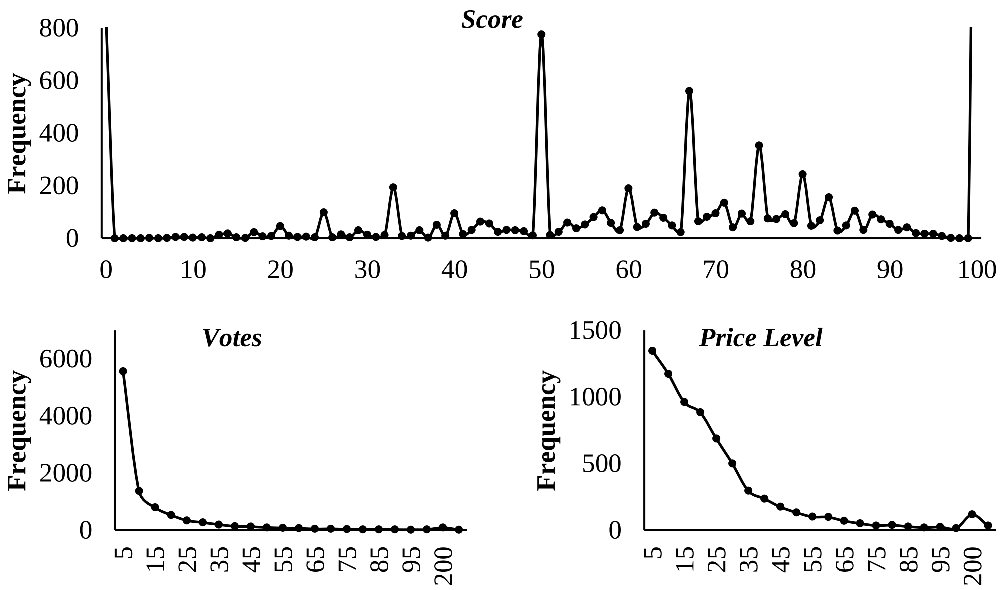
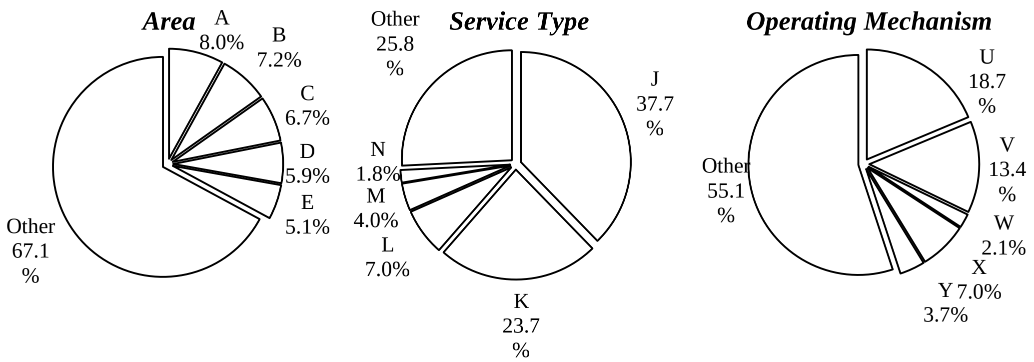


Figure 2.4 examines merchant segments by location, service type and operating mechanism. While the merchants operated different venues in the region,

more than 30% were located in 5 *areas* (A, B, C, D and E), covering around 40% of the most popular merchants, with more than 4 votes, and which scored higher than 75. Also, merchants in upscale shopping districts had the highest sales and quality levels. Two *service types* (J, K) dominated the market, and merchants used different *operating mechanisms* (U, V, W, X, Y and Other) to deliver their products and services. The statistics portray the market structure, based on which we built our analysis.

Figure 2.4. Merchant Market Structure



2.4.3. Transactions and Customer Data

To measure and report on consumer purchasing behavior in response to card promotions, we acquired anonymized transaction and customer data from a large financial institution. It is typical for banks that their data cover detailed information but only for anonymized customer transactions, as this is a result of their compliance efforts to ensure they protect all personally-identifying information of their customers. And yet, it is also their practice to bring together internal data on their customers' transactions from many business activities and different data sources within the boundaries of their firm. As a result, it was possible for us to acquire data that include descriptors related to the standing of customers with the bank, such as the duration of their accounts, the credit card types that they have used, and their spending levels each month. Demographic data, such as age, gender, income, education, marriage, nationality and number of children, which our field study work suggests, were also made available so we could leverage them to gain deeper insights into customer behavior for card marketing through big data analytics.

2.4.4. Fuzzy Matching to Build the Dataset

We use a *fuzzy matching algorithm* to connect the multiple datasets acquired in the public domain. This way, we are able to create insights about the business strategies for banks to use in their card-based partnerships.[2] Table 2.1 suggests that banks generally partnered with more popular merchants that created relatively good customer satisfaction. For price level however, Bank I tended to partner with the pricier merchants to attract affluent customers, while the other banks targeted lower-priced merchants.

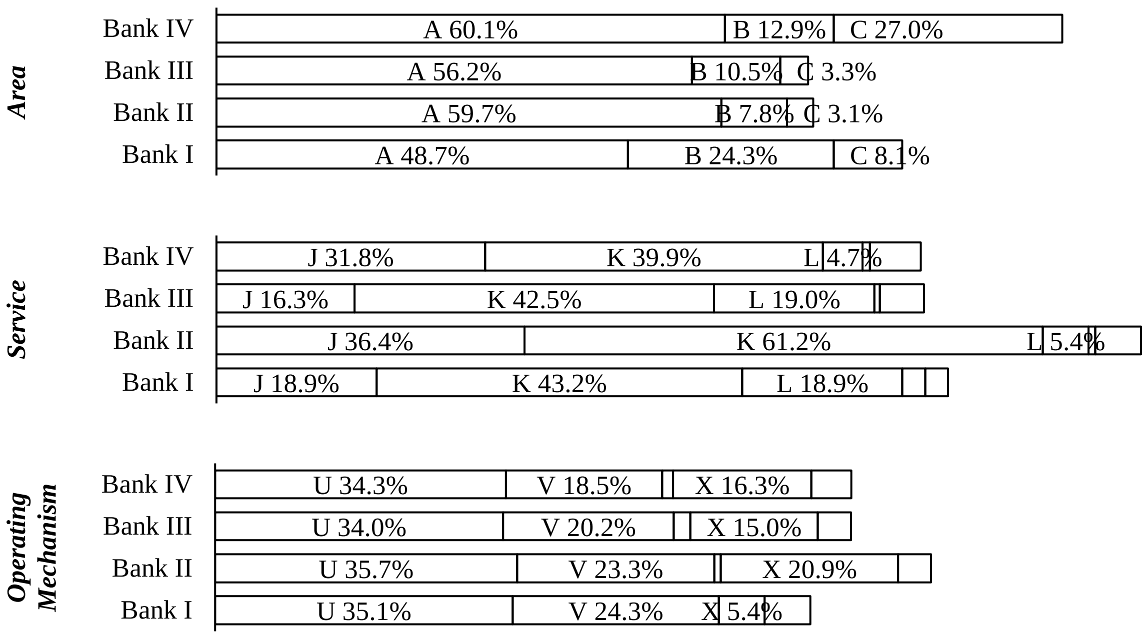
Table 2.1. Merchant Partner Averages for 4 Banks

	BANK I		BANK II		BANK III		BANK IV	
	Median	**Mean**	**Median**	**Mean**	**Median**	**Mean**	**Median**	**Mean**
Score	72.0	69.8	60.5	54.0	67.0	63.24	72.5	69.4
Votes	15.0	26.2	11.0	17.3	14.0	27.9	13.5	24.2
Price	50.0	61.6	23.5	28.0	30.0	36.5	31.0	39.3

Figure 2.5 shows that most banks focused on merchants in Area I, provided services J and K, and used operating mechanisms U, V and X. The consistency in merchant selection suggests that banks preferred to partner with more attractive merchants, but they seemed not to have tailored relevant strategies to support card-based partnerships that were specifically suited to their own customers' profiles and business goals. As such, there is room for improvement in credit card program design.

[2] We matched the merchants in the different data sources by their names, addresses, phone numbers, zipcodes, and descriptions. We applied a *token set approach* (Cohen 2011), which tokenizes strings that contain merchant information. The tokens of two strings are then split into two parts – an *intersection* and a *remainder*. These then are compared to compute the ratio of matching.

Figure 2.5. Partnering Merchant Characteristics



We next merged the external data with the proprietary data from the financial institution, and created a unique dataset that supports our econometric analysis. With the consolidated data, it is possible to observe customer purchasing behavior with merchants and the customers' responses to credit card promotions. The dataset used for analysis consists of 4,500+ merchants and about 400,000 customers during September to December 2015. Descriptive statistics are summarized in Table 2.2.

Table 2.2. Descriptive Statistics

VARIABLES	# OBS	MEAN	SE	MIN	MAX
Sales	15,860	12,852	41,304.52	0	1,296,929
Cust	15,860	149.74	880.87	0	34,244
Trans	15,860	189.93	1,466.07	0	58,636
MerchTenure	15,860	17.34	8.93	0	27.30
Score	7,677	48.24	14.90	0	70
Votes	7,677	14.90	18.12	0.70	194
Price	7,152	25.05	24.79	1.40	366.80
Store	8,946	1.85	4.83	0.70	90.30
Age	5,068,316	28.38	7.57	12.60	62.30
Income	5,068,316	143,268.98	2,331,664	84	62,222,219
Children	5,068,316	0.01	0.15	0	2.80
CustTenure	5,068,316	85.20	59.50	0	496.30

Notes. Merchant (*Sales*, *Cust*, *Trans*, *MerchTenure*) and customer data (*Age*, *Income*, *Children*, *CustTenure*) disguised with a multiplier, to protect the financial institution's identity.

2.5. Model and Methodology

We estimate two baseline models, a merchant-level and a customer-level model, to test our hypotheses related to card-based promotions on consumer behavior and merchant performance. We discuss our model development and estimation next.

2.5.1. The Merchant-Level Model

We use the *merchant-level* (*j*) *model* to test the Promotional Effects of Card Offers Hypothesis (H1) that assesses the direct promotional effects for how credit card promotions affect merchant sales. The model is specified as:

$$ln(Sales_{jt}) = \beta_0 + \beta_1\, PartnerBk_{jt} + \beta_2\, PartnerComp_{jt} + \beta_3\, PartnerBk_{jt} \times ParnerComp_{jt}$$
$$+ \beta_4\, ln(Score_j) + \beta_5\, ln(Votes_j) + \beta_6\, ln(Price_j) + \beta_7\, Stores_j + \beta_8\, MerchTenure_{jt}$$
$$+ \boldsymbol{\alpha}\, Service_j + \boldsymbol{\gamma}\, Mech_j + \boldsymbol{\sigma}\, Zip_j + \boldsymbol{\delta}\, Time_t + \varepsilon_{jt}$$

The dependent variable, $ln(Sales_{jt})$, is the natural log of the sales of merchant *j* at time *t*, which measures its performance each month. We also used the number of customers ($Cust_{jt}$) and transactions ($Trans_{jt}$) of merchant *j* at time *t* as alternate measures. To control for the up-and-down business performance in the selected sector over time, we used sales, customer traffic and merchant transaction volume as percentages of the overall market ($\%Sales_{jt}$, $\%Cust_{jt}$, $\%Trans_{jt}$) for robustness checks.

$PartnerBk_{jt}$ is binary, to indicate if merchant *j* had a card partnership with the bank at time *t*. To control for competing effects from other banks, merchant partnerships with rival banks ($PartnerComp_{jt}$) was included, along with an interaction term to gauge competitor credit card offer effectiveness. We also included variables with merchant information. First, we used data from the aggregator, such as the rating rated score ($ln(Score_j)$), number of votes ($ln(Votes_j)$), price level

($ln(Price_j)$), service types ($Service_j$) and operating mechanisms ($Mech_j$) as controls for merchant characteristics. Second, we counted the number of stores ($Stores_j$), and the tenure of the customers of the bank ($MerchTenure_{jt}$) to control for the scale and level of establishment of each merchant, as well as the likely uptake of their individual card offers. We further controlled for the variation in merchant locations at the 3-digit zip code-level (Zip_j), and for any time trends that were present in the brief period of our data ($Time_t$) too. ε_{jt} is an error term.

2.5.2. The Customer-Level Model

To evaluate individual differences, we further developed a *customer-level* (*i*) *model*, and used it to test three hypotheses: the Indirect Effects of Card Promotions Hypothesis (H2a), the Strength of the Indirect Effects Hypothesis (H2b), and the Moderating Effects of Competitive Offers Hypothesis (H3). As the monthly spending of a bank customer with a particular merchant is frequently 0, we also examined the probability of a consumer purchasing from a specific merchant using *logistic regression* (Hosmer et al. 2013):

$$Pr(Purchase_{ijt}) = \beta_0 + \beta_1\, PartnerBk_{jt} + \beta_2\, PartnerComp_{jt} + \beta_3\, PartnerBk_{jt} \times PartnerComp_{jt} + \beta_4\, ln(Score_j) + \beta_5\, ln(Votes_j) + \beta_6\, ln(Price_j) + \beta_7\, Stores_j + \beta_8\, CustTenure_{jt} + \boldsymbol{\alpha}\, Service_j + \boldsymbol{\gamma}\, Mech_j + \boldsymbol{\sigma}\, Zip_j + \boldsymbol{\phi}\, X_{it} + \boldsymbol{\delta}\, Time_t + \mu_{ijt}$$

$Purchase_{ijt}$ is binary to indicate whether customer *i* purchased from merchant *j* at time *t*. We used the number of transactions ($Trans_{ijt}$) to check for the robustness of our estimation work relative to how the dependent variable is specified. Besides merchant-level controls, we included X_{it}, a set of individual variables regarding demographics and banking status. We controlled for customer age (Age_{it}), gender ($Gender_i$), income ($Income_i$), marital status ($Marriage_i$), education level ($Educ_i$), nationality ($Nationality_i$) and number of children ($\#Children_i$). We also included how long the customer was with the bank ($CustTenure_i$), the types of credit cards held ($CardType_i$), and whether the customer has past purchase experience with the merchant ($Experience_i$) as a control for the customer's standing with the bank. As with the merchant model, we controlled for the 3-digit zip code-level variation in merchant locations (Zip_j), and any time trends ($Time_t$) that were present. We also included an error term μ_{ijt}.

2.5.3. Econometrics Methods

We use different response variables in our merchant-level models: the natural log of sales is continuous, and the number of customers and transactions both involve count data. Thus, we used *negative binomial regression* and *Poisson regression* to estimate the models with customer traffic and transaction volume as the dependent variables (Cameron and Trivedi 1998, Hilbe 2011). We also applied *quantile regression* to stratify the effects of card-based promotions for different percentage bands of merchant sales. And, since there are proportional dependent variables ($\%Sales_{jt}$, $\%Cust_{jt}$, $\%Trans_{jt}$) for robustness checks, we used a *beta regression;* it includes a beta distribution for the error term for efficient estimation (Cribari-Neto and Zeilis 2010). Similar methods are used for the customer-level estimation, except for the baseline model. It applies logit to deal with the binary dependent variable.

2.6. Results

We next present the results of the four hypotheses: the Promotional Effects of Card Offers Hypothesis (H1), the Indirect Effects of Card Promotions Hypothesis (H2a), the Strength of the Indirect Effects Hypothesis (H2b), and the Moderating Effects of Competitive Offers Hypothesis (H3), based on the estimation of the merchant-level and customer-level models. This way, we will be able to assess the efficacy of the *indirect effects of credit card promotions hypothesis* and theory proposed for the bank-merchant partnership setting. We estimated the merchant-level model using a matched merchant sample to test H1, and looked at the customer-level model in detail to assess H2a, H2b, and H3. Last, we present a series of additional results including the stratification analysis, segment analysis, and robustness checks.

2.6.1. Direct Sales and Volume Effects of Credit Card Promotions

We start from *ordinary least squares* (OLS) results for merchant sales, and the negative binomial models' results for the number of customers and transactions shown in Table 2.3.[3]

Table 2.3. Baseline Merchant-Level Model Results with Full Merchant Set

VARIABLES	*LN*(*SALES*)	*CUST*	*TRANS*
Intercept	-1.98 (1.312)	2.30*** (0.863)	1.90** (0.865)
PartnerBk	0.59*** (0.165)	1.02*** (0.100)	1.00*** (0.102)
PartnerComp	0.22** (0.094)	0.18*** (0.054)	0.20*** (0.054)
PartnerBk × *PartnerComp*	-0.55* (0.274)	-0.42** (0.182)	-0.35* (0.186)

Notes. 15,860 obs.; std. errs. in parens. OLS used for *ln*(*Sales*); neg. bin. used for *Cust* and *Trans*. Poisson model estimated for robustness. Control var. estimates suppressed to save space. Signif. * $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$. The coefficients for the output variables suggest positive effects of card-based partnerships on *Sales*, *Cust* and *Trans* from the bank ($\beta_{PartnerBk} = 0.59$ for *ln*(*Sales*); $\beta_{PartnerBk} = 1.02$ for *Cust*; $\beta_{PartnerBk} = 1.00$ for *Trans*; all with $p < 0.01$). The coefficients of *PartnerComp* were also positive ($\beta_{Comp} = 0.22$, $p < 0.05$ for *ln*(*Sales*); $\beta_{Comp} = 0.18$, $p < 0.01$ for *Cust;* $\beta_{Comp} = 0.20$, $p < 0.01$ for *Trans*), suggesting the impact of credit card promotions. But, negative coefficients for the interaction term ($\beta_{Partner \times Comp} = -0.55$, $p < 0.10$ for *ln*(*Sales*); $\beta_{Partner \times Comp} = -0.42$, $p < 0.05$ for *Cust*; $\beta_{Partner \times Comp} = -0.35$, $p < 0.1$ for *Trans*) mean that promotions from competitors partially offset the effect on merchant performance with customers from the bank.

Although the results showed positive and significant market responses to card-based promotions, there is likely to be *endogeneity* with merchant selection by the bank, as noted in our descriptive analysis in Table 2.4. The first two columns of

[3] For the full dataset estimation, we imputed values for missing data with averages for the numeric variables and a "missing value" indicator for the categorical variables. We also examined the models using two other samples: one without imputed values for missing data; and another where only missing values due to "No Review" from the aggregator were imputed. The results are consistent among the different samples, so we only show the results when the full set of observations were used to save space.

Table 2.4 suggest that a bank had a strong preference to partner with merchants that had higher sales, higher price levels, and more stores. Thus, the endogeneity with merchant partnerships may have led to over-estimation of the coefficients in the models.

Table 2.4. Results of Merchant Matching

VARIABLES	PARTNERS	NON-PARTNERS	MATCHED NON-PARTNERS
Sales	70,371 (-167,008)	16,979 (-41,476)	69,465 (-155,816)
Score	61.73 (20.71)	69.19 (22.47)	61.68 (21.00)
Votes	23.52 (22.62)	21.25 (26.09)	29.66 (32.28)
Price	50.61 (72.38)	34.95 (32.92)	50.93 (55.41)
Stores	10.50 (23.06)	2.37 (5.52)	9.59 (20.63)
MerchTenure	21.25 (5.06)	18.04 (8.06)	21.04 (5.45)
Obs.	64	2,212	64

Notes. Std err. in parens. 1:1 *matching ratio* applied. 1:2, 1:5, and 1:10 matches used for comparisons. Merchant (*Sales*, *MerchTenure*) disguised with a multiplier, to protect the identity of the financial institution from being disclosed.

Ensuring there was statistical comparability for the various attributes between the partner and non-partner merchants motivated our application of *propensity score matching* for sampling the merchants. We matched the merchant partners with non-partners based on their average monthly values of prior year sales, evaluated score, votes, price level from the aggregator, number of stores, and tenure with customers of the bank, together with service type, operating mechanism and location.[4] We see from the third column in Table 2.4 that the gaps for the different variables narrowed after the data matching was done.

So we re-estimated our baseline merchant-level model using the matched merchant sample and show the new results in Table 2.5. We found that card-based

[4] We used *propensity score matching* based on Prob(*Partner* Bk_j = 1) = *f*(*ln*($Sales_j$), *ln*($Score_j$), *ln*($Votes_j$), ln($Price_j$), $MerchTenure_j$, $Service_j$, $Mech_j$, Zip_j). We applied 1-to-1 matching since it gave the best results with the closest numbers for the attributes between the partner and non-partner group among the ratios we tried.

promotions attracted more consumers and increased transaction volume, consistent with the full merchant set findings. The number of visiting customers and transactions increased by 28.02% and 25.99%.[5] However, the results showed an insignificant impact of card promotions on merchant sales after adjusting for endogenity, which did not support the Promotional Effects of Card Offers Hypothesis (H1), as a result. Why? Possibly due to cannibalization of merchant revenues from existing customers, when there are extra price discounts. Thus, the overall impact of card-based programs on merchant sales depended on the tradeoff between the increase in the quantities and the reduction in the prices. Also, loyalty programs that discriminated against non-loyal customers may have led to their dissatisfaction, and they can be targeted by competitors (Shugan 2005). Bank customers who were infrequent buyers or strongly preferred non-promoted merchants may have spent less or used other banks with card promotions.

Table 2.5. Baseline Merchant-Level Model Results with Matched Merchant Sample

VARIABLES	*ln*(*Sales*)	*Cust*	*Trans*
Intercept	-6.65*** (1.724)	-5.80*** (1.139)	-5.83*** (1.159)
PartnerBk	-0.00 (0.187)	0.25** (0.119)	0.23* (0.122)
PartnerComp	0.46 (0.325)	0.08 (0.194)	0.06 (0.198)
PartnerBk × *PartnerComp*	-0.61 (0.387)	-0.20 (0.235)	-0.17 (0.239)

Notes. 508 obs.; std. err. in parens. OLS used for *ln*(*Sales*), neg. bin. used for *Cust* and *Trans*. Poisson model estimated for robustness. Control var. estimates suppressed. Signif. * = $p < 0.10$; ** = $p < 0.05$; *** = $p < 0.01$.

2.6.2. Indirect Effect of Credit Card Promotions

The results of the customer-level model estimation, as shown in Table 2.6, suggest that card-based promotions resulted in a 62.8% increase in the bank's cus-

[5] The negative binomial models the log of the expected count as a function of the independent variables (Statistical Consulting Group 2017). The estimated coefficients are interpreted as changes in the log expected counts with a unit change in a variable. So *Change*% = $(e^{\text{coef}} - 1) \times 100\% = (e^{0.247} - 1) \times 100\% = 28.02\%$.

tomers' likelihood to purchase. This is consistent with what we found for the merchant-level model's estimation. The negative binomial model with monthly transactions as the dependent variable showed similar results. Interestingly, the positive and significant coefficient of parallel promotions suggest that card promotions from competing banks increased the willingness to purchase of customers from the partnering bank, even if they did not enjoy the benefits of the offers. Specifically, when a merchant partnered with a rival bank and gave exclusive card promotions to customers from that bank, customers of our focal bank were surprisingly 11.1% more likely to transact with the merchant. This result supports the Indirect Effects of Card Promotions Hypothesis (H2a), and implies that there is an advertising exposure effect of credit card offers.

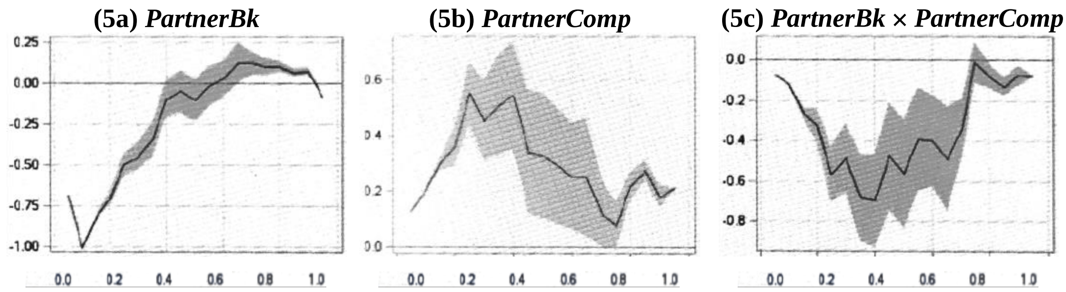
Table 2.6. Baseline Customer-Level Model Results

VARIABLES	*Purchase*	*Trans*
Intercept	-15.91 (16.314)	-25.77*** (1.191)
PartnerBk	0.63*** (0.032)	0.64*** (0.030)
PartnerComp	0.11*** (0.027)	0.08*** (0.028)
PartnerBk × *PartnerComp*	-0.27*** (0.038)	-0.21*** (0.038)
Notes. 5,068,316 obs.; std. errs. in parens. Logit used for *Purchase*; neg. bin. used for *Trans*. Poisson model estimated for robustness. Control var. estimates suppressed. Signif. * = $p < 0.10$; ** = $p < 0.05$; *** = $p < 0.01$.		

The coefficient of the interaction term is negative though, indicating that competitive credit promotions from rival banks offset the overall promotion effects of offers by the partnering bank. That means, if a merchant partner of the bank also partnered with other banks for their credit card promotions, customers may have been led to make other less favorable choices for the merchant based on those offers. Then the increased transaction volume is moderated and the bank is worse off compared with the case of exclusive partnership. The Moderating Effects of Competitive Offers Hypothesis (H3) is supported by the result.

To explore the effects of card promotions on merchant sales based on the distribution, we stratified the outcome variable in the merchant-level model using quantile regression. From this, we obtained the probability distributions of the dependent variable (*ln*(*Sales*)) for the different quantiles, ranging from 5% to 95% in 0.05-step intervals. (See Figure 2.6.)

Figure 2.6. Quantile Regression Results



Stratification analysis allowed us to build a more comprehensive understanding about the impact of card-based promotions based on the merchant sales distribution. Several interesting findings from the quantile regression results for the main variables are shown in Figure 2.6. First, as shown in the Figure 2.6a, the effects of card promotions were very negative in the lower quantiles and increased for the higher quantiles. The effects became positive between the 60th to 90th quantiles. This result implies that the lack of significance of the overall effect of credit card promotions on merchant sales, as we discussed in Section 6.1, was probably due to inappropriate partnerships with less popular merchants with very low sales.

Second, the sales associated with card offers from competing banks in Figure 2.6b shows that the advertising exposure effect varied across the different merchant partnerships. Although the offers by rival banks positively affected customer purchases and merchant sales in general, the effect is quite weak for merchants that had a more well-established business with higher sales. In contrast, merchants that were not as well-known and had lower sales were more likely to feel the good effects of the promotional exposure, and thus were able to benefit more from the increase in purchase transactions by non-targeted customers from other banks. This supports the Strength of the Indirect Effects Hypothesis (H2b).

In addition, we observed interesting relationships for the coefficients of Figure 2.6c. The offsetting effects of parallel offers from competitors were lower above the 70th quantile, while it was the largest between the 20th and 65th quantiles.

2.6.3. Robustness Checks

To check the robustness of our results, we used merchant sales as a share of total sales, the number of customers as a share of total customers, and the number of transactions as a share of total transactions in the business sector, based on the bank's data. Since the dependent variables are proportional, we used *beta regression* (Kieschnick and McCullough 2003, Ferrari and Cribari-Neto 2004).

Table 2.7. Robustness Estimation Results

VARIABLES	RELATIVE MARKET SHARES			CAMPAIGN CONTROL	
	%Sales	***%Cust***	***%Trans***	***Purchase***	***Trans***
Intercept	-7.86*** (0.269)	-7.04*** (0.292)	-7.11*** (0.297)	-15.95 (16.305)	-25.7*** (1.191)
PartnerBk	0.08 (0.051)	0.21*** (0.059)	0.22*** (0.059)	0.61*** (0.036)	0.62*** (0.036)
PartnerComp	0.18** (0.071)	0.16* (0.080)	0.10 (0.086)	0.10*** (0.027)	0.07*** (0.028)
PartnerBk × *PartnerComp*	-0.17* (0.088)	-0.15 (0.098)	-0.09 (0.102)	-0.26*** (0.038)	-0.21*** (0.038)
Campaign				0.06*** (0.011)	0.06*** (0.012)
PartnerBk × *Campaign*				0.01 (0.012)	0.01 (0.013)
Obs.	508			5,068,316	

Notes. Std. errs. in parens. Beta regression for *%Sales*, *%Cust* and *%Trans*; neg. bin. used for *Trans*; and logit used for *Purchase*. Poisson model estimated for robustness. Control var. estimates suppressed. Signif. * = $p < 0.10$; ** = $p < 0.05$; *** = $p < 0.01$.

We rescaled the dependent variables to shrink the intervals to (0.005, 0.995) with the equation $Y = (Y \times (N - 1) + 0.5) / N$, to avoid 0s and 1s. We estimated our model assuming the error term has a beta distribution. Table 2.7's results are consistent with our earlier analysis, which supported our conclusions.

All banks leverage advanced IT for e-marketing these days. For example, they target EDM and SMS campaigns to customers to notify them about large-scale card-based promotions. These improve consumer informedness, affecting the banks' key business outcomes of the credit card promotions. We next assess a variable, $Campaign_{it}$, to examine the robustness of our customer-level model. The variable refers to the total EDMs and SMSs customer *i* received in month *t*. The results in Table 2.7 show that the coefficients of the main effects were qualitatively similar after controlling for marketing activities. The marketing campaigns increased customers' likelihood to buy from a merchant by 5.70% and monthly transactions by 6.18%.

2.7. Conclusion

The proliferation of credit card products and card-based programs has created opportunities for banks to acquire new accounts and enhance their profitability. To strengthen their business strategies in a saturated card market, banks need to understand the market's response to their card-based promotions, and the extent to which they create benefits by making more compelling offers to the existing card customers, or which they yield indirect effects that benefit the customers of other banks who are not directly targeted by the promotions

2.7.1. Contributions

This research investigated how consumer behavior and merchant performance may be affected by card-based programs. Our results suggest that card-based partnerships between banks and retailers are likely to increase traffic and transactions from bank customers in direct and indirect ways. Based on our stratification and segmentation analysis, the effects of card-based promotions showed both expected and unexpected effects, while the impacts of non-price offers yielded somewhat higher benefits but only under some circumstances. Partnerships with more popular and upscale merchants led to more traffic and transactions. In addition, consumers who spent more were less likely to respond to promotions. And parallel offers from competitors were not likely to hurt the willingness to make purchases by bank customers.

Our research contributes to knowledge about card marketing between banks and their merchant partners. We assess the efficacy of the *indirect effects* of credit card promotions in mandatory participation third-party payer (MP3PP) markets. We did so by examining the impacts of credit card promotions in bank-merchant partnerships in a retail financial services setting in a large Asian credit card market. Our work offers useful policy analytics ideas, and supports the reconsideration of traditional business policy in the card products domain.

For example, banks and merchants should consider sales performance besides the customer, increasing transaction volumes, and the redemption rate or card rewards. These have been the major metrics used in assessing the effectiveness of a promotion in marketing literature. Although credit card promotions may lead to positive effects on customer traffic and transaction volume, their impact on merchant sales may only be substantial under certain circumstances. So getting the sizing and design of credit card promotions right is critical for a successful partnership between a bank and a merchant.

As shown in our analysis of different sizes of promotion discounts, price discounts sometimes may lead to undesirable revenue outcomes, even though generous discounts are likely to attract more consumers to purchase from the merchant. Thus, banks should properly determine the strength of their price discounts, instead of going too low or too high, and losing revenue in the process. Besides pure price discounts, some other types of promotions including instant cash rebates and one-paid-one-free shown to be very effective. We suggest banks to consider these alternative offer types when design their credit card programs, which may help to improve the overall outcome.

Moreover, the indirect effect and the effects of exclusive and parallel offers from retail banking competitors that we have identified, suggest that banks should take a strategic perspective on merchant selection and credit card promotion planning. Since the incremental consumer purchase due to card offers may spill over to non-targeted customers, the bank may wish to extend its marketing effort and broadcast its promotions beyond its customer base, to help the partnering merchant to increase revenue. Or they can limit their budget just the bank's own customers, so they can leverage rival banks' spillovers. Meanwhile, considering the effectiveness of exclusive and parallel promotions from competitors for different merchants, we suggest a bank in this kind of situation should avoid making tie-ups with other merchants, especially those with lower sales and that are less well-known, but that have collaborated with other banks. This way, it is possible for the bank to maximize its benefits and improve its credit card-based programs.

Last, this research has delivered results that pave the way for decision support in banks so they can more deeply probe credit card rewards and loyalty program behavior for their customers. They can do so by asking additional questions that build on the kind of analysis that has been demonstrated here. Our data analytics offer a proof-of-concept to demonstrate a modeling and estimation approach for the impact of card programs on merchant partners. By applying the data acquisition methods that were used to collect and consolidate data from multiple sources, a bank can monitor its credit card partner programs in the market and improve its business strategies through more informed decision-making.

2.7.2. Limitations

The pervasive lack of access to large-scale data has been a major barrier to conducting research on consumer behavior in retail financial services for some time. This research, leveraged big data analytics techniques to acquire data from the public domain and combine it with the proprietary data of a large financial institution. In spite of this, we recognize several limitations.

First, the merchant sales data that we have access to is constrained within customers of the partnering bank. That is, we cannot observe the real merchant sales, which should include purchase from all other customers. This prevented us from directly evaluating the impact of the card-based partnership on the overall performance of the merchant. However, we were able to assess the efficacy the indirect effects of card promotions using data we have access to. Based on our results, we were able to infer that the overall performance of the partnering merchant would be positive given the positive direct and indirect effects of credit card promotions.

Second, our work identified just one type of indirect effect, and so there is a natural path forward in this kind of research to explore other types of indirect effects that may also arise. For example, does a merchant gain additional business from consumers who are card holders at the partnering bank after the promotion ends? This may be a more important question for running promotions like this, because they are likely to yield high value, even though the promotion themselves are quite expensive. Unfortunately, techniques such as screen-scraping and database harvesting did not allow us to obtain historical data. Thus, we were unable to observe the start and end dates for the credit card offers, a form of both left censoring and right censoring in this empirical research. This prevented us from addressing the above question and conducting "within" comparisons for estimates of higher fidelity.

Third, the merchant data we obtained from the online dining aggregator was from a single point in time. As a result, we were unable to capture the changing quality attributes of the merchants that are represented in our model. Given the four-month time period for our study, the merchants' attributes would not have changed much though, so this lessened our concern about this issue. Instead, this would have been of greater concern for an analysis that involves 12 or 24 months of card promotion data and merchant discount offers. Also, the card promotions captured for this research were drawn from bank websites, which tend to cover longer-term partnerships with retailers. Ad hoc offers, which were not displayed on the webpages, were not included in our analysis. Our matching process may partially resolve this concern, though not completely. This is because the matched set of merchants appears to have equivalent standing as the merchant partners of the bank do in terms of customer traffic and sales, among other metrics, prior to the promotion period. So they should have a roughly similar likelihood of offering ad hoc card promotions to the customers of the bank.

Last, we focused on the food and dining sector that has been a prime target for credit card purchase discounting and rewards marketing. This gave us fuller access to rich merchant data. Clearly, this sector is just one among many others in which consumers use their credit cards to spend money on goods and services, and acquire the related benefits. However, the insights revealed in our research may shed light on consumer behavior in other business segments, even though each sector has different characteristics, use and spend levels, and brand-related implications. Also the approaches that were used in this work have the potential to offer new and useful insights on customer behavior for firms and organizations in many different sectors that explore the ways in which they can be applied.

Chapter 3. When the Bank Comes to You: Branch Network and Customer Omni-Channel Banking Behavior

3.1. Introduction

Bank branches, as the traditional banking channel, have played an important role in interactions between banks and customers. However, the rapid adoption of technology in the financial services industry and the changing demand of customers today have led to a dramatic rise in digital channels and a sharp decline in branch traffic. Industry surveys show that the percentage of Internet users that adopted online banking grew from 58% in 2010 to 61% in 2013 (Fox 2013), while the percentage of customers preferring branches for routine transactions continuously declined, from 34% in 2011 to 23% in 2014 (Novantas 2014).

In response to the 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. Although they have been reducing their physical presence to stem rising costs, the effects of this strategy are not yet well understood, as we learned in our field study discussions with managers at several leading banks. Banks should be aware of the factors that may contribute to adverse effects due to the inappropriate management of branch networks. For example, customers' channel preferences differ for transaction types (Ernst and Young 2014). While branches are handling fewer routine transactions, such as deposits, withdrawals and balance checks, most customers still prefer face-to-face interactions when seeking advice or purchasing complex products such as home mortgages and investment products. 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). Moreover, bank branches remain important for building and maintaining long-term customer relationships. Given the sophisticated omni-channel setting, for bank managers to make informed decisions when restructuring their branch network, it is critical that they gain a solid understanding of customers' multi-faceted behavior.

This is not only an important business problem for financial institutions, but also an interesting research question from an academic perspective. The prior literature has studied the adoption of online banking and its impact on existing channels (Campbell and Frei 2009; Xue et al. 2007; and Xue et al. 2011). However, few papers have systematically studied physical store network changes, due mainly to the unavailability of fine-grained individual-level data. We aim to complement current omni-channel research by addressing the effects of branch network changes on customers' omni-channel banking behavior, using an extremely large and novel dataset. We address the following research questions: What are the effects of branch openings and closures on customers' omni-channel usage? How do the effects change over time? And how do the effects vary across the customer segments?

We empirically examine the research questions using anonymized data from a large commercial bank in the U.S. The raw data contain banking transactions of around 600,000 of the bank's customers. The main attributes include the transaction date, amount, channel, and service type. We have access to complete information on the bank's branch network, including the name, zipcode, and opening and closure dates of each branch. We also acquire customer demographics and banking profiles. By combining the branch and customer data with the transaction data, we construct a unique panel dataset with sampling, which consists of about 0.85 million anonymized monthly observations of 25,727 customers over 33 months. We use this panel dataset to estimate a difference-in-differences model, which separately examines the effects of branch openings and closures on each service channel.

We find that branch openings create awareness effects and lead to a synergistic increase in transactions across channels, and that the positive impacts are strengthened with the first branch established in a local market. There is no reversal of this effect though. After a nearby branch closes, customers migrate from alternative channels to online banking due to the joint effects of negative perceptions and substitutions. However, this favorable migration pattern will be reversed when the last branch closes. Our analysis of the dynamic effects of branch network changes shows that the synergistic increase due to branch openings diminishes over time. Branch closures, on the other hand, lead to customers being substituted away by other channels in the short term but general declines in transactions through all channels eventually. We also observe heterogeneous effects of branch network changes, which are mediated by customers' interactions with physical branches and online banking. Generally, the physical presence of a bank contributes to closer customer relationships, which help customers to be less negatively affected by branch network changes, especially branch closures. Although online users can move to online banking swiftly after branch closures, it turns out that they are disloyal and tend to decrease transactions with their bank even through the online channel, probably due to increased service uncertainty and loss of trust.

Our paper contributes to the literature on consumer behavior in the omni-channel financial services. Prior research has focused on online banking and its impact on other channels (Campbell et al. 2009; Xue et al. 2007; and Xue et al.

2011). However, what banks should do with their physical facility networks, especially considering the cost-effective tradeoff among alternative service channels, remains unclear. We start from a different perspective and examine the effects of branch network changes. We also contribute to the empirical literature that investigates physical store entry in the retailing context (Forman et al. 2009; Pauwels et al. 2011) by providing further insights into branch closures. This is worth exploring as a main strategy deployed by companies in various industries today.

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. 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. The results are discussed in Section 5, and Section 6 concludes.

3.2. Related Literature

Our work is related to omni-channel studies that investigate consumer behavior between the online and offline channels in the financial services and retailing contexts.

3.2.1. Online Banking Adoption 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 the new channel. Hitt and Frei (2002) explore the demographical differences between online banking users and traditional channel users and find that customers in the former group are more profitable and have higher retention. Xue et al. (2007) incorporate channel usage and find that higher consumer efficiency in the online channel results in greater banking profitability. Xue et al. (2011) further investigate the drivers of online banking adoption and point to higher transaction demand, consumer efficiency and local penetration as the primary motivations. They also find that customers significantly increased their banking activities, acquired more products and conducted more transactions after adopting online banking.

Campbell and Frei (2009) focus on customer channel preferences after online banking adoption and identify substitution effects of online banking on self-service channels, including automated teller machines (ATMs) and voice response units (VRUs), and augmentation effects on human-service channels, including branches and call centers. 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, the improved financial controls after online banking adoption will improve customers' willingness to access all the available service channels and, consequently, increase the transaction volumes through other channels. Hernando and Nieto (2006) support this finding through their firm-level analysis and find that banks use online banking as a complement instead of a substitute for physical branches.

3.2.2. 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 the relatively better channel integration. Studies in this context focus on quantifying the pressure on physical stores with 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 et al. (2003) analyze data from Tower Records and conclude that the addition of the online channel did not significantly substitute sales away from offline channels, but contributed to amplifying the share of purchase overall. Ansari et al. (2008) also supports 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 substituted away but are more likely to have synergistic growth with the introduction of the online channel.

Several papers discuss the impact of physical store entries on customer channel preferences. They consistently find that the presence of a physical retail store increases store sales (Avery et al. 2012; Bell et al. 2015; and Kumar et al. 2014), due to the reduced transaction costs (e.g., transportation cost, time cost, uncertainty, etc.) and increased accessibility to the physical facilities. However, the prior literature does not offer clear results about the impact of physical store entry on the online channel. Some papers suggest that the large online disutility cost and decreased distance to offline stores will shape customers' choice to switch from the online channel to physical stores after store entries. For example, Forman et al. (2009) study sales of online and physical book stores and find that when a physical store opened locally, customers substituted away from online purchasing. Other studies empirically identify increased online purchases after physical store entries (Avery et al. 2012; Bell et al. 2015, Kumar et al. 2014). They suggest that higher exposure to retail stores reduces the customers' risks of purchasing online by providing them a physical place for product evaluation and after-sale trouble resolution. It also strengthens brand awareness and customer loyalty, which might transfer to other channels as a halo effect (Jacoby et al. 1984; Keller 1993; Kwon et al. 2009).

The prior research generally starts with the online channel and looks at its impact on customer channel choices and other behavior. But studies that focus on physical facility networks are not sufficient. Although some papers in the retailing context investigate the physical store entries, their results on how customers behave after the opening of a local store are unclear. Plus, none of the prior research analyzes the effects of store closures, which is also important because banks and retailers are closing their physical stores more aggressively than they are opening new ones. Moreover, consumer behavior in omni-channel financial services may be largely different from that in the retail setting, due to the more complex channel system and the lower level of channel integration for products and services. Thus, our work aims to complement the existing literature by exploring customers' omni-channel usage, as well as account opening and closing behavior after physical facility network changes occur.

3.3. Context, Data and Variables

The data we use consist of anonymized individual transactions from a large commercial bank in the U.S. 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 in the financial services industry during the last decade, the bank has been making great effort to accommodate changing customer preferences, including a migration from physical channels to digital channels for routine transactions. At the same time, it has been actively restructuring its existing channel distribution by gradually scaling down its retail banking branch network over the last several years, after a huge expansion due to a series of merger and acquisition activities.

The leading position of the bank in omni-channel financial services makes it a suitable research site for our study. And the fact that the bank opened (inclusive of the merged bank branches) and closed a considerable number of branches between October 2007 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 branch openings or closures (e.g., Forman et al. 2009; Pauwels et al. 2011).

3.3.1. Raw Data and Panel Dataset Construction

Our raw data contain anonymized customer transactions, which are summarized by month so that each observation describes a customer's monthly transaction volume and amount through each channel. We created 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. Using a propensity score matching method, we drew observations on a sample of customers by considering their experiences with nearby branch network changes. The matching process is described in detail in Section 4.1, and it yields an unbalanced panel dataset that we use for econometric modeling and estimations.

Table 3.1. Summary Statistics for Dependent, Main Effect and Control Variables

VARIABLES	DEFINITIONS	MEAN	STD. ERR.	MIN.	MAX.
DEPENDENT VARIABLES					
BRH	Number of transactions through branches.	1.45	2.82	0	162
OLN	Number of transactions through online banking.	37.95	82.81	0	9,772
ADC	Number of transactions through alternative delivery channels, which include ATM, VRU and CCT.	6.96	11.66	0	2,066
ATM	Number of transactions through ATMs.	3.67	5.69	0	151
VRU	Number of transactions through the VRU channel.	1.33	7.06	0	368
CCT	Number of transactions through call centers	0.52	4.07	0	2,045
BRHoutzip	Number of transactions through branches outside the customer's residential zipcode area.	0.47	1.36	0	49
#Channels	Number of channels used.	3.92	2.28	0	9
#NonBRHChls	Number of channels used, exclusive of BRH.	3.42	2.11	0	8
MAIN EFFECT VARIABLES					
BranchOpening	Count variables for each additional branch opened.	0.42	0.68	0	6
BranchClosure	Count variables for each additional branch closed.	0.18	0.42	0	3
FirstBranch	Number of occurrences of first branch entries, inclusive of abandonment and re-entry.	0.08	0.27	0	3
LastBranch	Number of occurrences of last branch exits, inclusive of abandonment and re-entry.	0.02	0.13	0	1
CONTROL VARIABLES					
Age	Age of the customer.	47.50	19.28	1	115
Tenure	Number of months that the customer has stayed with the bank.	209.80	126.72	40	1,353
#DepositAccts	Number of deposit accounts in use.	2.48	2.02	0	42
#LoanAccts	Number of loan accounts in use.	0.68	1.41	0	27
#InvestmentAccts	Number of investment accounts in use.	0.17	0.56	0	18
$DepositAccts	Balance of deposit accounts.	21,914	73,012	-281,823	7,420,750
$LoanAccts	Balance of loan accounts.	9,796.6	32,969	-170,942.4	1,699,737
$InvestmentAccts	Balance of investment accounts.	7,429	59,662	-27,052	4,191,776
LogTransaction$	Logarithm of the transaction amount.	7.18	3.22	0	16.91
#Customers	Number of the bank's customers within the customer's residential zipcode area.	2,030	1,447	1	5,211
LowIncome	Indicator of the customer's income level, 1 if the he or she is from the low-income group.	0.14	0.34	0	1

Note. The final panel dataset includes 848,991 observations. Customers whose branch transaction locations cannot be detected are excluded for the *BRHoutzip* observations, resulting in 463,254 observations for this channel.

The final panel data consist of 848,991observations for 25,727 customers of the bank. 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 differentiated locations by zipcodes, which represent the residential districts of customers. There are 1,798 distinct zipcodes overall, with the number of bank branches ranging from 0 to seven in each area. Our data cover 33 months from February 2011 to October 2013. In the next sub-sections, we will describe the dependent variables, main effect variables and control variables that we use in our analysis. Summary statistics of these variables are provided in Table 3.1.

3.3.2. Dependent Variables: Customer Omni-Channel Usages

We use the number of transactions to measure the channel usage by customers. 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 (PCC); point of sale by debit card (PDC); telephone bill payment (TBP); and voice response unit (VRU). We focus on five major channels—ATM, BRH, CCT, VRU and OLN—and eliminate others 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, online banking as a digital channel, and ATM, VRU and CCT as alternative delivery channels (ADC). Then, we examine the impact of branch network changes on customers' transactions via the three types of service delivery channels (BRH, OLN and ADC) and investigate each separate channel as well. We also examine two additional variables, *#Channels* and *#NonBRHChan-*

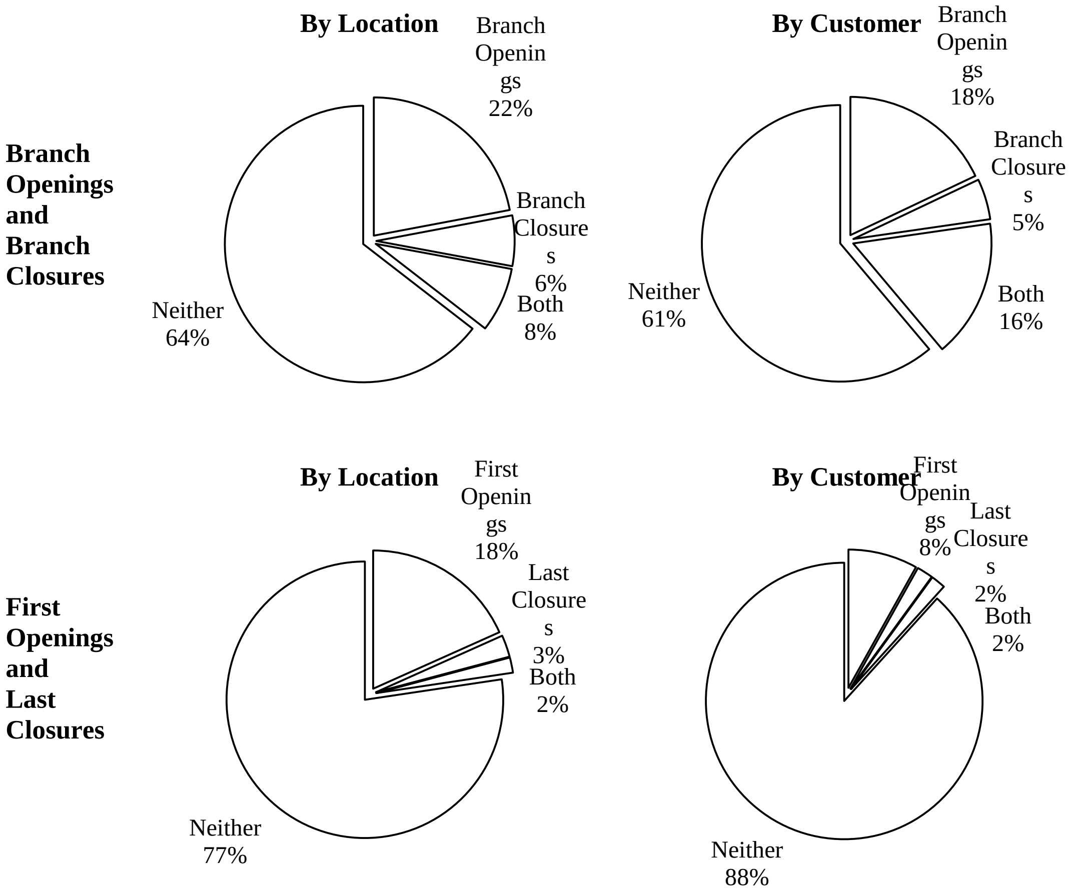
[6] For example, ACH is used only for debit and credit money, and PCC and PDC are used only for payments with retailers.

nels, which count the number of channels in use, inclusive and exclusive of BRH, respectively.

3.3.3. Bank Branch Network Changes: Branch Openings and Closures

We observe branch network changes, including branch openings and closures, through access to complete branch information of the bank. We create two main effect variables, *BranchOpening* and *BranchClosure*, which are count variables for each additional branch opened and closed. The branch networks across locations changed during the 33-month study period.

Figure 3.1. An Overview of Branch Network Changes by Zipcode Locations and Customers



As Figure 3.1 shows, 396 (22.0%) locations and 4,618 (18.0%) customers experienced branch openings, while 106 (5.9%) locations and 1,225 (4.8%) customers experienced branch closures. In addition, 136 (7.6%) locations and 4,157 (16.2%) customers experienced both, while 1160 (64.5%) locations and 15,727 (61.1%) customers experienced neither.

The entry of the first branch in a region usually implies a bank's ambition to achieve market expansion and brings strong branding effects to customers in that area. In contrast, closing the last branch in a region signals a bank's exit from the local market. The two situations are likely to result in extra influences on consumer behavior. To capture these effects, we use *FirstBranch* and *LastBranch*, which refer to the number of occurrences of first branch entries and last branch exits, inclusive of abandonment and re-entry. We observe that 361 (18.3%) locations and 2,526 (8.2%) customers experienced first branch openings, and 78 (2.6%) locations and 926 (1.9%) customers experienced last branch closures. We find that 32 (1.8%) locations and 439 (1.7%) customers experienced both, while 1,391 (77.4%) locations and 22,714 (88.3%) customers experienced neither.

3.3.4. Control Variables in Propensity Score Matching

We use a variety of control variables in a logit model in our matching process to account for customer heterogeneity in characteristics and transaction behavior. They 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 location-level information, including the bank's number of customers and the number of branches for each zip-code level, for more efficient propensity score predictions.

3.4. Model and Methodology

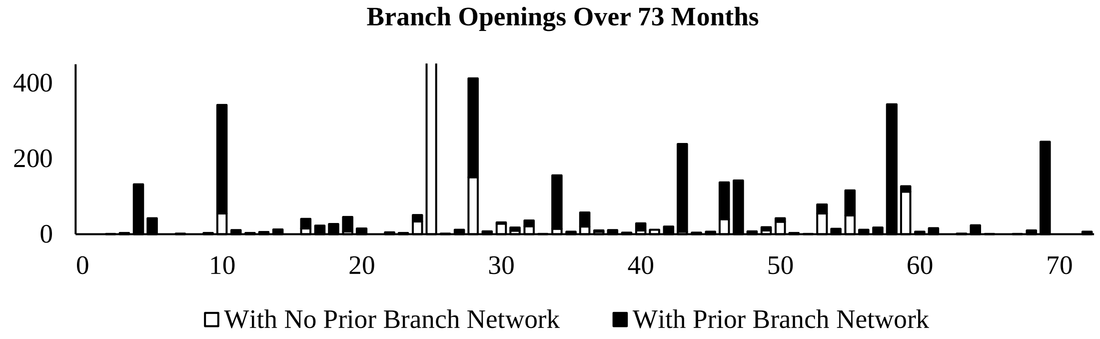
We use a difference-in-differences model to examine the causal effects of branch network changes on customer channel usage. Prior to estimation of the model, we apply propensity score matching to resolve the potential customer endogeneity with branch network changes. The matching process yields a control group, in which customers have not experienced either a branch opening or a closure throughout our study period but have comparable characteristics and transaction patterns with customers in the treatment group. We then use the matched dataset to estimate the difference-in-differences model. In the following subsections, we explain the matching process and model development.

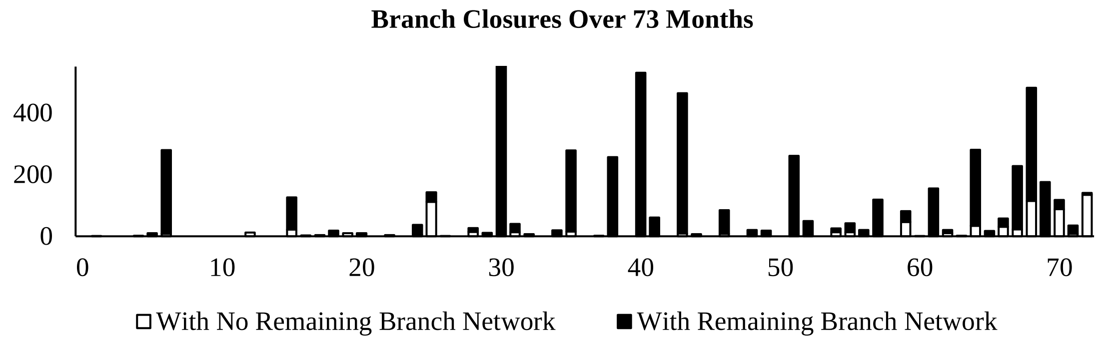
3.4.1. Propensity Score Matching to Resolve Customer Endogeneity with Branch Network Changes

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. As the overview of branch network changes in Figure 3.1 shows, the percentage of customers who experienced branch openings and closures is significantly larger than the proportion of zipcode locations. This suggests that the bank's strategy has led to more branch network changes in places with a higher customer population. Propensity score matching resolves the potential customer endogeneity with branch network changes in the first stage of our analysis.

We apply time-dependent propensity scores and match each treated customer with one control customer in each month. This allows us to accommodate the different timing for branch openings and closures, and to balance the distributions of the observed covariates in the treated group and the control group 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. In the matching process, we start with a treated group, a random sample of 10,000 customers with experiences of branch openings or closures. Among them, 4,618 customers are treated with branch openings, and 1,225 are treated with branch closures. There is an overlap of 4,157 customers who have experienced both.

Figure 3.2. Branch Network Changes over 73 Months





For simplicity, we discuss the detailed steps of matching for branch openings and apply a similar method for matching branch closures. Figure 3.2 shows the dynamic treatments over 33 months. Within each month, we divide the treated customers into two groups, based on whether there were prior established branch networks of the bank within their residential zipcode location.[7] 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 experienced no branch openings or

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

closures throughout the study period but have the same local branch networks of the bank as those in the treated group. We acquire the average transaction and account data within six months prior to the treatment for each customer. Together with customer characteristics and other information, we estimate a logit model at the individual level in Equation (1).

$$\Pr(\text{Dummy factors: } BranchOpening_{it}, BranchClosure_{it} = 1 \mid \cdot\,) = f\,(Age_i,\ LowIncome_i, Tenure_i, ln(TransactionAmount_{it}), \#Channels_{it}, BRH_{it}, ATM_{it}, VRU_{it}, CCT_{it}, OLN_{it}, \#DepositAccts_{it}, \#LoanAccts_{it}, \#InvestmentAccts_{it}, \#OtherAccts_{it}, \$DepositAccts_{it}, \$LoanAccts_{it}, \$InvestmentAccts_{it}, \$OtherAccts_{it}, \#Customers_i, Month_T) \quad (1)$$

An indicator of treatment is modeled as a function of the customer's age (Age_i), income level ($LowIncome_i$), tenure with the bank ($Tenure_i$) and average transaction behavior and account profile, 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 ($\#DepositAccts_{it}$, $\#LoanAccts_{it}$, $\#InvestmentAccts_{it}$, $\#OtherAccts_{it}$, $\$DepositAccts_{it}$, $\$LoanAccts_{it}$, $\$InvestmentAccts_{it}$, $\$OtherAccts_{it}$).

We use the number of customers in the local market ($\#Customers_i$) to control for the scale of the bank, as well as a month dummy ($Month_T$) to capture the time fixed effects. Based on the predicted propensity scores, we match one treated customer with one customer from the control group using the nearest neighbor (NN) algorithm and with no replacement, and we create a final sample that consists of 25,727 customers for further analysis. The results of the propensity score matching are summarized in Table 3.2, which shows that customers in the treated group and the control group are properly matched. This way, we need only include the main effect variables in our difference-in-differences model.

Table 3.2. Propensity Score Matching Results

	BRANCH OPENINGS					
	No Prior Branch Network			Prior Branch Network		
	Treated	**Control**	**Matched**	**Treated**	**Control**	**Matched**
Age	44.266	46.517	44.530	44.537	46.188	44.374
Tenure	175.019	192.234	178.279	179.812	184.190	178.535
LowIncome	0.130	0.143	0.129	0.129	0.152	0.140
#Channel	3.576	3.596	3.597	3.686	3.775	3.665
ATM	3.425	3.450	3.274	3.707	3.939	3.706
BRH	1.181	1.477	1.129	1.420	1.603	1.443
CCT	0.806	0.742	0.793	0.744	0.799	0.722
VRU	2.045	1.955	1.992	1.886	1.972	1.859
OLN	26.598	24.790	28.887	27.067	25.606	26.005
Ln(*Transaction$*)	6.781	6.989	6.764	7.103	7.329	7.133
#DepositAccts	2.046	2.097	2.073	2.241	2.275	2.236
#LoanAccts	0.570	0.527	0.573	0.512	0.464	0.505
#InvestmentAccts	0.128	0.122	0.128	0.146	0.125	0.145
#OtherAccts	0.751	0.746	0.749	0.755	0.791	0.764
$DepositAccts	13.400	17.260	12.607	17.525	18.266	18.229
$LoanAccts	8.515	11.180	8.518	8.390	9.101	8.856
$InvestmentAccts	4.557	4.587	4.401	7.171	5.339	6.634
$OtherAccts	0.292	0.367	0.401	0.232	0.323	0.268
#Customers	858.626	291.092	765.563	2336.720	939.937	1928.550
Observations	2,130	10,650	2,466	7,749	38,745	10,693
	BRANCH CLOSURES					
	No Remaining Branch Network			Remaining Branch Network		
	Treated	**Control**	**Matched**	**Treated**	**Control**	**Matched**
Age	48.760	48.487	49.397	46.763	49.308	47.670
Tenure	214.667	209.538	212.581	199.843	199.452	197.611
LowIncome	0.158	0.166	0.168	0.107	0.109	0.152
#Channel	3.929	3.849	3.881	3.884	3.773	3.828
ATM	3.937	3.983	3.877	3.558	3.592	3.611
BRH	1.588	1.566	1.592	1.646	1.670	1.694
CCT	0.603	0.573	0.586	0.604	0.598	0.625
VRU	1.510	1.807	1.299	1.349	1.408	1.520
OLN	32.000	29.677	30.553	31.364	27.530	28.759
Ln(*Transaction$*)	7.637	7.447	7.649	7.412	7.451	7.398
#DepositAccts	2.333	2.411	2.276	2.440	2.376	2.380
#LoanAccts	0.612	0.548	0.606	0.633	0.490	0.518
#InvestmentAccts	0.160	0.154	0.154	0.155	0.145	0.144
#OtherAccts	0.802	0.817	0.803	0.803	0.894	0.838
$DepositAccts	20.870	21.291	22.304	20.952	22.096	20.986
$LoanAccts	10.451	10.531	12.094	9.411	9.686	8.836
$InvestmentAccts	7.977	6.485	7.328	6.526	7.646	7.325
$OtherAccts	1.684	1.401	1.567	1.285	1.088	1.048
#Customers	1005.19	1061.010	1002.250	2378.820	1109.640	1515.610
Observations	885	4,425	959	4,963	24,815	17,301

Note. Customers treated with branch openings and closures are matched separately. For branch opening treatments, we look at whether there is a prior branch network around the customer. And for branch closure treatments, we look at whether there is a remaining branch network around the customer. One control customer with the similar branch network environment is matched with the treated customer.

3.4.2. 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 counter-factual framework from the treatment effects literature (Imbens et al. 2007) and adjust the standard specification for our case.

First, while most zipcode locations in our data have, at most, one occurrence of branch opening or closure, several places have experienced multiple treatments. Thus, we use two count variables—the number of branches opened and closed—in our base model, instead of binary variables to capture the repeated treatments. Second, there are likely to be unobserved differences among customers with different characteristics, which may lead to different transaction patterns. We incorporate individual fixed effects in our model to control for time-invariant individual heterogeneity. Third, since our outcome variables— the number of transactions by each channel—have discrete values, we use Poisson models. Formally, the difference-in-differences model is specified in Equation (2).

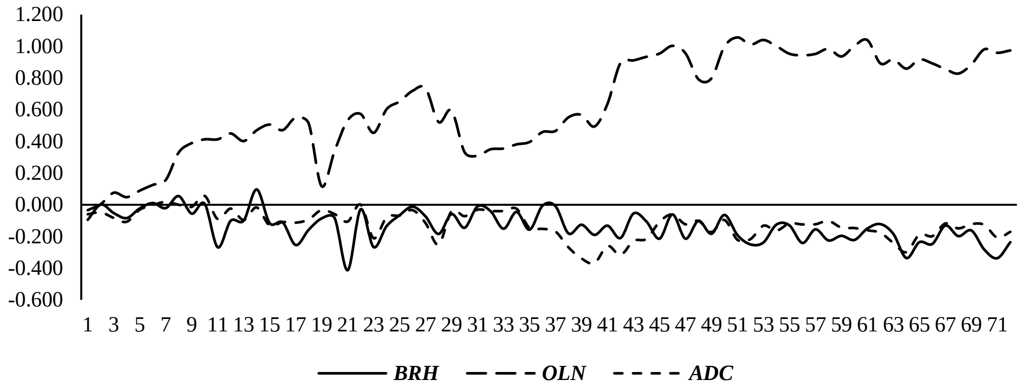
$$Y_{it} = C_i + \beta_1\, BranchOpening_{it} + \beta_2\, FirstBranch_{it} + \beta_3\, BranchClosure_{it} + \beta_4\, LastBranch_{it} + \delta_T\, Month_T + \varepsilon_{it} \quad (2)$$

Y_{it} is the outcome variable for the number of transactions through each channel by customer i in month t. We estimate the model using customer transactions through the three channel types, including branch (*BRH*), online (*OLN*) and alternative delivery channels (*ADC*), and then examine each alternative channel (*ATM*, *VRU* and *CCT*) separately. $BranchOpening_{it}$ and $BranchClosure_{it}$ are count variables for the numbers of branches that were opened and closed. We assume independent decision making for branch openings and branch closures by the bank, so we can put the two treatments in one model. $FirstBranch_{it}$ and $LastBranch_{it}$ capture the extra effects of the first branch opened and the last branch closed on the outcomes. C_i is individual fixed effects, $Month_T$ is time fixed effects, and ε_{it} is the error term.

3.5. Results

In this section, we discuss the estimation results of the difference-in-differences models. The main results that we have identified include the effects of branch openings and closures on customer omni-channel transactions, followed by the dynamic impacts over time. We end with a discussion of the customer segmentation analysis.

Figure 3.3. Time Fixed Effects for Branch, Online and Alternative Channels over 73 Months



We first estimate the difference-in-differences model using 73 months' data from October 2007 to October 2013. Coefficients of the time fixed effects for the three types of channels are plotted in Figure 3.3. Over time, there is a general increase in transactions through online banking and a decrease through branches and alternative channels, including ATMs, VRUs and CCTs. There also appear to be larger fluctuations before the 40th month, February 2011, probably due to the big financial crisis in the U.S. and its subsequent impacts. As a result of this, for our main analysis, we use the time frame from February 2011 to October 2013, during which the macroeconomic environment was more stable.

3.5.1. Contributions of Branch Openings to Customer Omni-channel Banking

The estimation results on the number of channels used in Table 3.3 show that customers generally used more channels for banking after branch openings ($\beta_{BranchOpening}$ = -0.008; p < 0.001). This is true when we consider only non-branch channels, as well ($\beta_{BranchClosure}$ = -0.006; p < 0.001). This first result suggests that branch openings helped to change customers to omni-channel users.

Table 3.3. Effects of Branch Openings on the Number of Channels Used

	#Channels		*#NonBRHChans*	
BranchOpening	0.018***	(0.003)	0.017***	(0.003)
FirstBranch	0.008	(0.007)	0.007	(0.007)
Log-Likelihood	-1266330		-1183898	
Observations	848,991		848,991	

Notes. Standard errors are in parentheses. Regressions include individual fixed effects and time fixed effects. *Significant at 10% level; **significant at 5% level; ***significant at 1% level.

Table 3.4. Effects of Branch Openings on Branch, Online and Alternative Channel Transactions

	BRH		*OLN*		*ADC*		*BRHoutzip*	
BranchOpening	0.039***	(0.006)	0.014***	(0.001)	0.017***	(0.003)	-0.082***	(0.013)
FirstBranch	-0.012	(0.014)	0.022***	(0.002)	0.014**	(0.006)	-0.037	(0.031)
Log-Likelihood	-912086.2		-7874176		-2062661		-239878.6	
Observations	848,991		848,991		848,991		463,254 [a]	

Notes. Standard errors are in parentheses. Regressions include individual fixed effects and time fixed effects. [a] Customers whose branch transaction location cannot be detected are excluded. *Significant at 10% level; **significant at 5% level; ***significant at 1% level.

Table 3.4 summarizes our main results for three types of service channels: branch, online and alternative. The results show that branch openings resulted in increasing customer transactions through all three channel types. For example, customers increased their branch transactions by 4.0%[8] after a nearby branch opened. The growth came primarily from increased transactions at branches with-

[8] Since we use a Poisson regression, which models the log of the expected count as a function of the independent variables, the coefficients can be interpreted as the change in the log of expected counts with a unit change in the independent variable. Then, *change%* = (e^{coef} – 1) * 100% = ($e^{0.039}$ – 1) * 100% = 4.0%.

in customers' residential zipcode areas because we see that outside branches suffered from a 7.9% decline in transaction volumes. This suggests that branch openings contributed to moving customers back to their residential locations for branch banking. Customer transactions through online banking and alternative channels also increased by 1.4% and 1.7%, respectively, and the effects were strengthened by the entry of the first branch in a market ($\beta_{FirstBranch}$ = -0.051, $p < 0.001$). Our findings are in line with prior multi-channel studies in the retailing industry, which suggest that the presence of new physical stores increase store sales and serve as complements to the online channel (Kumar et al. 2014). The overall improvements in transactions through different channels suggest that branch openings are likely to confer awareness, branding and credibility effects to the local market, which will increase customers' interactions with the bank through existing channels (Bell et al. 2015).

Table 3.5. Effects of Branch Openings on Separate Alternative Channels

	ATM	*VRU*	*CCT*
BranchOpening	0.018*** (0.003)	0.045*** (0.007)	0.026*** (0.009)
FirstBranch	0.032*** (0.008)	-0.034*** (0.014)	-0.061*** (0.019)
Log-Likelihood	-1,357,019	-496,519.4	-795,039.2
Observations	848,991	848,991	848,991
Notes. Standard errors are in parentheses. Regressions include individual fixed effects and time fixed effects. *Significant at 10% level; **significant at 5% level; ***significant at 1% level.			

As Table 3.5 shows, the estimations of each alternative channel consistently exhibit the positive effects of branch openings. When a new branch opened nearby, customers increased their transactions through the ATM, voice-response phone banking and the call center by 1.8%, 4.6% and 2.6%, respectively. This finding supports the above-mentioned significant increase in customer transactions through alternative channels. However, first branch entries show different impacts on separate alternative channels *t.* While transactions via ATM and voice-response phone banking increased, the call center experienced a surprising decrease of 3.4% in transaction volume.

The varying effects indicate the existence of substitutions among channels in omni-channel service delivery systems, which some prior studies also identify. For example, Pauwels and Neslin (2009) find that new physical stores cannibalized the purchase frequencies of customers from the alternate catalog channel in the retailing industry. The substitution effect was caused by reduced transaction costs and increased accessibility to the physical facilities. When a new branch was set up, customers nearby incurred lower transportation costs to visit branches. They also incurred lower costs on waiting time and service uncertainty with a higher density of the branch network. Thus, customers were likely to be drawn away from other channels.

However, the strengths of substitution may differ for channels due to their different capabilities. In our case, ATM and VRU are both automated channels that allow customers to do basic transactions such as deposit, withdraw, transfer and check their balance. Call centers provide human-assisted phone banking services such as account maintenance and complex product advisory. As the capabilities of call centers more closely resemble those of branches, there is likely to be a higher substitution effect between these two channels (Deleersnyder et al. 2002; Moriarty and Moran 1990). This explains the opposite net effects of first branch entries on ATM and VRU, compared with those on call centers.

3.5.2. Migrations from Alternative Channels to Online Banking as a Result of Branch Closures

The insignificant coefficients on the number of channels in Table 3.6 suggest that closing a branch, even if it is the last branch in the neighborhood, will not lead customers to abandon the other channels that they have used. Interestingly, a closure results in customers' migration from alternative channels to online banking. According to the results in Table 3.7, branch closures decreased customer transactions through alternative channels by 1.8% and increased their use of online banking slightly, by 0.3%. There was no significant impact on branch transactions though, including those through branches inside and outside the zip-code areas.

Table 3.6. Effects of Branch Closures on the Number of Channels Used

	#Channels		*#NonBRHChans*	
BranchClosure	-0.000	(0.004)	0.000	(0.004)
LastBranch	-0.002	(0.010)	0.003	(0.011)
Log-Likelihood	-1266330		-1183898	
Observations	848,991		848,991	

Notes. Standard errors are in parentheses. Regressions include individual fixed effects and time fixed effects. *Significant at 10% level; **significant at 5% level; ***significant at 1% level.

Table 3.7. Effects of Branch Closures on Branch, Online and Alternative Channel Transactions

	BRH		*OLN*		*ADC*		*BRHoutzip*	
BranchClosure	-0.002	(0.006)	0.003**	(0.001)	-0.018***	(0.003)	0.019	(0.015)
LastBranch	-0.062***	(0.017)	-0.092***	(0.002)	0.106***	(0.007)	0.347***	(0.034)
Log-Likelihood	-912,086.2		-7,874,176		-2,062,661		-239,878.6	
Observations	848,991		848,991		848,991		463,254 [a]	

Notes. Standard errors are in parentheses. Regressions include individual fixed effects and time fixed effects. [a] Customers whose branch transaction location cannot be detected are excluded. *Significant at 10% level; **significant at 5% level; ***significant at 1% level.

Table 3.8. Effects of Branch Closures on Separate Alternative Channels

	ATM		*VRU*		*CCT*	
BranchClosure	0.004	(0.004)	-0.061***	(0.007)	-0.102***	(0.011)
LastBranch	0.009	(0.011)	0.065***	(0.018)	0.919***	(0.021)
Log-Likelihood	-1,357,019		-496,519.4		-795,039.2	
Observations	848,991		848,991		848,991	

Notes. Standard errors are in parentheses. Regressions include individual fixed effects and time fixed effects. *Significant at 10% level; **significant at 5% level; ***significant at 1% level.

The results indicate no simple reversal of the influences of branch openings and confirm the importance of branches as the core of a bank in omni-channel financial services. When a nearby branch closed, customers tended to use other branches in their neighborhoods as replacements. But branch closures, according to our findings, are likely to result in negative perceptions and the loss of customer trust. While simple transactions can be migrated seamlessly to online banking due to the low transaction cost, it appears that customers reduced the use of alternative banking channels for certain services that were based in branches. This is supported by the results on specific alternative channels in Table 3.8, which show declines of 6.3% and 10.7% in customer transactions through VRU and call centers.

There were strong negative impacts on the online channel when the last local branch closed. As Table 3.7 shows, there was a 9.3% decrease in customers' online transactions subsequent to that closure. With the loss of convenient access to physical bank facilities, customers sought services provided by human beings through alternative channels and branches outside their residential locations, leading to a 9.2% and 41.5% increase in transactions through these two channel types. On further exploration of each alternative channel, we are ableto report in Table 3.8 that the increase in transactions came primarily from call centers, while the VRU and ATM channels experienced little or no impact. The findings also shed light on our earlier discussion about call centers being a human-service channel that assists the functionality of branches by providing similar services and that serves as the main substitute for the physical service channel of a bank.

Overall, the results reveal an interesting customer migration pattern from alternative channels to online banking after branch closures. However, when the last branch in a market closed, the direction of this migration may be reversed due to negative perceptions and loss of trust from customers, together with the necessity for human-assisted banking services. Since the alternative channels, especially human-serviced call centers, generally incur higher operating costs than the online channel, the reverse customer migration may not be favorable for banks. Hence, banks need to pay special attention to the last branch in a market in their strategic decisions about branch networks.

3.5.3. Dynamic Treatment Effects of Branch Openings and Closures

To explore the dynamic effects of branch openings and closures on consumer omni-channel banking behavior, we replace the main effect variables, $BranchOpening_{it}$, $BranchClosure_{it}$, $FirstBranch_{it}$ and $LastBranch_{it}$, in the main model with three dummy variables that indicate the short-, medium- and long-term post-treatments. We look at the effects within three months of the branch network changes as their short-term impacts; those between three months and one year as medium-term impacts; and those after one year as long-term impacts.

In addition, the bank has different business strategies for branch openings and branch closures due to regulation requirements and marketing needs. When the bank was opening a branch, it usually spent funds on marketing to notify its customers. However, when it was closing a branch, it was required by law to inform its customers three months in advance, and there was typically no associated marketing activity related to branch closures. Hence, we add another two variables, $ClosureAdv_{it}$ and $LastAdv_{it}$, which reflect the effects during the legal notification period before branch closures. Formally, we change our main model to Equation (3).

$$Y_{it} = C_i + \beta_1 \, OpeningShort_{it} + \beta_2 \, OpeningMedium_{it} + \beta_3 \, OpeningLong_{it} + \beta_4 \, FirstShort_{it} + \beta_5 \, FirstMedium_{it} + \beta_6 \, FirstLong_{it} + \beta_7 \, ClosureAdv_{it} + \beta_8 \, ClosureShort_{it} + \beta_9 \, ClosureMedium_{it} + \beta_{10} \, ClosureLong_{it} + \beta_{11} \, LastAdv_{it} + \beta_{12} \, LastShort_{it} + \beta_{13} \, LastMedium_{it} + \beta_{14} \, LastLong_{it} + \delta_T \, Month_T + \varepsilon_{it} \quad (3)$$

Estimation results are summarized in Table 3.9. We plot the coefficients of the short, medium, and long term in Figure 3.4. The results arrived at with our main model estimations are generally supported in the dynamic treatment effects analysis, and we observe additional behavioral patterns of customers over time.

Table 3.9. Dynamic Treatment Effects of Branch Openings and Closures

	BRH		***OLN***		***ADC***		***BRHoutzip***	
OpeningShort	0.055***	(0.013)	0.041***	(0.002)	0.040***	(0.006)	0.111***	(0.030)
OpeningMedium	0.050***	(0.009)	0.018***	(0.002)	0.028***	(0.004)	0.073***	(0.021)
OpeningLong	0.031***	(0.006)	0.010***	(0.001)	0.008***	(0.003)	-0.143***	(0.014)
FirstShort	0.055**	(0.025)	0.038***	(0.004)	0.038***	(0.011)	0.115**	(0.057)
FirstMedium	-0.013	(0.018)	0.019***	(0.003)	0.004	(0.007)	-0.160***	(0.041)
FirstLong	-0.046***	(0.017)	0.007***	(0.003)	0.005	(0.007)	-0.042	(0.036)
ClosureAdv	0.021**	(0.010)	0.031***	(0.002)	0.017***	(0.005)	0.015	(0.023)
ClosureShort	0.019**	(0.009)	0.034***	(0.002)	0.008*	(0.004)	0.037	(0.023)
ClosureMedium	-0.000	(0.008)	-0.010***	(0.001)	-0.020***	(0.003)	0.025	(0.018)
ClosureLong	-0.012	(0.008)	-0.017***	(0.002)	-0.022***	(0.004)	0.017	(0.018)
LastAdv	-0.015	(0.022)	-0.033***	(0.005)	-0.032***	(0.010)	0.083	(0.051)
LastShort	-0.082***	(0.025)	-0.070***	(0.005)	-0.054***	(0.011)	0.335***	(0.048)
LastMedium	-0.065***	(0.023)	-0.119***	(0.005)	0.263***	(0.009)	0.327***	(0.042)
LastLong	-0.011	(0.030)	-0.086***	(0.006)	0.110***	(0.013)	0.388***	(0.055)
Log-Likelihood	-912,061.1		-7,873,308		-2,062,253		-239,792.8	
Observations	848,991		848,991		848,991		463,254 [a]	

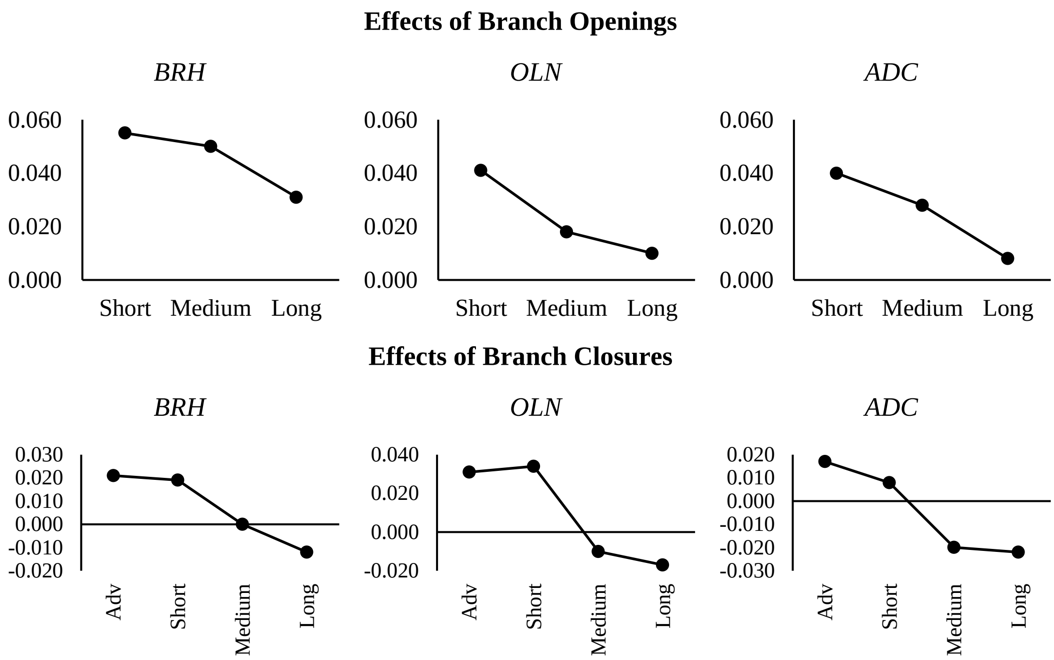
Notes. Standard errors are in parentheses. Regressions include individual fixed effects and time fixed effects. [a] Customers whose branch transaction location cannot be detected are excluded. *Significant at 10% level; **significant at 5% level; ***significant at 1% level.

	ATM		***VRU***		***CCT***		***#Channels***		***#NonBRHChans***	
OpeningShort	0.020***	(0.007)	-0.009	(0.018)	0.321***	(0.017)	0.036***	(0.007)	0.033***	(0.007)
OpeningMedium	0.031***	(0.005)	-0.011	(0.013)	0.100***	(0.014)	0.026***	(0.005)	0.024***	(0.005)
OpeningLong	0.013***	(0.004)	0.058***	(0.008)	-0.043***	(0.009)	0.012***	(0.003)	0.012***	(0.004)
FirstShort	0.051***	(0.014)	0.012	(0.027)	-0.096***	(0.033)	0.010	(0.013)	0.004	(0.014)
FirstMedium	0.019**	(0.010)	-0.027	(0.020)	-0.093***	(0.025)	0.004	(0.009)	0.003	(0.010)
FirstLong	0.032***	(0.009)	0.014	(0.018)	-0.150***	(0.024)	0.005	(0.008)	0.005	(0.009)
ClosureAdv	0.014**	(0.006)	-0.003	(0.011)	0.022	(0.016)	-0.002	(0.006)	-0.002	(0.006)
ClosureShort	0.007	(0.006)	-0.011	(0.011)	0.043***	(0.015)	0.002	(0.006)	0.001	(0.006)
ClosureMedium	0.016***	(0.005)	-0.080***	(0.009)	-0.163***	(0.012)	0.000	(0.005)	0.001	(0.005)
ClosureLong	0.009*	(0.005)	-0.090***	(0.009)	-0.137***	(0.013)	-0.009*	(0.005)	-0.008	(0.005)
LastAdv	0.002	(0.014)	-0.168***	(0.025)	0.024	(0.037)	-0.011	(0.014)	-0.013	(0.015)
LastShort	-0.031**	(0.015)	-0.116***	(0.026)	-0.056	(0.041)	-0.010	(0.015)	-0.007	(0.016)
LastMedium	0.034**	(0.014)	0.168***	(0.023)	1.551***	(0.024)	-0.012	(0.014)	-0.008	(0.015)
LastLong	0.163***	(0.019)	0.073**	(0.030)	0.250***	(0.039)	0.037**	(0.017)	0.041**	(0.018)
Log-Likelihood	-1,356,957		-496,391.8		-793,187.3		-1,266,312		-1,183,884	
Observations	848,991		848,991		848,991		848,991		848,991	

Notes. Standard errors are in parentheses. Regressions include individual fixed effects and time fixed effects. *Significant at 10% level; **significant at 5% level; ***significant at 1% level.

While branch openings led to synergistic growth in transactions across channels, the impacts peaked in the short term and diminished over time. In contrast, the negative effects of branch closures, which are probably due to negative perceptions and loss of trust from customers, became more significant in the long run. Although customers could switch to other channels after branch closures, the switching pattern seemed to be temporary and appeared only in the short term. In the long run, the negative effects dominated and led to declining customer traffic, even through the online channel. Furthermore, the substitution effects of human-service channels, such as call centers and branches outside the zipcode locations, also appeared primarily in the medium and long terms.

Figure 3.4. Dynamic Treatment Effects on the Branch, Online and Alternative Channels



The dynamic effects of adding a physical channel are determined by the channel's capabilities. There are likely to be short-term effects on consumer behavior if the added channel has conspicuous capabilities—such as convenience, reduced transaction costs and enhanced confidence—and long-term effects if the added channel has experiential capabilities, such as billboard effects, an enjoyable transaction experience and customer loyalty (Avery et al. 2012). In our case, the awareness that comes with branch openings is conspicuous and may bring a short-term boost in customer transactions. Likewise, the inconvenience and sudden increase in transaction costs due to branch closures are likely to create short-term migrations to other channels, especially online banking. But the negative impacts of branch closures tend to occur in the medium and long run because the loss of credibility takes time to manifest in customers' banking behavior. Substitutions from call centers after the first branch opened and to call centers after the last branch closed emerge in the medium and long terms, as well, and are attributed to customers' switching costs and learning processes.

3.5.4. Omni-Channel Banking Behavior among Customer Segments

We next segment our customer sample based on their dependencies on branches and online banking for transactions. Using monthly data for 2010, we define heavy branch users as customers whose average branch transactions are higher than the median, and light branch users as those whose average branch transactions are equal to or lower than the median. Heavy and light online users are defined in a similar way. Based on these definitions, we categorize the customer sample into four groups: heavy branch and heavy online users; heavy branch and light online users; light branch and heavy online users; and light branch and light online users. We then estimate the model for each customer group.

Table 3.10 summarizes the results for the four customer groups. Figure 3.5 compares the coefficients on the examined channels among the customer groups. We find significant differences in banking behavior among the four groups after branch network changes. Generally, the physical presence of a bank, especially the first branch in a local market, is helpful for maintaining close customer relationships. In particular, customers who were light branch and light online users and were more distant from the bank increased their transactions by 12.2%, 30.1% and 14.3% through branches, online banking, and alternative channels, respectively, when the first branch opened nearby. Also, customers who interacted with bank branches more frequently were less negatively affected by branch closures. While heavy branch users were more likely to switch to online banking for transactions, light branch users responded to branch closures by decreasing their transactions through either the online or alternative channels without increasing their transactions in others.

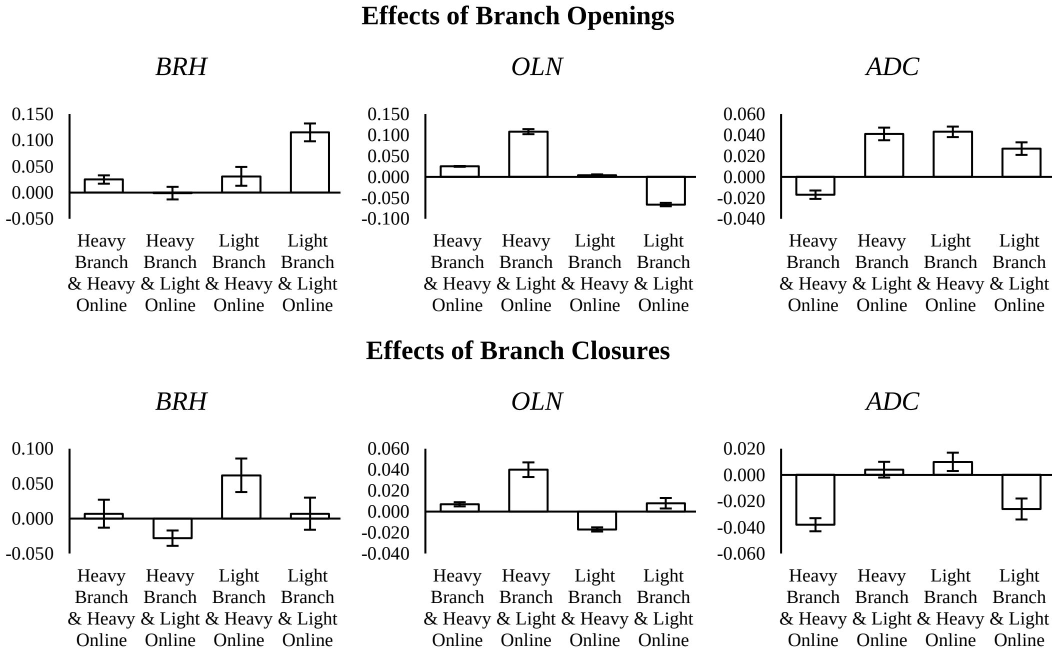
Table 3.10. Omni-Channel Banking Behavior among Customer Segments

	BRH		***OLN***		***ADC***	
HEAVY BRANCH AND HEAVY ONLINE USERS						
BranchOpening	0.025***	(0.008)	0.025***	(0.001)	-0.017***	(0.004)
FirstBranch	-0.036*	(0.009)	-0.042***	(0.003)	-0.019**	(0.009)
BranchClosure	0.007	(0.020)	0.007***	(0.002)	-0.038***	(0.005)
LastBranch	-0.082***	(0.024)	-0.103***	(0.005)	0.298***	(0.010)
Log-Likelihood	-391403.2		-3942618		-733015.2	
HEAVY BRANCH AND LIGHT ONLINE USERS						
BranchOpening	-0.001	(0.012)	0.108***	(0.006)	0.041***	(0.006)
FirstBranch	-0.104***	(0.028)	-0.054***	(0.014)	-0.022*	(0.012)
BranchClosure	-0.028**	(0.011)	0.040***	(0.007)	0.004	(0.006)
LastBranch	-0.014	(0.031)	-0.096***	(0.016)	-0.158***	(0.016)
Log-Likelihood	-265962.5		-668764.3		-510707.9	
LIGHT BRANCH AND HEAVY ONLINE USERS						
BranchOpening	0.031*	(0.018)	0.004**	(0.002)	0.043***	(0.005)
FirstBranch	0.161***	(0.038)	0.046***	(0.004)	0.039***	(0.011)
BranchClosure	0.062**	(0.024)	-0.017***	(0.002)	0.010	(0.007)
LastBranch	-0.134*	(0.073)	-0.062***	(0.006)	-0.090***	(0.020)
Log-Likelihood	-123799.1		-2252165		-407310.8	
LIGHT BRANCH AND LIGHT ONLINE USERS						
BranchOpening	0.115***	(0.017)	-0.066***	(0.004)	0.027***	(0.006)
FirstBranch	0.049	(0.041)	0.329***	(0.008)	0.107***	(0.014)
BranchClosure	0.007	(0.023)	0.008	(0.005)	-0.026***	(0.008)
LastBranch	-0.045	(0.062)	-0.155***	(0.016)	0.081***	(0.022)
Log-Likelihood	-129,021.4		-894,790.8		-399,359.9	

Notes. 255,156 observations for *heavy branch and heavy online users*; 177,903 observations for *heavy branch and light online users*; 169,696 observations for *light branch and heavy online users*; and 247,236 observations for *light branch and light online users*. Standard errors are in parentheses. Regressions include individual fixed effects and time fixed effects. *Significant at 10% level; **significant at 5% level; ***significant at 1% level.

More importantly, although online users could move to online banking seamlessly with low switching costs, they tended to be very disloyal. As the results reveal, light branch and heavy online users, who were likely to be more tech-savvy, decreased their online transactions by 1.7% after branch closures, with no migration behavior discovered. This negative effect was stronger when the last branch closed. The result suggests that online users incur lower switching and learning costs in cross-channel banking transactions. Even though they can use the online channel for banking after branch closures, they also can switch to other banks easily. Thus, the uncertainty of services and loss of trust that come with branch closures are very likely to lead to a higher churn rate among these customers.

Figure 3.5. Effects of Branch Network Changes for the Customer Segments



3.5.5. Robustness Checks

We conduct several robustness checks. First, we focus only on network changes in the conventional branches, as opposed to all types of branches, in the main analysis. Conventional branches represent the main way that banks present themselves and account for a major proportion of branch types. In the process of branch transformations, the bank tries to set up more compact branches and shut down traditional branches to reduce operating costs and meet customer demand. We conduct this test to eliminate the varying influences of different branch types.

Table 3.11 shows qualitatively consistent coefficients of *BranchOpening* and *BranchClosure* on different channels, suggesting that our main results remain significant. When a conventional branch opened, customers increased their transactions through online banking and alternative channels by 2.9% and 3.3%, respectively. When a conventional branch closed, customers decreased their transactions through alternative channels by 2.5%. More importantly, customers tended to decrease their online transactions by 0.7% after conventional branch closures, which is different from an increase after general branch closures. Obviously, the results reveal that openings of conventional branches have greater positive impacts on consumers' omni-channel behavior, while closures of such branches may lead customers to have substantial negative perceptions, compared with closures of other types of branches.

Table 3.11. Robustness Checks

	BRH		***OLN***		***ADC***	
CONVENTIONAL BRANCHES						
BranchOpening	0.057***	(0.007)	0.029***	(0.001)	0.032***	(0.003)
FirstBranch	-0.003	(0.016)	0.040***	(0.002)	0.015**	(0.007)
BranchClosure	-0.004	(0.007)	-0.007***	(0.001)	-0.025***	(0.003)
LastBranch	-0.089***	(0.019)	-0.054***	(0.004)	0.127***	(0.008)
Log-Likelihood	-912067.2		-7873917		-2062603	
SEPARATE MODELS						
BranchOpening	0.078***	(0.010)	0.042***	(0.002)	0.012***	(0.004)
FirstBranch	-0.041**	(0.019)	-0.033***	(0.003)	0.045***	(0.008)
Log-Likelihood	-309694.2		-2708755		-703187	
BranchClosure	0.040**	(0.017)	0.050***	(0.003)	-0.018**	(0.008)
LastBranch	-0.110***	(0.031)	-0.209***	(0.006)	0.156***	(0.014)
Log-Likelihood	-76,245.6		-661,476.7		-166,148	

Notes. 848,991 observations for the conventional branches robustness test; 295,647 observations for the branch openings robustness test in separate models; and 68,178 observations for the branch closures robustness test in separate models. Standard errors are in parentheses. Regressions include individual fixed effects and time fixed effects. *Significant at 10% level; **significant at 5% level; ***significant at 1% level.

For the second robustness check, we estimate two separate models to eliminate the potential relationship in decisions of branch openings and branch closures of the bank. The results shown in the second panel of Table 3.11 remain qualitatively consistent with our earlier findings, affirming the specification of our difference-in-differences model and strengthening our confidence in the conclusions that can be drawn about customer omni-channel banking behavior in the context of branch network changes.

3.6. Conclusion

Disruptive technology in the financial services industry led us to rethink the distribution of physical bank branches in this paper. We investigate branch network changes—a major strategy that leading banks are actively deploying in the retail banking industry today to accommodate changing customer preferences—and their impact on customers' omni-channel banking behavior.

Our empirical analysis suggests that branch openings create awareness and cross-channel synergies. Branch closures facilitate customer migrations from alternative channels to online banking, while this pattern is likely to be reversed when the last branch closes. By looking at the dynamic effects of branch network changes, we identify the diminishing positive effects that accompany branch openings and long-term declines in customer transactions after branch closures. We also observe varying effects among customer segments, based on their interactions with physical branches and online banking. As revealed in our results, heavy branch users who frequently interact with the bank are less negatively affected by branch network changes, especially branch closures. Online users who have lower learning and switching costs turn out to be very disloyal and tend to decrease transactions even through the online channel after branch closures.

Our work emphasizes the importance of investigating physical facility network changes and their impact on consumer behavior, especially under the complex omni-channel settings with technology disruptions in the current financial services industry. 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 that focuses on the effects of bank branch network change. We provide some first results on consumer behavior in response to branch network changes in the context of financial services. Some papers in retailing have investigated the impact of physical store entries in local markets, but few of them offered empirical evidence to quantify the effects of store closures. Our work also complements this stream of research by providing insights into consumer behavior from the perspective of physical store closures.

We highlight strategic implications for branch network restructuring in omni-channel financial services. First, our results offer new insights into customers' migration pattern from alternative channels to online banking after branch closures. Such insights allow banks to have clearer foresight about consumer behavior and enhance their confidence in making strategies to shrink their branch networks. Second, by looking into different customer segments, locations and time frames, we point to important targeted marketing strategies in branch network restructuring. Banks can utilize knowledge of the relative magnitudes of the estimated parameters to optimize their branch network distribution. Third, our analysis of the long-term effects on tech-savvy customers suggests potential risks of customer churn in response to branch closures. Our research will help senior managers in commercial banks to develop a more realistic view of consumer behavior in omni-channel financial services and to deploy branch network transformations in a more effective way. Furthermore, our research has suggestive implications for firms with omni-channel service delivery systems in other industries. However, the differences in products and services offered by various firms must be considered for external application. 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 services.

The difficulty of generalizing our results in multiple contexts is one of the main limitations of this paper. Our work focuses on the financial services industry to achieve higher statistical power in this specific context, so the insights from this work will be especially useful to financial institutions. The findings will be harder to apply in other industries, restricting us from building more-generalized knowledge of customer omni-channel behavior. Another limitation is that our data come from a single U.S. bank; more generalizable insights into consumer behavior will require data from more banks with different demographics and banking profiles. Since our data consist of a large sample of customers from a major commercial bank in U.S., we are confident that the distribution of our sample customer profiles is in line with that of other financial institutions. The conclusions we draw will shed light on branch network distributions more broadly. Furthermore, the lack of data from other banks prevents us from controlling for competing effects in the local market. Our reasonable assumption of individual fixed-effects based on a three-year study, during which the financial services industry in the U.S. experienced steady growth nationwide, at least partially resolves our concerns about the effects from rival banks on our results. As a result, future research with data from broader sites or other behavioral or survey approaches may provide further insights into customers' omni-channel banking behavior in the context of physical branch network changes.

Chapter 4. Bitcoin’s Global Penetration and the Spatiotemporal Effects of Security Events

4.1. Introduction

Bitcoin has been attracting growing public interest since its invention in the late 2000s (Nakamura 2009), and represents a widely-recognized breakthrough in Computer Science (Andreessen 2014). The price of bitcoin (as a foreign exchange currency, BTC) had a sharp rise from below USD 14 to above USD 979 in 2013, and was highly volatile in the range of USD 214 and USD 985 in 2015 and 2016 (CoinDesk 2015, 2016; Bovaird 2017) The volume of bitcoin exchange trading also surged to as high as USD 240 million in one day in late 2015 (Blockchain 2017a). The fluctuation in bitcoin prices has resulted in the widespread perception that this virtual currency is primarily a vehicle for speculation, but also an important lever for new innovation (Vigna and Casey 2015).

Meanwhile, bitcoin has been under strict regulatory prohibition in many countries during its early years, which has held it back from rapidly penetrating into different countries around the world. However, the main features and advantages of this cryptocurrency and its underlying blockchain technology, which include decentralization verification, anonymity, transparency, low price and high speed, have convinced many academic researchers and industry pioneers of the huge potential for bitcoin to fundamentally change how the financial industry operates in the near future (CoinDesk 2016).

There has been evidence to support this point of view. From 400 in 2012, the number of blockchain wallet users has increased exponentially to nearly 13 million in 2017 (BlockchainInfo 2017b), with the confirmed number of transactions rising to more than 200,000 per day (Jackson 2016). This implies that more and more people have adopted the emerging digital currency over time, and are using it for different transaction purposes. Meanwhile, a number of online and offline retailers, such as Overstock and Newegg began to accept bitcoin as a payment option in 2014 (Metz 2014), but other vendors, such as TigerDirect that initially announced its adoption, have recently shut down (Kirsch 2015). Also, more than USD 1.1 billion of venture capital was invested in bitcoin and blockchain start-ups through the first quarter of 2016 (Hileman 2016). With many firms becoming involved with bitcoin and blockchain-related business models while they are still in an early stage of diffusion, much is at stake for industry to understand which markets and consumer segments will prove to be the most fertile for the growth and acceptance of this cryptocurrency. Framing an answer to this question will also help governments and regulators to understand the economic opportunities and potential risks presented by bitcoin.

Numerous industry reports have shared updates on relevant topics, trends and data related to venture capital investments and bitcoin ATMs (e.g., Hileman 2014b). According to this source, bitcoin start-ups have followed a relatively decentralized footprint around the world. While the majority of these companies are based in North America, 30% of them have initiated their businesses in Asia and 10% have done so in Europe. At the country level, the United States is home to 53% of these venture-capitalized firms, while China accounts for 10%, followed by the U.K., Canada, Australia, South Korea and Singapore. Within each continent, the penetration of the cryptocurrency also has varied across the regions. The U.K., Finland, Netherlands, Sweden, Denmark, and Estonia are the most penetrated countries for bitcoin in Europe (Scott 2016). Earlier, European countries had the highest number of bitcoin ATMs installed per capita (Sharkey 2014b). And among the 35 states that have bitcoin ATMs in U.S., California, New York, Georgia, Illinois, Florida and Texas, have experienced the highest level of bitcoin penetration (Sharkey 2014a, Coin ATM Radar 2017a).

The acceptance of bitcoin has been influenced by the characteristics of the particular markets into which it has entered. The likely drivers include the income levels of the population, their familiarity with digital banking technologies, the nature of government regulation policies (Courtneidge and Clarence-Smith 2017, Global Legal Research Directorate Staff 2014), and the state of the economy (Polisik et al. 2015). Moreover, technology diffusion in different regions should be looked at as a network phenomena, in which each region is connected to others based on their geographical proximity, socioeconomic interactions, and cultural and historical relationships (Kauffman and Techatassanasoontorn 2009, Weber and Kauffman 2011). As a result, spatial connections need to be considered as important influential factors in the global penetration of an emerging technology, and should also apply in bitcoin's case.

In addition, there are a number of security issues that have affected the development of bitcoin as a new form of digital money. Thefts from bitcoin exchanges and their consequent shutdowns have occurred with alarming frequency (Kaminska 2016, Parker 2015).

Mt.Gox, one of the biggest bitcoin exchanges, filed for bankruptcy in February 2014 (Perez 2015). This led to a continuous fall in bitcoin prices from more than USD 1,000 to the USD 300-400 range by April 2014 (Greenberg 2014, Bolici and Della Rosa 2016). Mt.Gox, which handled 70% of all transactions in the digital currency, announced that around 850,000 bitcoins with a value over USD 480 million at the time were stolen due to a bug in its software in April 2013 (Dougherty and Huang 2014). This became the biggest bitcoin exchange theft at that time, and still is recognized as the most costly failure. So far, about a third of bitcoin trading platforms have been hacked, and nearly half of them closed during the nine years since the invention of bitcoin (Chavez-Dreyfuss 2016). Such hacks and security issues, and the perceptions that they have caused among observers, financial technology analysts, bankers, and regulators, pose rising risks to bitcoin holders. They also have created barriers for global penetration of the cryptocurrency.

While the market for bitcoin innovations and blockchain technology has been expanding, academic research has lacked sufficient scope, depth of inquiry, and understanding of the global marketplace for their use by financial technology and other sectors' firms. Various authors have investigated relevant current and future issues in the bitcoin context, but have started from a technical (Peck 2015, Underwood 2015, Zohar 2015), rather than a managerial, strategic or economic perspective. There also have been few quantitative studies that have explored the global penetration of bitcoin, although there are some notable and interesting exceptions (Polasik et al. 2015, Krause 2016, Schultz 2016). Moreover, the security issues associated with bitcoin, including theft and exchange shutdowns, and their influences on adoption have not been addressed in the technology adoption and diffusion literature. This research aims to investigate the spatiotemporal penetration of bitcoin in different countries around the world, and how the occurrence of security issues have profoundly influenced the overall diffusion process.

We drew upon multiple sources of data in the global public domain to build the dataset for this research. First, we obtained bitcoin ATM data and the Mt.Gox Exchange-related trading data as the primary sources. The geospatial and geotemporal contents of both data sources enable measures for adoption and trade transaction levels of bitcoin in various countries, and this supports a global-level spatiotemporal analysis. We also collected distances between countries, including physical distances, social and economic distances, and cultural and historical distances. With these, we created a *spatial weight matrix,* a common approach in spatial econometrics (Wooldridge 2002). We also combined these with other economic, regulatory and technology-related data as explanatory variables. The public domains that are represented include Coin ATM Radar (coinatmradar.com), the International Monetary Fund (IMF, imf.org), and the World Bank (worldbank.org), among others. Last, we acquired historical information related to bitcoin theft and exchange shutdown issues, based on news reported in the business press. These data enable us to examine the influence of these issues on the cross-country penetration of bitcoin around the world.

We apply spatial econometrics and spatial panel data models to address our key questions in this research inquiry. Since they use a spatial weight matrix, geospatial models can capture the statistical dependencies associated with different geographical units at different points in time (Anselin and Getz 1992, Anselin 2003). Such methods allow for mutual influences between pairs of geographical units, as well as different measures of spatial dependence (Elhorst 2014), which are appropriate in this research for cross-country analysis. The results presented in this chapter show evidence for spatial patterns in the penetration of bitcoin, as well as evidence that there are information security issues, including theft, exchange shutdowns, and other related events, that may have had impacts on the speed and breadth of bitcoin's global penetration.

This research contributes to the growing knowledge base of bitcoin and blockchain studies. Research in this context has focused on price fluctuations and the nature of bitcoin as an asset in the trading of the digital currency, and as a trading vehicle for a money-equivalent in advanced economies and the developing world (Glaser et al. 2014, Polisik et al. 2015). Others have explored related issues in the mechanisms of the underlying blockchain technology (Decker and Wattenhofer 2014, Luu et al. 2016). However, little has been done regarding the actual penetration of bitcoin, especially in spatial and temporal terms. This research also will support new thinking about business practices at the early stage of development of a cryptocurrency. We also provide useful insights for firms and start-ups to understand the global penetration patterns of bitcoin, and to identify the opportunities and risks in the process.

The chapter is structured as follows. Section 2 reviews the related literature and discusses the relevant theoretical background. Section 3 describes the data used in this study, and its collection from different sources. Section 4 introduces a panel model which is analyzed using spatial econometrics. The results are results are presented in Section 5, and discussed and interpreted in Section 6. Section 7 concludes.

4.2. Theoretical Background

The diffusion of innovation, including technical, product and process developments, has been studied in multiple disciplines and from different theoretical perspectives (Fichman 2004). This research relies on social contagion theory, and considers the global penetration of bitcoin arising as a result of the interactions among countries, as well as the influences of their characteristics. In this section, we discuss the theoretical background related to technology diffusion in a way that reflects its relevance for bitcoin. We also will discuss the useful theoretical and methodological ideas from the study of firm-level security breaches, event history methods, and how firm-level disclosures are investigated by researcher who utilize perspectives from Financial Accounting.

4.2.1. Social Contagion in Technology Diffusion

People, organizations or groups within a social network are connected to others through various interactions and communications, resulting in the possibility of social contagion in the activities of the participants inside the network (Granovetter 1978). Research in multiple areas, including economics, sociology and marketing, has been interested in social contagion in different contexts (Bikhchandani et al. 1992, Valente 1995, Albuquerque et al. 2007). The mechanisms underlying social contagion involve direct communication and information sharing between adopters and non-adopters, or an observation and learning process in which individuals or firms determine whether to follow the adoption decisions of others in their network (Strang and Soule 1998). Thus, prior adopters in a social network structure serve as the sources of contagious influence and may encourage the subsequent adoption behavior of others (Gaba and Meyer 2008).

As a result, the classical independent and identically distributed assumption for variables may not be appropriate in such contexts that have such associations among the different spatial units. Considering the social network structure of the population, the influence that prior adopters exert and its effects on non-adopters in a system both can be heterogenous (Strang and Tuma 1993). This is exhibited in diffusion studies that adopt a spatiotemporal lens and claim that physical and economic proximity have significant impacts on knowledge transfer and innovation diffusion (Albuquerque et al. 2007, Kalnins 2003). Literature that focuses on social networks has also applied this idea and suggested notable influence through linkages and ties among individual or organization entities within a system (Ahuja

2000).

Countries in the world, as the geographic units that are examined in this research, are connected in social interaction networks in different ways. Theoretical models have emphasized the importance of incorporating external effects in explaining the economic growth of one country (Romer 1990, Lucas 1988). In trade economics, for example, foreign R&D investments from trade partners are known to constitute a typical source of cross-country influence (Coe and Helpman 1995, Park 1995). Geographical proximity, based on the evidence in several prior research papers (Baptista 2000, Sonn and Storper 2003, Gallaud and Torre 2004), is likely to facilitate the diffusion of a new technology. Moreover, the social condition in one country, and its similarities to neighbouring economies, play an important role in the transfer of technology and adaption of innovations (Rodríguez-Pose 1999). Hence, the economic activities of one country – in our case, bitcoin penetration – are likely to be affected not only by the characteristics of the country itself, but usually by its neighbours as well. We next address the different types of spatial interactions that may occur among countries, and how these relationships affect bitcoin penetration.

4.2.2. The Nature of Spatial Interactions

The penetration of a new product, service or technology in the international context is related to the proximity of a country to other countries in terms of geography, socioeconomic aspects, and their culture and history in the global interaction network. Geographical proximity has been widely identified in existing literature as having an influence on adoption of new products and services among countries, and the mechanism of this influence has been explained at different levels of analysis.

Adams and Jaffe (1996) is representative of a line of research that has investigated the physical closeness between firms. They claimed that geographical proximity facilitates interactions among different firms and subsidiaries of the same firm. These intra- and inter-institutional communications permit access to sources of information, knowledge, funding and human capital (Murray 2004, Owen-Smith and Powell 2004, Zaheer and George 2004). They also enable firms, especially start-ups, to overcome the small sizes of their own knowledge bases. Other work has also found that the closeness of competing firms is associated with knowledge spillovers, product and service innovation, and firm improvements in competition (Audretsch and Feldman 1996, Glaeser et al. 1992). In addition, the formation of geographic clusters of firms in competitive regional markets has strengthened their interactions through strong social contacts and networking (Baptista 2000).

At an individual level, geographical proximity facilitates labor mobility, which in turn accelerates information sharing and the learning of new practice-related knowledge within a region (Almeida and Kogut 1999, Rosenkopf and Almeida 2003). As a result, geographical proximity may increase interactions with other countries through firm and individual connections, and improve the chances of successful commercialization and penetration of a product or service in a country.

Social and economic relationships constitute another type of proximity. Activities such as education, international business and bilateral trade among countries may result in higher level of stimulus and pressure for companies and individuals to adopt new technologies (Albuquerque 2007). They contribute to more rapid penetration for products, services and new technologies. Since country-level socioeconomic proximity focuses on abstract connectedness, it addresses other kinds of relationships that geographical proximity cannot address.

Furthermore, cultural and historical relationships, including language, religion and colonial history, may influence product and service introduction and technology penetration of a country by affecting its interaction with other countries. For example, linguistic, religion and colonial distance may create barriers for communication among people and corporations in different countries. In contrast, countries that have common culture and closer historical relations tend to have similar cognitive framework, which helps with smoother information exchange (Triandis and Suh 2002). As a result, culture similarity and historical relationship contribute to faster acceptance and adoption behavior. But, given the breadth of knowledge about these issues in past research, our approach will be mostly to use them to control for some of the known effects that are likely to be present, as opposed to main effects in this study.

4.2.3. Security Disclosures, Event History Methods, and Financial Accounting Disclosures

Prior research related to security and disclosures has covered diverse interdisciplinary topics, including the economics of information security breaches, vulnerability announcements by firms, and the impact of disclosures on firm performance and value in financial accounting.

Numerous researchers in various academic disciplines have focused on changes in the market value of firms in various settings where good news is likely to be the dominant force, but where bad news may also be experienced. They include the early empirical Finance work of Brown (1985) on the use of daily stock returns, that today represent the body of knowledge associated with *event study methods* from Accounting, to determine the impact of news and events on the market value of firms. The methods do so via the study of changes in operationally-defined and controlled *windows of time* to identify whether abnormal returns were determined to be present. Another fairly early empirical study in Marketing was conducted by Agrawal and Kamakura (1995) in order to discover the impact of newly-hired celebrity endorsers on firms' equity value. Yet another Marketing research effort is attributable to the work of Chaney et al. (1991), who sought to measure the effects of new product introductions on the market value for the firm, again in terms of observations of abnormal returns beyond the typical returns of the companies' stocks. In the e-commerce and IT areas, quite a few studies have been done to explore the market value effects of technology and systems announcements. For example, Subramani and Walden (2001) demonstrated the market value impacts e-commerce innovation announcements on firm equity prices in the market, and took special care to do sensitivity analysis on the different event payoff window lengths that would best have best captured the extent of abnormal returns. Finally, Im et al. (2003) studied the extent to which IT investment announcements had beneficial impacts on the market value of publicly-traded firms. This effect which is still believed to be occurring today in many different industry settings when the innovations are unusual and of potential high impact.

Others have sought to understand the effects on the market value of firms due to information security breaches using similar kinds of methodology. Garg (2003) and Ettredge et al. (2003), in separate studies, examined the response of the stock market to the February 2000 *distributed denial of service* (DoS) attacks against several of the biggest Internet companies. They identified consistently negative returns on the affected firms' equity value in the market. The authors insightfully noted that the impacts typically are not restricted to the affected firms, but also spill over to affect other firms that are similar in size as the attacked ones. Apparently, the market tends to react to the potential losses that have occurred for specific firms while recognizing the new vulnerabilities for future losses of other firms that are similar to them. Acquisti et al. (2006) studied instances of exposure of the private information of customers at the firms they have had relationships with. Their focus was on security failures that involved hacking and the loss of equipment and data. Their results also suggested that significant market value was lost on the day that the attacks were announcement, as well as during a short period after the event. These studies provided useful theory and empirical methods ideas for the discovery of more negative market valuations of firms due to information security breaches in their industry sector, and among their competitors.

There has been a substantial body of work that reflects the widespread interest in the outcomes, issues, and staging of in the literature in the Financial Accounting discipline. Most relevant to the present research is a primary topic in this stream of research that is referred to as *association-based disclosure*. It studies the relationship between exogenous disclosures in financial reporting and the responses of investors, based on analysis of firm asset equilibrium price changes and trading volumes under the assumption of market efficiency (Verrecchia 2001). Other authors have worked to develop theory for this area, starting from a simple model (Subramanyam 1996, Holthausen and Verrecchia 1998) that depicts the disclosure association, to the incorporation of a variety of characteristics of investors' agents and assessment of their impacts. Some of the issues that have been studied include: the breadth of informedness (Lintner 1968); changes in how investors make their own private inferences about firm value in the presence of new information, and how their anticipation of market value changes depending on the timing and the content of a firm's disclosure (Hellwig 1980, Brown and Jennings 1989, Kim and Verecchia 1991b); and different ways of learning about a firm's disclosures, and how they should be interpreted (De Long 1990, Kim and Verrecchia 1991a, Kyle and Wang 1997, Marzano 1999).

The present work differs from the above streams of literature in that it is grounded in the context of financial technology innovation. Bitcoin trading and bitcoin ATM penetration in the cross-country global environment are not subject to issues of equity value related to their adopters. However, it should be recognized that many of the variables that have been explored in past event studies of firm-level market value are of potential relevance to a study like this one on bitcoin – if not their dependent variables related to abnormal returns. Nevertheless, the kind of market thinking on valuation that is pervasive in many of the past studies suggests that financial technology innovations, as well as diminished security due to bitcoin theft and exchange hacking, have the potential to create fundamental disturbances to the perceived value of bitcoin and bitcoin-related assets. Since bitcoin is already recognized as a disruptive financial technology, it is fair to say that weak bitcoin security are essentially a "disruption in the market value of the disruptive technology. In addition, we seek to explain whether disclosures of security incidents have any influence the spatial and temporal dimensions of bitcoin cross-country penetration and trading. These issues have not yet been studied, to our knowledge, although the general response to security breaches and firm-level disclosures of operational and legal problems, product development and delivery delays, and insider trading problems have been widely documented, and the market value impacts of security breaches has been well recognized in the literature and in industry.

4.3. Bitcoin as a Research Context: Data Collection, and Variables

Transaction transparency is one of the major advantages of bitcoin as a cryptocurrency. The details of every single transaction, including the time, input address, output address, transaction amount and fee are stored in blockchain, which serves as a public ledger in the network. Also, the number of bitcoins in each bitcoin wallet and the associated transactions are publicly available and can easily be retrieved by anyone. The open data sources of bitcoin provide convenience for academic research as well, since data accessibility is a usually not easy. (See Appendix Table C1 for the variables, definition, and data sources.) The anonymity of bitcoin raises challenges too. No personally-identifying information is linked to bitcoin addresses, so users can make their payment activities more opaque by using multiple bitcoin addresses simultaneously for various transactions. So it is hard to acquire deep insights on consumer behavior.

Table 4.1. Summary of the Data Sources for This Research

DATASET	SOURCE	DESCRIPTION
Mt.Gox exchange trading data	Mt.Gox leaked data	Data contain paired bitcoin transactions settled at the exchange from November 2012 to November 2013. Typical information includes the user ID, transaction date, bitcoins traded, equivalent amount in USD, and the country and city or state of users
Bitcoin ATM data	CoinATMRadar	Bitcoin ATM data include: installation date, location coordinates, and other relevant information for every bitcoin ATM machine in the world
Bitcoin venture capital data	CoinDesk	Over USD 1.1 billion has been invested in start-ups involving bitcoin businesses to date. Additional information includes: date, name, classification, headquarters country, location of start-up company, and USD funding size
Geography and time-based explanatory variable-related data	World Bank Census Bureau GSMA Intelligence	Population, economic, regulatory, technology, culture and banking data

Since individual adoption and usage of bitcoin are not directly observable, we decided to use trading data from the Mt.Gox bitcoin exchange in Japan, as well as bitcoin ATM data. A summary of the data sources is listed in Table 4.1. We next will describe how we drew data from the different sources and use it to create variables in our dataset.

The latter is intended to proxy for the penetration of cryptocurrency in this research. We start from the global level and explore bitcoin usage and relevant investments in different countries over time. This provides alternative insights on how and why this cryptocurrency is diffusing among populations around the world, and how security events may have an influence in this process. We include 217 sovereign countries defined by the World Bank in our analysis. The primary datasets we use include the Mt.Gox exchange trading data and bitcoin ATM data. Both data sources involve geography and time information. Together with the country distance data that we acquired, they support our spatiotemporal analysis at the global level. We also combine them with other data sources, such as economic, regulatory and technology data, as explanatory variables. All data were collected from the public domain, and include Coin ATM Radar, International Money Fund, and the World Bank, among others.

4.3.1. Mt.Gox Exchange Trading Data

We use the exchange trading data from Mt.Gox, one of the largest online exchange platforms for bitcoin trading that was originally based in Japan. The company was founded in 2010, and was handling 70% of all bitcoin trading transactions by 2013. As a result, trading data from this platform in that timeframe constituted a representative sample of all bitcoin exchange transactions in the world. Mt.Gox was forced into bankruptcy in February 2014, due to the 2103 hacking incident loss of 800,000-850,000 bitcoins that were valued at more than USD 450-480 million at the time. This became the biggest bitcoin-related hacking event, resulting in the largest theft in the history of bitcoin (Adelstein et al. 2016).

Table 4.2. Summary Statistics

VARIABLES	MEAN	MEDIAN	MIN.	MAX.	OBS.
Transactions	335.30	27	0	53,820	61,225
BTCATMs	0.14	0	0	5.11	217
Inflation	4.37	1.63	-3.75	121.74	178
ShadEcon%	30.98	31.34	8.08	63.34	160
AvgRemits	369.83	40.11	-7.27	19,110.03	176
Internet	48.36	50.14	0	98.32	205
Mobile	107.49	109.34	7	324.44	208
R&D	1.01	0.67	0.02	4.29	96
Crises	1.26	1	1	4	117
Restrictions	11.38	12	1	20	191

Notes. Obs.: 217 countries. Bitcoin trading transactions contain panel data from November 2012 to November 2013. Bitcoin ATM data and country-level explanatory data are cross-sectional observations for 217 countries. Missing data are imputed via average values from the model estimations that we perform in this research.

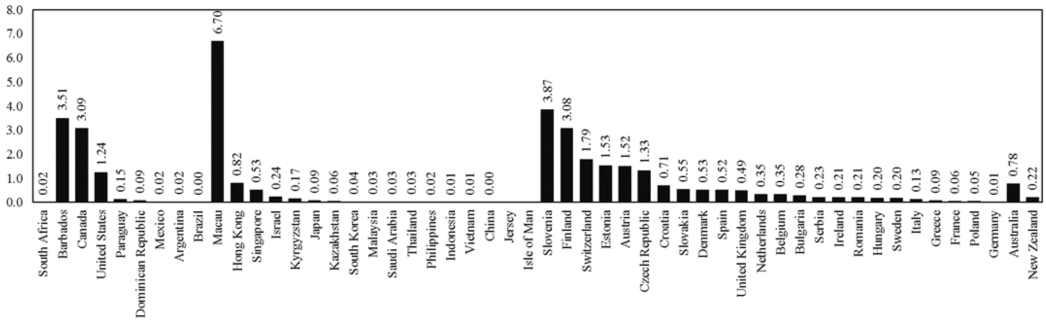
The bitcoin trading data that we have access to contains paired bitcoin transactions settled on the back-end of the exchange platform from November 2012 to November 2013. Summary statistics are provided in Table 4.2. Each transaction record has information includes the user ID, transaction date, number of bitcoins traded, the USD-equivalent value, and country and state of users. By aggregating the transactions by country for daily data, we obtained 61,225 observations for our final panel dataset. The Mt.Gox exchange data actual bitcoin transaction behavior of individuals, and location information for where the buyers and sellers were located. This makes the discovery of the spatial patterns of bitcoin use possible.

4.3.2. Bitcoin ATM Data

Bitcoin ATMs (*BTCATMs*) are Internet-based kiosks that allow people to instantly purchase bitcoins as well as redeem bitcoins for cash. They look like traditional ATMs, and bitcoin ATMs provide physical experiences for their users, especially first-time buyers. They have proven to be critical for transforming onlookers into active users (Coindesk 2014). The machines have been popping up rapidly in different places around the world, with over 50 countries involved and nearly 2 bitcoin ATMs installed every day. The installations of bitcoin ATMs are based on the activities of 21 service providers. It is reasonable to rely on the relationship of supply and demand and look at the number of bitcoin ATMs per capita as a measure of the popularity of bitcoin. Thus, we obtained the raw data from Coin ATM Radar (2017b), which recorded the installation date, location, and other information for every bitcoin ATM in the world.

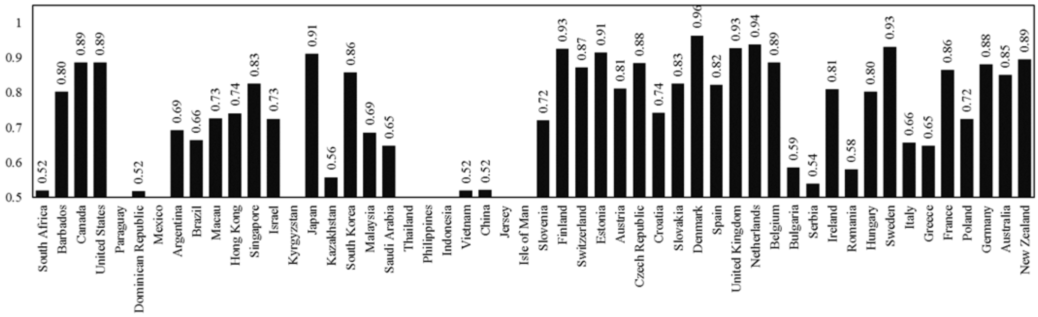
Up to October 2016, 825 bitcoin ATMs were installed in different countries around the world. The U.S. has the highest number of ATMs (403) installed to date, followed by Canada (112) and U.K. (32). Taking the population of each country into consideration, we plotted the number of bitcoin ATMs per 1 million population to represent its penetration rate in Figure 4.1. We observe that Macau, with relatively small space and population, has seen the highest popularity of bitcoin, with about 6.7 bitcoin ATMs for every 1 million people. This may be related to the culture and policies of the region. Other countries that have high demand for bitcoin ATMs include Slovenia, Barbados, Canada and Finland.

Figure 4.1. Number of Bitcoin ATMs Per 1 Million Population



By comparison with the Internet penetrations of these countries in Figure 4.2, we note that the diffusion of this financial innovation and that of pure technology. While Finland has the third highest Internet penetration rate in the world, Macau, Slovenia, Barbados and Canada are not among the most high-tech countries. In addition, countries with the highest technology adoption and literacy (e.g., Denmark, Netherlands, UK, Sweden, Japan) have not experienced more pervasive adoption of bitcoin for transactions and bitcoin ATMs.

Figure 4.2. Internet Penetration



4.3.3. Country Distances

In this research, we started from the perspective of social contagion. We considered the influence of the interactions among different countries as a key determinant of the bitcoin penetration. Thus, how we measure the country distances, which determine the weights of network effects for each pair of countries, is critical in our work. Prior research has suggested different types of distances among countries, including physical, socioeconomic, and cultural and historical distances (Martín and Drogendijk 2014). Based on this classification, we collect data on each type of distance. We use physical distance as the primary measurement to examine the strength of cross-country influences. Socioeconomic and cultural and historical distances are used for robustness checks.

Physical distance. The country distance data were acquired from the Centre d'Etudes Prospectives et d'Informations Internationales (CEPII) in Paris, France, which provided the physical distances of each country to every other country. The *physical distance between two countries* is defined as the air distance, or great circle distance in kilometres between the capital cities of the countries. For example, the physical distance between China and the U.S. is 10,994 km, which is the air distance between Beijing, the capital of China, and Washington DC, the capital of the U.S. The longest distance in our data is 19,951 km between Paraguay and Taiwan, and the countries that are closest are the Democratic Republic of the Congo and the Republic of Congo, with 10.5 km between each other.

Socioeconomic distance. We use the *bilateral trade value* as the measurement for the socioeconomic distances among different countries. The data were acquired from the Direction of Trade Statistics (DOTS) publication of the IMF. The reports describe the monthly value of merchandise exports and imports of each country with its primary trading partners. Imports are reported on a *cost, insurance and freight* (CIF) basis and export are reported on a *free on board* (FOB) basis. In our analysis, we use bilateral trade data in the year 2015 and sum the export and import value of each country.

Cultural and historical distance. We also obtained language and colony data from CEPII, which we use to measure cultural and historical distances between countries. Authoritative information is reported on the official language and historical colonial relations of all of the countries in the world. We use a binary variable, which equals 1 if two countries share a common official language or have colonial relations in their common history, and 0 otherwise.

4.3.4. Country-Level Explanatory Data

In the intersecting disciplines of Finance and Information Systems (IS), bitcoin is jointly influenced by the economics, technology and policy of a country (Hileman 2014a). We include a time-series of explanatory data associated with the new locations into which bitcoin has penetrated.

Economic development. We use metrics that are widely adopted in the existing literature in Economics, Finance and Information Systems to measure a country's economic development and standard of living. We include the annual inflation rate (*Inflation*), the research and development expenditure as a percentage of gross domestic product (GDP) (*R&D*), and the number of economic crises from 1970 to 2011 (*Crises*), based on Laeven and Vanencia (2009). We also collected data from the World Bank database, which are updated yearly. The latest update was in 2015.[9] Considering the features of bitcoin, we also controlled for the financial environment of a country with variables including the estimated percentage of the shadow economy (*ShadowEcon%*) (Elgin and Oztunali 2012), the average remittances per person in U.S. dollars (*AvgRemits*), and the number of bitcoin exchange arrangements and restrictions (*Restrictions*) of the country (IMF 2014).

Technology. We consider two different measures for the technology development of a country: the extent of the *penetration of mobile phones and cellular services* (M), along with the extent of the *penetration of the Internet* (I) in a country. Data for these are both drawn from the World Bank database. *Internet penetration* refers to the number of Internet users per 100 in the population, while *mobile penetration* counts the mobile cellular subscriptions on the same basis. In the 2015 data, the global Internet penetration ranges from 1 or 2 people per 100 population for some African countries, to 96 to 98 people per 100 population for several European countries. Mobile penetration in countries around the world is generally consistent with Internet penetration across the countries of the world. The lowest rates of Internet penetration occur in many African countries as well. Macao, Kuwait and Hong Kong, instead of the European countries, have the highest mobile phones service subscriptions, with the number reaching 324 per 100 peo-

[9] For all the data and variables that we used in this research, we collected the newest information and data for 2015. This is what was available from the World Bank database, which constrained what we could find. When the newest data were not available for some countries, we performed backward searches for the latest data in the database, and when we found it, we validated its continuing appropriateness by comparing to other alternative sources. The World Bank is the most authoritative source in most cases.

ple in Macao. The mobile penetration data provide an alternative measure for a country's technology development in addition to its Internet penetration. Together, they create a rigorous basis in high-quality data, and offer a rigorous basis for our study. Since these two measures are correlated, we define another variable that we call *Tech*, an average of Internet and mobile penetration, to control for the technological development of a country.

Policy and regulation. Although bitcoin is being increasingly accepted around the world, it is still under strict regulation and prohibited by law in some countries. In addition, related policies including tax regulations have not been very beneficial in most areas for bitcoin to be able to grow. Hence, the penetration of the crypto-currency is substantially influenced by the policy and regulation of a country. We capture this effect by acquiring data from Bitlegal (bitlegal.io), which provides legality-related information on bitcoin in each country around the world.

The data also contain four country-level *LegalStatus* variables that represent some of the legal issues and state of the country environment for this sort of fintech innovation. They include: (1) whether the country is open to bitcoin, and allows the full operation of bitcoin exchanges and bitcoin ATMs (*Open*); (2) whether there are contentious issues and difficulties, including warnings of regulation and limitations on bit exchange trading and bitcoin ATMs (*Warnings*); (3) whether there is outright hostility based on laws and the commercial code that make it very difficult or impossible to use the cryptocurrency for transaction-making in the country (*Hostile*); or (4) whether it is hard to determine the legal status of bitcoin in the country's economy (*Unknown*). Additional regulatory details, including the basic transaction rights, taxation, and other legal and official guidance information were also provided, but not uniformly, which made it difficult for us to take advantage of some of this information.

A correlation matrix of the explanatory variables is reported in Table 4.3. All the numbers are relatively small, with the highest correlation at -0.46 between *ShadEcon%* and *MIPenetrRate*. This supports our use of the variables in our econometric estimation work.

Table 4.3. Pairwise Correlation between the Explanatory Variables

VARIABLES	*Inflation*	*Shad Econ%*	*Avg Remits*	*R&D*	*Crises*	*Restric-tions*	*MIPenetr Rate*
Inflation	1.00						
ShadEcon%	0.09	1.00					
AvgRemits	-0.06	-0.25***	1.00				
R&D	-0.10**	-0.42***	0.01	1.00			
Crises	0.06	0.09	-0.07	-0.10	1.00		
Restrictions	0.15	0.19***	-0.03	-0.14**	0.10	1.00	
MIPenetrRate	-0.13*	-0.46***	0.25***	0.15**	-0.01	-0.22***	1.00

Notes. Obs.: 217 countries for each variable. The least correlated variables are *AvgRemits* and *R&D* (0.01), and the most correlated ones are *ShadowEcon%* and *MIPenetrRate* (-0.46) for mobile phones and the Internet. Signif.: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

4.4. Model and Methodology

Spatial econometrics was introduced by Anselin (1988) and others. It has been further developed and increasingly applied in research in various fields (Griffith 1988, LeSage and Pace 2009, Corrado and Fingleton 2012). Similar to time-series models that consider the correlation of observations over time, spatial econometric models incorporate the interactions of geographical units across space. Spatial econometrics differs from a straightforward extension of time-series models, however, for two reasons. First, the specification of the spatial weights matrix allows each pair of geographical units to affect each other mutually, while it is usually "one-way" effects in time-series models. Second, several types of measurements (distance, neighbours, links, etc.) can be used to model spatial dependence, as opposed to a single temporal measurement in time-series literature the (Elhorst 2014).

We use spatial econometrics to model the global penetration of bitcoin, with 217 countries as the geographic units in our analysis. We next discuss the preliminaries for our implementation of a spatial model for empirical estimation in the bitcoin context. The methods require a spatial panel data model and the creation of a spatial weights matrix.

4.4.1. Spatial Econometrics and Spatial Panel Data Model

The *benchmark spatial dependence model* is specified in Equations 1 and 2. *Y* denotes the outcome variable, which is the daily trading volume at Mt.Gox (*TradeVol*) of each country and the number of bitcoin ATMs (*BTCATMs*). *X* is a set of explanatory variables, including *Inflation*, *ShadowEcon%*, *AvgRemits*, *R&D*, *Crises*, *Restrictions*, *MIPenetrRate* and *LegalStatus*. In addition, *W* indicates a spatial weights matrix.

A spatial econometrics model is used to estimate the drivers of the global penetration of bitcoin. We use *countries* as the geographic units in our analysis. We next explain the specifications of a workable spatial model for our context, and discuss the creation of a spatial weights matrix.

$$Y = \rho WY + \alpha + X\beta + WX\theta + \mu \tag{1}$$

$$\mu = \lambda W\mu + \varepsilon \tag{2}$$

The model can be extended to a series of *spatial dependence models* under different theory-based hypotheses for the types of spatial interaction effects that are likely to be present (Elhorst 2014). The term, *WY*, denotes the endogenous interaction effects of the dependent variable of a particular country to another. *WX* represents the exogenous interaction effects of the independent variable of one country on the dependent variable of another country. $W\mu$ reflects the spatial pattern followed by the error terms, as unobserved shocks. Hence, several alternative spatial models are derived under different assumptions, with the parameters ρ, θ and λ set to 0.

Since the Mt.Gox Exchange data have cross-sectional and time-series structure, we begin by estimating a *static spatial panel data model* that incorporates spatial interactions across the geographical units and over time. The spatial panel data model extends the basic spatial econometric model by including the temporal variation of the geographic units. It also considers the heterogeneity of various graphical units by controlling for random spatial effects. Formally, the model is specified as:

$$TradVol = \lambda(\mathrm{I_T} \times \mathrm{W_N})TradVol + \alpha + X\beta + \varepsilon \qquad (3)$$

TradVol is an $N_{Country}T_{Day} \times 1$ vector of observations on the trading volume of bitcoins at Mt.Gox. X is an $N_{Country}T_{Day} \times k$ matrix of observations for the country-level independent variables. I_T is an identity matrix and W_N is the spatial weight matrix for the N countries. λ is a parameter that captures the *spatial autocorrelation*.

4.4.2. Construction of the Spatial Weights Matrix

The spatial weights matrix W is critical in all spatial dependence model. This is because, in the bitcoin context at least, all three of the spatial interaction effects, WY, WX and $W\mu$, rely on it. It is a normalized square matrix with known constants that can be used to describe the spatial relationships between the country units in our data. As we have discussed, there are multiple ways to create such a matrix, including using distance, neighbors, links, and so on, as measurements of *geographical dependence.* We use the air distance between countries and choose the nearest 5 country neighbors. The weights of each pair of countries in the *physical distance weights matrix* (*PhysDistW*) are then defined as:

$$w_{ij} = \begin{cases} 1, \text{ if country } j \text{ is one the 5 nearest neighbors of country } i \\ 0, \text{ otherwise.} \end{cases}$$

Spatial econometrics can also be leveraged to explain the relationships between various kinds of economic units – countries in our case, of course – beyond their geographical connections. This type of research has been less well developed in the literature, according to Elhorst (2014). Yet countries around the world interact with each other through their social and economic activities, and are connected for cultural and historical reasons as well. Hence, we extend our basic empirical model-based investigation by considering the socioeconomic, cultural and historical relations of different countries, and create a *socioeconomic spatial weights matrix* (*SocioEconW*) using bilateral trade data, as well as a *cultural and historical spatial weights matrix* (*CultHistW*) using linguistic and colonial relationship data.

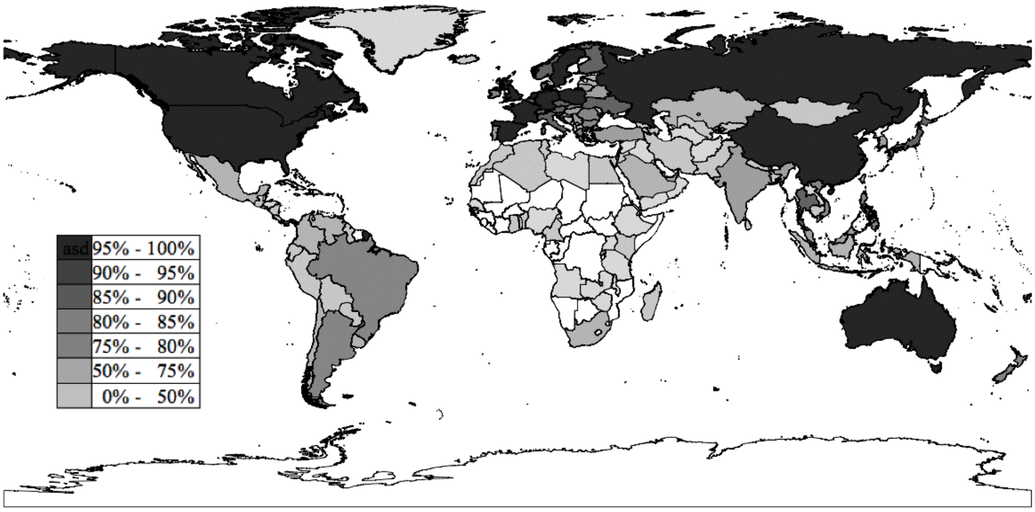
4.5. Results

We next discuss the results on the estimation of the models to identify and explain the drivers of global bitcoin trading volumes. We start this part of our results presentation with a *global Moran's I test* (Moran 1950, Anselin 1988, 1995). The purpose is to examine the extent of *cross-country autocorrelation* in bitcoin trading volumes. We then estimate a baseline model without spatial effects, and thereafter explore the influences of physical distance between countries before and after the occurrence of relatively negative security events related to bitcoin's operations, usefulness, and sustainability. Last, we conduct robustness checks using socioeconomic distances, as well as cultural and historical distances between the countries in the dataset for the discovery of spatial patterns.

4.5.1. Global Moran's I Test for Spatial Spillover Effects

The global distribution of bitcoin transactions that were made via the Mt.Gox exchange are shown in Figure 4.3, in which the darker regions indicate higher transaction volumes. The plot clearly reveals clustered patterns in bitcoin trading transactions. Most transactions occurred in North American, Asian and Europe and Australian regions, and countries tend to have more transactions as well.

Figure 4.3. Geographic Distribution of Bitcoin Trading Transactions Based on Correlations



Notes. This figure reports on the values of the global Moran's I indices for the countries around the world. High values of autocorrelation for countries (75% to 100%) are colored in dark gray to black highlights. They show spatial autocorrelation of their values (bitcoin transactions). In contrast, countries highlighted with the lighter gray to white range have low *spatial autocorrelation*.

We computed the *global Moran's I index* to examine the spatial autocorrelation that is present based on the geography of the countries and their associated *average daily trading volumes*. This index evaluates whether an associated attribute involved a *clustered, dispersed* or a *random spatial pattern* across the countries. (Refer to Table 4.4.)

Table 4.4. Bitcoin Prices from November 2012 to November 2013

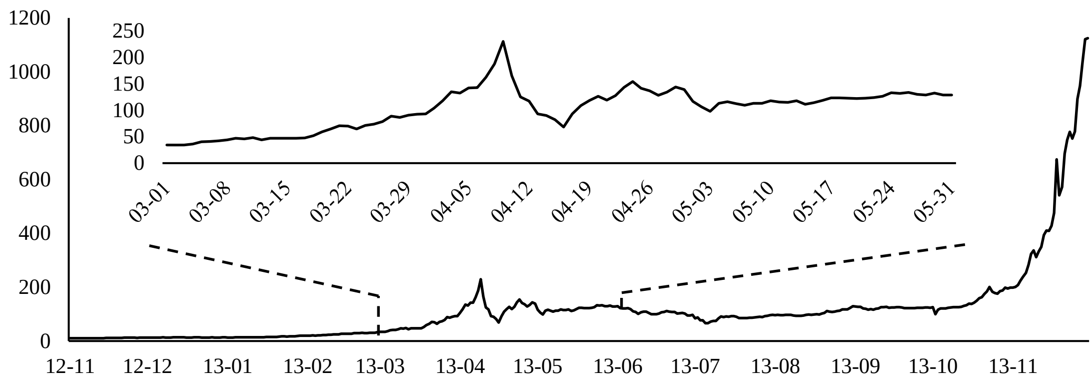
OBSERVED INDEX VALUE	EXPECTED INDEX VALUE	STD. DEV.	*p*-VALUE
0.07	-0.01	0.032	0.02

By comparing the observed overall global index value and the expected index value, we observe that there is a statistical difference at the 5% level of significance. This result indicates the existence of a clustered spatial pattern in bitcoin trading volumes across countries, and supports our spatiotemporal analysis in the context.

4.5.2. Price Fluctuation and Security Events

The occurrences of security events related to bitcoin are usually reflected in its price changes. Bitcoin prices have often fallen after hacking incidents hit the news. For example, a security breach in June 2011 at one of the oldest bitcoin wallets, MyBitcoin, is believed to have triggered a massive sell-off in bitcoins, and led to a subsequent drop in market price of the cryptocurrency from over USD 30 back to USD 2 (Jeffries 2011). Another well-known example is Mt.Gox, which announced bankruptcy in February 2014, the result that the bitcoin price decreased by 80% in one year.

Figure 4.4. Bitcoin Prices from November 2012 to November 2013



Notes. The *x*-axis for the outer figure is stated in (Year, Month) format for November 2012 (12-11) to 2013 (13-11), and the inner figure is stated in (Month, Day) format from March 1 (13-01) to May 31 (05-31).

Figure 4.4 shows that the price of bitcoin steadily grew during our study period from USD 10 in November 2012 to USD 200 in October 2013, and later surged to over USD 1,000 one month after that. In the middle of the study period in April 2013, there was a relatively large fluctuation, with the bitcoin price falling to USD 230, and then down to below USD 70. This was caused by a serious incident with security that happened during the month. On April 3, 2013, bitcoin wallet provider, Instawallet, announced that it was hacked, resulting in a theft of over 35,000 bitcoins valued at USD 4.6 million at the time (Merz 2013). The firm suspended its operations indefinitely as a result. Technical problems during the same month arose for payment processors, Mt.Gox and BitInstant, which went out of business in 2014, and may also have influenced bitcoin's market prices during that time. Since April 2013 saw major security events related to bitcoin service providers, we looked tat he spatial pattern of bitcoin penetration using data from March to May 2013, which were before and after the occurrence of the security incidents.

4.5.3. Spatial Spillovers Before and After Security Events

The estimation results of the base model using the full 395-day range of data with no spatial effects show that the penetration the R&D investments of a country significantly contributed to its bitcoin trading volume. (See Table 4.5.) Specifically, an additional percentage point higher mobile and Internet technology penetration rate resulted in about a 1.4% increase in bitcoin trading volume across the countries, while a 1.0% increase in R&D investment was associated with 69.7% more bitcoin exchange transactions at Mt.Gox during the study period. We also found that personal remittances and restrictions on bitcoin trading and exchanges had negative effects on bitcoin trading transactions in the countries.

According to our prior analysis, in April 2013 there were major security events related to bitcoin service providers. So we estimated the spatial panel model using data from March and May 2013 to examine the spatial spillover effects that occurred before and after the occurrence of a well-known security incident. We include fixed effects for the different days to capture the time trend observed in bitcoin trading behavior at the exchange platform level. Since our country-level explanatory variables are time-invariant, we use country-level random effects for the model estimation. The results are shown in Table 4.5.

Table 4.5. Results of Spatial Spillover Effects Before and After Security Events

VARIABLES	BASE MODEL		PRE-SECURITY EVENTS		POST-SECURITY EVENTS	
	Coef.	Std. Err.	Coef.	Std. Err.	Coef.	Std. Err
W × TradeVol			0.17***	(0.019)	0.16***	(0.019)
Intercept	1.80*	(1.017)	1.96*	(1.029)	2.64**	(1.102)
Inflation	0.01	(0.009)	0.01	(0.010)	0.01	(0.010)
ShadEcon%	-0.01	(0.012)	-0.01	(0.012)	-0.00	(0.013)
AvgRemits	-0.15**	(0.057)	-0.15**	(0.058)	-0.18***	(0.062)
MIPenetrRate	0.01***	(0.005)	0.01***	(0.005)	0.02***	(0.006)
R&D	0.71***	(0.156)	0.70***	(0.158)	0.72***	(0.169)
Crises	0.13	(0.271)	0.18	(0.275)	0.13	(0.294)
Restrictions	-0.05**	(0.026)	-0.05*	(0.026)	-0.06**	(0.028)
Hostile	-2.40**	(0.941)	-2.95***	(0.953)	-2.59**	(1.020)
Open	0.03	(0.601)	-0.28	(0.608)	0.07	(0.651)
Unknown	-2.08***	(0.596)	-2.40***	(0.603)	-2.28***	(0.646)

Notes. Obs.: 61,225. *W* is the spatial weight matrix. Time-wise fixed effects and country random effects are included. Standard errors are in parentheses. The base case for *LegalStatus* is *Warnings.* Signif.: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

We observe that the estimation results for the spatial panel model generally match the results of the baseline model. More importantly, the results provide statistical evidence for cross-country spillover effects. While the spatial coefficient on the spatial lag variable is 0.17 ($p < 0.01$) using the March data, the number fell to 0.16 ($p < 0.01$) after the security events happened. This suggests that the cross-country spatial effects related to bitcoin trading behavior weakened due to the occurrence of the bitcoin theft incidents.

4.5.4. Robustness Checks

We also used socioeconomic distance as well as cultural and historical distance to create the spatial weights matrix (*SocioEconW* and *CultHistW*) so we can perform the robustness checks. Similar to our assessment of the geographical dependencies, we explored the effects of socioeconomic interactions among countries for bitcoin trading volumes using bilateral trade data, and cultural and historical relationships using linguistic and colonial data. The results are presented in

Table 4.6.

Table 4.6. Robustness Checks with Socioeconomic Distance and Cultural and Historical Distance

VARIABLES	SOCIO-ECONOMIC DISTANCE				CULTURAL & HISTORICAL DISTANCE			
	Pre-Security Event		Post-Security Event		Pre-Security Event		Post-Security Event	
	Coef.	**Std. Err.**	**Coef.**	**Std. Err.**	**Coef.**	**Std. Err.**	**Coef.**	**Std. Err.**
W × TradVol	0.12***	(0.028)	0.10***	(0.029)	0.08***	(0.025)	0.07***	(0.025)
Intercept	1.67	(1.045)	2.35**	(1.120)	2.14**	(1.055)	2.93***	(1.127)
Inflation	0.01	(0.010)	0.01	(0.010)	0.01	(0.010)	0.01	(0.010)
ShadEcon%	-0.01	(0.012)	-0.01	(0.013)	-0.01	(0.012)	-0.01	(0.013)
AvgRemits	-0.11*	(0.059)	-0.15**	(0.063)	-0.14**	(0.059)	-0.18***	(0.063)
MIPenetrRate	0.01**	(0.005)	0.02***	(0.006)	0.01***	(0.005)	0.02***	(0.006)
R&D	0.76***	(0.160)	0.79***	(0.172)	0.77***	(0.162)	0.79***	(0.173)
Crises	0.19	(0.279)	0.13	(0.299)	0.18	(0.282)	0.13	(0.301)
Restrictions	-0.05**	(0.027)	-0.07**	(0.029)	-0.06**	(0.027)	-0.07**	(0.029)
Hostile	-3.02***	(0.968)	-2.58**	(1.038)	-2.85***	(0.977)	-2.47**	(1.044)
Open	-0.28	(0.618)	0.11	(0.662)	-0.17	(0.624)	0.16	(0.667)
Unknown	-2.48***	(0.612)	-2.33***	(0.657)	-2.48***	(0.618)	-2.36***	(0.661)

Notes. Obs.: 61,225. Dep. var.: *TradeVol.* Standard errors are in parentheses. *W* is used to indicate that a spatial weight matrix is involved in a variable for the estimation. The base case for *LegalStatus* is *Warnings*. Time-wise fixed effects and country-specific random effects also are included. Signif.: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Our investigation of the spatial effects that are at work in supporting different levels of cross-country bitcoin trading volumes has yielded results that are qualitatively consistent with our expectations for the different forms of proximity that we have studied. Table 4.6 shows that the coefficients for the country-level explanatory variables are robust, and generally consistent with the previous estimates. In addition, we consistently found that there were somewhat less spatial spillovers after the occurrence of security events, when the socioeconomic, cultural and historical spatial model was estimated. With the socioeconomic spatial dependence model, the coefficient on the spatial lag term is 0.12 ($p < 0.01$) before the security incidents, and this decreased to 0.102 ($p < 0.01$) after them. Similarly, the coefficient of spatial autocorrelation in the cultural and historical model dropped from 0.080 ($p < 0.01$) to 0.067 ($p < 0.01$) after the breach incident happened.

Based on the results for the bitcoin trading data from the Mt.Gox exchange platform, we offer the following preliminarily conclusion: threats that people think are real or perceived related to the security of bitcoin are likely to result in reduced cross-country penetration effects, which have the overall effect of preventing this cryptocurrency from diffusing around the world as rapidly as it might have diffused, with all of the other factors held constant. In addition, the models that are tested consider the influences of other variables that are fairly well-known in the technology diffusion literature. They include geographical and socioeconomic factors, as well as cultural and historical dependencies,

4.6. Discussion and Interpretation

This research draws on literature related to social contagion theory, technology diffusion, and security disclosures, and studies the impacts of occurrences of security incidents on the spatial and temporal penetration pattern of bitcoin trading transactions and bitcoin ATMs around the world. Our empirical analysis and preliminary findings stimulate discussion on several aspects of the related business problems.

4.6.1. Discussion

Using the Mt.Gox trading transaction data, our preliminary results show that, although physical proximity, social and economic interactions, and cultural and historical relationships between countries may contribute to the global penetration of bitcoin, these cross-country influences are weakened due to the occurrence of related security incidents. This may be attributed to the more general concerns regarding the security of cryptocurrency, which hold it back from penetrating more widely around the world.

Our study contributes to multiple streams of literature. First, we add insights to the growing knowledge base of bitcoin and blockchain studies. Prior research has primarily looked at bitcoin as a premature digital currency and has been focused on the stability of its trading value (Glaser et al. 2014, Polisik et al. 2015), or purely technical issues related to the mechanisms of the underlying blockchain technology (Decker and Wattenhofer 2014, Luu et al. 2016). Our research draws on social contagion theory, and offers new findings about how bitcoin as a cryptocurrency has been diffusing globally, by incorporating cross-country influences based on geographical proximity, socioeconomic interactions, and cultural and historical relationships in our investigation.

Second, we contribute to the literature on the diffusion of technology and innovation. Although a considerable literature has developed around the technology acceptance model (TAM) and the Bass diffusion model that explore the determinants or mechanisms of technology diffusion, little has been done to understand the influence of the perceived security of such emerging technologies in their diffusion process – to the best of our knowledge. This is important in the context of fintech innovations, since frequent occurrences of security incidents may lead to economic loss by corporate and individual adopters. Hence security issues may consequently result in the hold-up of the penetration of these technologies in the financial services industry. Our study complements this stream of literature by investigating how the perceived security of bitcoin plays a role in the penetration process.

Third, we contribute to research related to security and disclosures. Prior studies have focused on the economics and market value of information security breaches, the vulnerability announcements by firms, and the impacts of disclosures in Financial Accounting. But the impact of security and disclosures on the spatial penetration of new technologies has not been well explored. This research started with a spatiotemporal perspective and revisited the issues and outcomes of information security and systems data breach incidents, and their effects on the penetration of technology in the cross-country context.

4.6.2. Fintech Innovation: Interpretation

Our work is grounded in the context of fintech innovations, which have been penetrating at extraordinary speed around the world. Major technological advances in the financial services industry include mobile payments, e-commerce, peer-to-peer lending, crowdfunding, bitcoin, and blockchain technology. These innovations promise to transform the traditional finance sector by lowering service cost, improving financial inclusion, and creating new business models that offer expanded services and new revenue opportunities (McKinsey 2016).

A number of issues arise with IT adopted in financial services at the same time. While financial institutions have taken advantage of the Internet, mobile telephony, cloud computing, social networks, and other emerging technologies to achieve improved customer centricity and experiences, as well as revenue growth, they have simultaneously become high-value targets in the crosshairs of cybercriminals who look for the most vulnerable systems on which to launch damaging attacks and create havoc. Cybersecurity incidents, such as phishing, hacks, ransomware, and DDoS attacks, have become more pervasive and sophisticated, leading to substantial economic cost and long-term domino effects, such as brand reputation damage, loss of customer trust, and greater regulatory scrutiny. Research by a global law firm, Simons & Simons (2017), found that although most large financial services companies have identified the importance of partnering with fintech firms for better services. 71% of them see cybersecurity as a major risk, and the biggest barrier to success with financial innovation. Moreover, cloud services that handle more private and sensitive data, together with the ever more popular artificial intelligence and blockchain technologies implemented in financial services, have subjected the industry to ever higher risks.

New approaches and compliance with cyber-standards need to be implemented to combat such cybersecurity risks. Many financial service organizations have been increasing their investment budget and making an effort to beef up security and strengthen their risk management capabilities as a result. They have also been working with government bodies and regulatory institutions, including the National Association of Insurance Commissioners (NAIC), the Office of the Comptroller of the Currency (OCC), and the Federal Deposit Insurance Corporation (FDIC), to implement newly-issued cyber-standards and prevent cyberattacks (PwC 2017).

This discussion suggests the critical role of security in the development and diffusion of financial technology innovations, and emphasizes the importance for financial services providers to build a more comprehensive understanding of cybersecurity-related issues, as an extension to all their business strategies. Using the context of cryptocurrency, our research contributes new and useful insights on how perceived security will have an influence on the spatial penetration of financial innovations. This helps firms as well as regulatory institutions to manage cybersecurity more efficiently.

4.7. Conclusion

This research explored the global penetration of bitcoin using trading transaction data at a major digital currency exchange platform that ceased operation some time ago: Mt.Gox in Japan. Our preliminary theoretical and empirical analysis indicated that the diffusion of bitcoin around the world has been jointly influenced by economic, technological, and policy issues, and the perceived security issues associated with bitcoin as a cryptocurrency have held it back from penetrating more widely around the world.

We applied spatial econometrics and spatiotemporal analytics to discover cross-country patterns in bitcoin transactions and bitcoin ATM deployment, as they have penetrated different countries around the world. The methods allowed us to incorporate cross-country influences, based on geographical proximity, socioeconomic interactions, and cultural and historical relationships, in our investigation. We contribute to the literature on the diffusion of fintech innovations, by offering new findings about how bitcoin has been diffusing globally, especially how the perceived security of the cryptocurrency has been playing a role in this process. Our study also contributes to studies on geospatial phenomena in financial services. Last, we contribute to understanding bitcoin in industry, and for corporations that have business activities related to bitcoin, especially in the present early phase of development of this digital currency around the world.

Our work emphasized the importance of understanding the influence of security in financial technology innovations, which is a major challenge in the various types of fintech developments in business practice today. Although there is a rich body of literature that has intensively investigated security issues and technology diffusion in various contexts, the topic has not been adequately studied in the financial services industry, especially from the perspective of spatial and temporal interaction among countries around the world. We have drawn on social contagion and technology diffusion theories, and contributed new knowledge by extending the theories in a way that incorporates the influences of security incidents, and geospatial and geotemporal considerations into the process. As a result, our research has created new knowledge that contributes to a more comprehensive understanding of the global fintech revolution.

This study has several limitations. First, the primary metrics that we use for the response variable, bitcoin trading volume on the Mt.Gox trading platform, may not be adequate to measure the penetration of bitcoin in a country. Since the trading data primarily reflect consumer behavior based on viewing bitcoin as a “penny stock,” especially in the early years of its development, it may not be an accurate way to measure the potential of bitcoin as a medium of financial exchange. The actual usage of this form of digital currency is related to a variety of business activities, but there are no uniform or widely-accepted metrics appropriate for measurement at this time.

Similarly, there are different measures for the explanatory variables, including the economic, technological, and policy issues in a country. Also, there are different ways to create the spatial weight matrix with respect to geographic, socioeconomic, cultural and historical dependence. To date in this research, we have selected only one variable for each factor that we wish to explore – primarily to avoid the inevitable multicollinearity issues that are likely to arise. A methodological alterative is that we can adopt a partial regression methodology, and use the predicted values in the main model to improve the explanatory power of the model’s estimation to support deeper insights.

Last, we examined the influence of perceptions about bitcoin security by looking at trading transactions before and after a single month, April 2014, when the shutdown and insolvency of the Mt.Gox Exchange occurred in Japan (Reuters 2013). This may have led to some loss of information, including the general trend in bitcoin trading transactions that had been developing over time. However, since we studied a relatively short time period with just three months of data, our results about the effects of the security incidents related to bitcoin and its cross-country diffusion should still be valid. Further analysis can explore multiple security events instead of a single one, as in the present study. Longer periods of bitcoin trading activity with more data and observed location information must be acquired to make this possible. Another avenue that is worthwhile to explore is to collect data on social sentiment over time, since that too has been reported to have possible effects on bitcoin trading. So data on different kinds of sentiment and adoption levels can be leveraged. These provide feasible ways to address the research questions in this research in different ways.

Chapter 5. Data Analytics in the Corporate Trenches

My first two essays are sponsored research projects, one with Citibank in Singapore, and the other with PNC Bank in the U.S. These relationships were developed through the Living Analytics Research Centre at Singapore Management University (SMU) and Carnegie Melon University (CMU). I have had access to a massive amount of data related to customers, channels and card services through two large commercial banks. I framed the research ideas based on prior IS research, and discussion with industry professionals and my advisors in Singapore Management University and Carnegie Mellon University. The collaboration with banks has added interesting business and industry dimensions to my research.

For the first project, I also had a chance to have a Doctoral Research Internship with Citibank on a project from January to April 2016 with 5 months of prior preparatory work with the bank. As a result of this, I have had an industry mentor for part of my thesis in Singapore, a Vice President who previously managed data analytics for retail banking operations, and now is the head of the Decision Management unit of the bank. I also worked closely with a Senior Vice President, who headed the country data analytics activity, and a Managing Director, who manages analytics in the Asia Pacific region.

Skills and technique demonstration. Today, corporations seek technological innovations by collaborating with universities and research institutions. I started my research project with PNC Bank by being involved in the PNC Center for Financial Services Innovation. It was established based on the long-term research partnership between Carnegie Mellon University and PNC. For the Citibank project, I had to make more effort in talking with and discussing my research game plan with my industry mentor, a Vice President at the bank who helped to get me involved as Doctoral Research Intern from SMU's PhD Program via an ongoing project at the School of Information System's Living Analytic Research Centre (LARC).

To get the approval from Citibank's management team, I needed to demonstrate advanced skills and techniques that they did not have access to at the time. I conducted proof-of-concept work by collecting data from the public domain, and showed how it was possible to combine external data with their internal data to create meaningful business insights through data analysis that they were not able to do. I also gave a successful presentation to senior managers to explain the ideas and processes before I could join them as a research intern.

Goal setting and alignment. Another important thing that had to be done before I could have a sponsored project was to determine the expected research directions and stay aligned with the existing lines of business at the two banks, to make the research relevant for their business practice. Also, this process was interesting from an academic perspective. For both the Citibank and PNC projects, I submitted my project proposals based on group forum or private discussions with managers from the banks. This way, I was able to create value for the sponsors, as well as produce interesting academic research articles by using unique proprietary data, blended with other data that I was able to able to acquire from public sources.

Progress reporting and communication. Industry projects usually differ from those in academia in that they have shorter timespans and stricter deadlines. As a result, a well-designed timeline needs to be thought through and agreed upon, and all of the subsequent work has to be accomplished based on the targeted data access and the required resources, with sufficient time to figure things out and create innovative solutions. In addition, I reported regularly to the managers and my advisors so they were well connected and confident that the projects were progressing in the right direction.

Resources: Infrastructure, knowledge and people. Besides unique datasets, collaboration with industry professionals enriched my research experience and allowed me to access other resources, including infrastructure, knowledge and people. For example, by participating in the assessment of Citibank's 'Merchant Recommendation Engine' that was earlier deployed in Hong Kong market and was to be implemented in Singapore, I learned about the past experience of the bank, and this knowledge also contributed to my ability to complete my own project. I also had immediate access to other colleagues in the bank so I could gather relevant information and develop my research more smoothly.

Business insights and academic research output. As companies increasingly look for insights from collaborative research projects, my research was timely. I provided meaningful models, findings and implications for business practice, and communicate them to the managers in a professional way. I focused more on the results of the analysis, as in the current best practices with research translation in sponsored projects. I suppressed the theory and methodology parts, and reserved them for my doctoral dissertation, and my academic audiences in the conference and journals. I also developed presentation materials with an appropriate level of motivation, details, and visual style to deliver the main messages of the research effectively to business professionals.

In contrast, bringing my sponsored project work up to the standards of academic research required me to focus on the scientific content and go deeper in terms of theoretical and methodological advances. Hence, I needed to expand the results and deepen the scientific sophistication of my research for academic publication. It was difficult to balance the industry and academic requirements, but it was important to meet expectations from both sides to achieve success in sponsored research.

Relationship management. Last, since academic papers usually take months to years to publish, it is always good to keep a close relationship with the sponsor for the long term. This is extremely important for iterations and revisions of the work, based on comments received from reviewers. And it is also possible this way to create new sponsored research opportunities in the future.

My sponsored research experience has given me a better understanding of the focus of industry work related to data analytics involving Financial Services, Marketing and Technology, and how I can shape my future research in ways that will allow me to create value as an applied scientist. Together with advising assistance from faculty members at SMU and CMU, my exposure and experience in academic and industry research has been solid.

Chapter 6. Conclusion

This dissertation was motivated by the technological innovations that are going on in the financial services industry today. I investigated interesting issues related to credit card rewards marketing, bank branch network and omni-channel consumer behavior, and spatiotemporal penetration of bitcoin. Through empirical analysis and data that were acquired in sponsored research projects, I assessed the efficacy of the indirect effects in the context of card reward marketing, which increase purchases by customers who are not from the bank that is running the promotions. I also found evidence for increases in customer transactions after new branches were opened, and an interesting customer migration pattern from alternative channels to online banking after branches were closed. Furthermore, I explored the global penetration pattern of bitcoin, and the effects of security and legal issues in this process.

My first essay contributes new theoretical knowledge on loyalty programs and price promotions by examining customer behavior in response to card-based partnership-driven promotions in financial services. My unique access to merchant and customer information allowed me to study a broad set of relevant variables, and compare the effectiveness of credit card programs that operate in different consumer segments. My research also offers new knowledge about credit card programs and paves the way forward for decision support in banks to understand credit card customer rewards and loyalty program behavior.

The second essay emphasizes the importance of investigating physical facility network changes and their impacts on consumer behavior, especially in complex omni-channel settings that are affected by technology disruption in the current financial services industry. This work provides insights into consumer behavior in response to bank branch network changes. It also complements studies on physical stores by adding insights on consumer behavior from the perspective of their closures. The results of this work provide strategic implications on branch network restructuring in support of omni-channel financial services strategy. It also has implications for firms with omni-channel service delivery systems in other industries.

Essay 3 studies the global penetration of bitcoin from a spatial and temporal perspective by using the trading transaction data at a major exchange platform. I apply spatial econometrics and spatiotemporal analytics to discover spatial and temporal patterns. This allows me to contribute knowledge about how bitcoin is diffusing globally, and how security of the cryptocurrency plays a role in this process. This is an interesting question for research institutions as well as a potentially important problem for firms, especially at the early phase of development of bitcoin around the world. The study also contributes to future research on geospatial studies in financial services.

My dissertation essays combine big data techniques with econometric modelling to conduct fusion analytics for business policy research in the financial services industry. I employ multiple methods in my dissertation work. To consolidate data from multiple sources in Essay 1, I leverage *screen-scraping* with various software tools and a *fuzzy matching algorithm*. I use *propensity score matching* to resolve endogeneity issues with branch network changes, and a *difference-in-differences* model to deal with staggered and repeated branch openings and closures in Essay 2. I use spatial and temporal analytics in Essay 3 and conduct a geography-based spatiotemporal study on bitcoin penetration. The results create insights to address how technological innovations are reshaping the financial services sector and how banks can use data analytics for informed decision-making.

There are several limitations though. For example, the first essay has identified one type of indirect effect, and a natural inquiry related to another type of indirect effect is not well addressed due to unavailability of historical data. The data limitations, which is a common problem in quantitative empirical research, have also led to difficulties in the econometric modeling and estimations. The merchant data from an online dining services aggregator in Essay 1 was from a single point in time. Also, the card promotions drawn from bank websites tended to cover only longer-term partnerships with retailers, and ad hoc offers were not included. Last, the difficulty to generalize the results in all contexts is another limitation of this dissertation. All the three essays focus on the financial services industry, so the insights I achieve will be useful for financial institutions. The findings will be harder to be applied in other industries, restricting me from building more generalized knowledge about customer behavior. Another limitation involves the data from a single bank in Essay 1 and Essay 2. More generalized insights on consumer behavior will require data from more banks with different demographics and banking profiles.

My future research will establish firmer theoretical foundations for credit card-based promotions, customer omni-channel banking behavior when branch network changes occur, and the effects of bitcoin security threats relative to its global penetration. I will expand my research by exploring additional theory-driven consumer behavior issues. I also plan to implement other methodologies including Natural Language Processing and Sentiment Analysis in Machine Learning, and combine them with econometric modelling to tame business data for theory-driven causal inference analysis. Moreover, I will explore other opportunities around the high-level theme of my work, Financial Information Systems and Technology (FIST) and fintech (financial technologies), and investigate business problems characterized by extensive use of IT and seek to produce useful insights on customer behavior and managerial implications for financial institutions that pursue competitive advantage and a leading brand image for technological innovation in the financial services industry.

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Appendix A. Indirect Effect in Credit Card Rewards Marketing: The Impacts of Cards in Bank-Merchant Partnerships

Figure A1. Timeline of Card, Loyalty and Related Technological Evolution

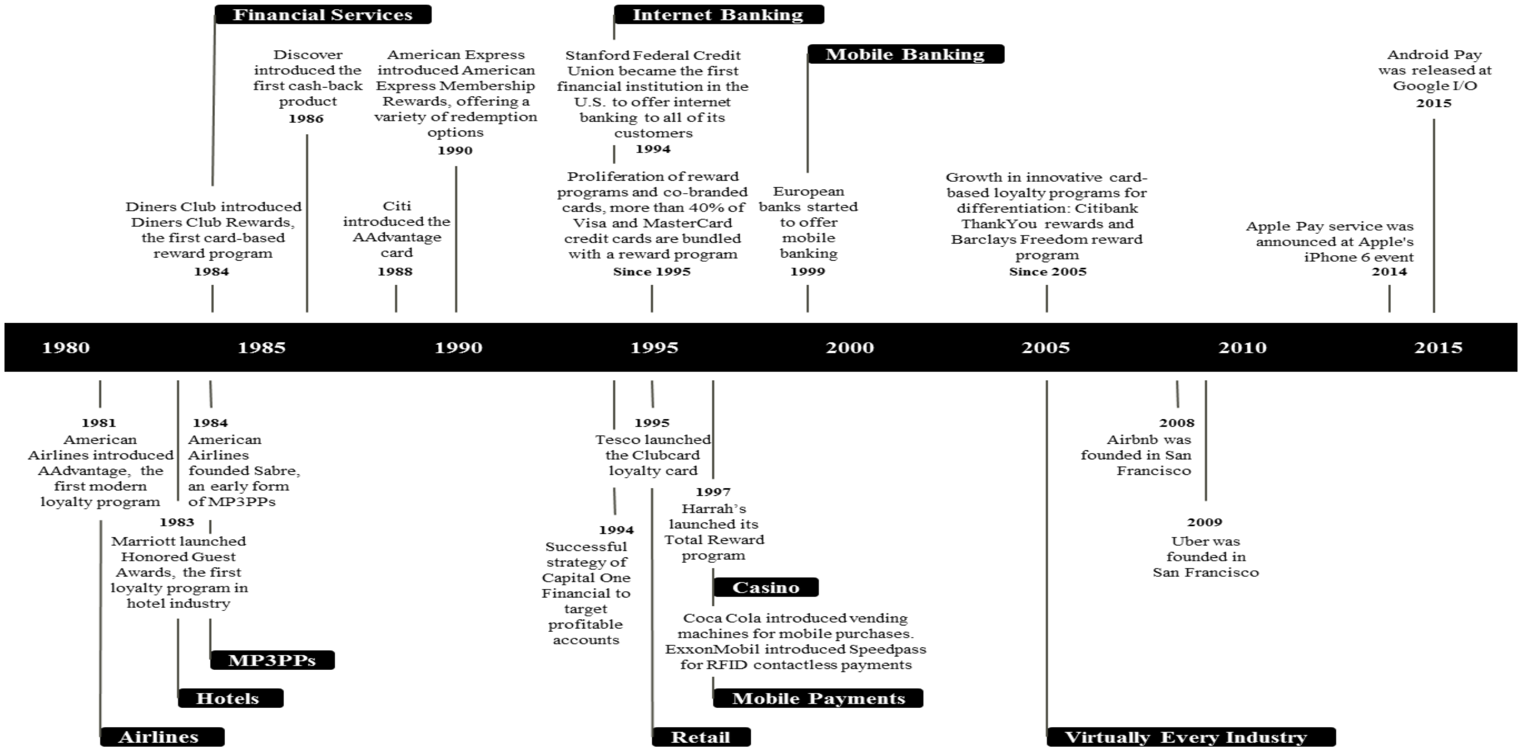
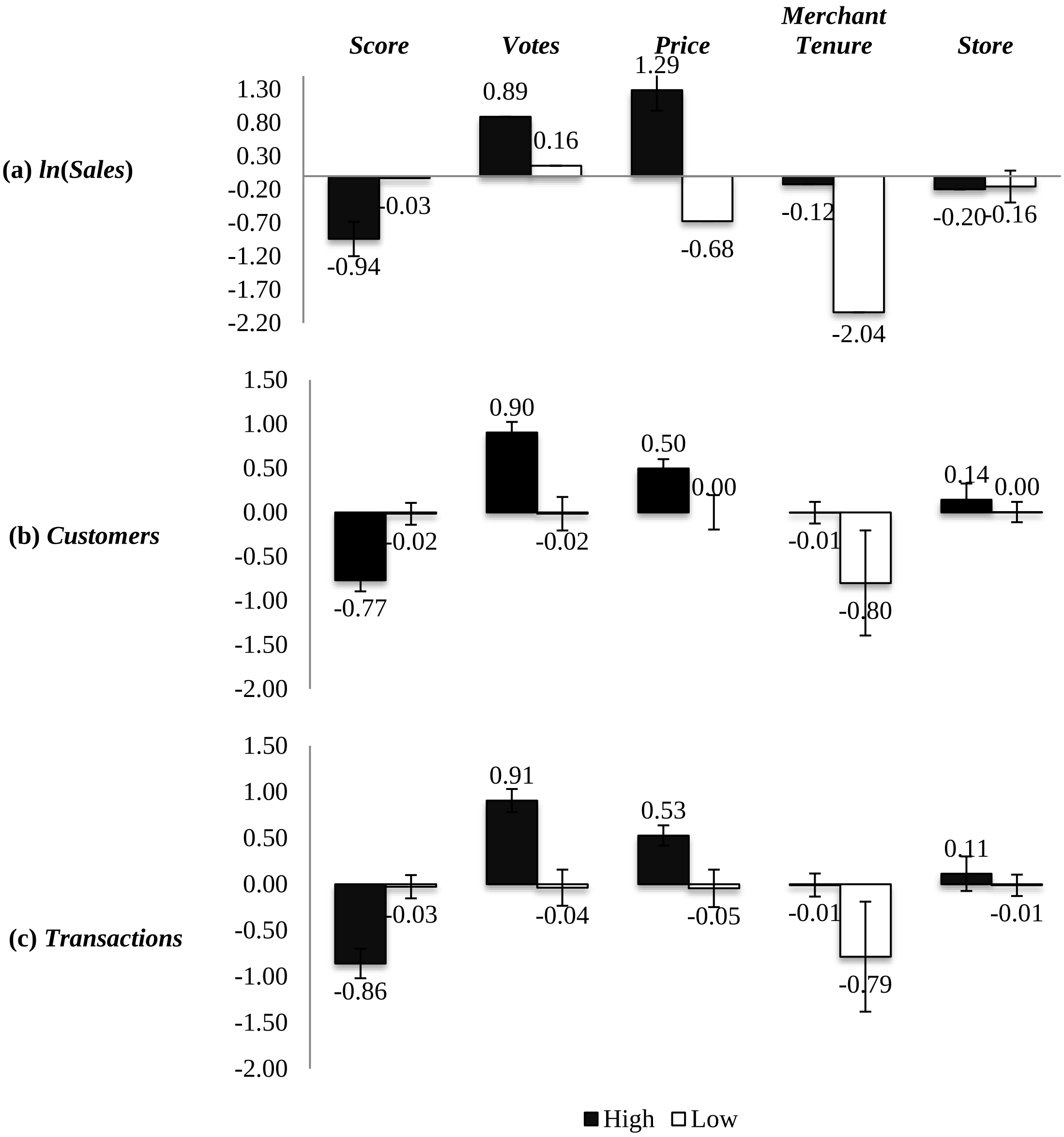


Table A1. Results for Promotion Size

VARIABLES	MERCHANT-LEVEL			CUSTOMER-LEVEL	
	***ln*(*Sales*)**	***Cust***	***Trans***	***Purchase***	***Trans***
Intercept	-7.20*** (1.831)	-1.37 (1.160)	-16.33 (16.243)	-10.63*** (1.050)	-2.11* (1.187)
PartnerBk: 10% Discount	-0.70*** (0.265)	-0.19 (1.152)	-0.44*** (0.106)	-0.31*** (0.055)	-0.15 (0.156)
PartnerBk: 15% Discount	0.46 (0.437)	0.86*** (0.291)	0.21* (0.112)	0.14* (0.079)	0.74** (0.301)
PartnerBk: 18% Discount	-1.33 (1.010)	-3.35*** (0.570)	-2.76*** (0.625)	-2.77*** (0.714)	-2.81*** (0.582)
PartnerBk: 20% Discount	-0.12 (0.610)	0.18 (0.348)	0.57*** (0.102)	0.66*** (0.055)	0.07 (0.358)
PartnerBk: Other Promo	0.65 (0.499)	0.43 (0.363)	0.95*** (0.127)	1.01*** (0.094)	0.39 (0.385)
PartnerBk: Rebate	0.41 (0.385)	1.27*** (0.250)	1.70*** (0.101)	1.93*** (0.046)	1.30*** (0.258)
PartnerBk: Reward	0.13 (0.362)	0.10 (0.220)	-0.13 (0.100)	-0.05 (0.048)	0.05 (0.225)
Obs.	508	508	5,068,316	5,068,316	508

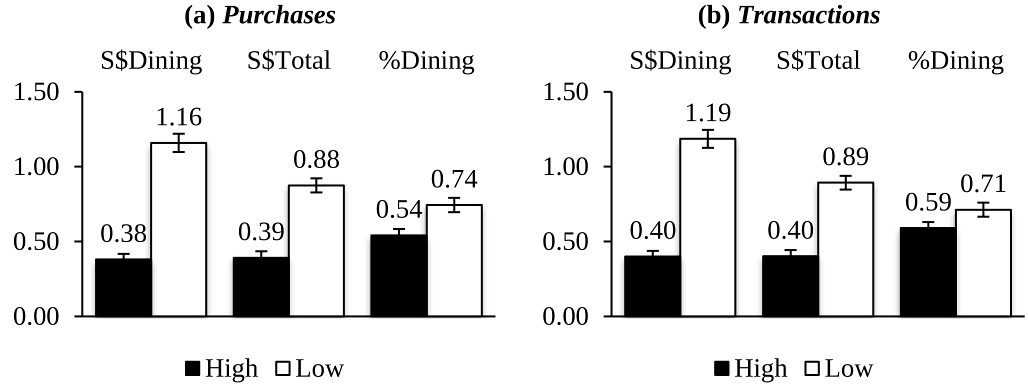
Notes. To examine the effects of different sizes and types of promotions, we separated the partnership indicator into specific offers: for discounts, cash rebates, rewards and other promotion types (one-paid-one-free, complementary goods). Following our prior methods sequence, we report results in Table A1. In price promotions, a 15% discount had the strongest impact on merchant sales, customer traffic and transactions ($\beta_{PartnerBk}$ = 0.94, $p < 0.05$ for *ln*(*Sales*); $\beta_{PartnerBk}$ = 1.07, $p < 0.01$ for *Cust;* $\beta_{PartnerBk}$ = 1.04, $p < 0.01$ for *Trans*). Lower or higher discounts showed weak effects on sales, traffic and transactions. There was more evidence of market responses to other promotion types, such as rewards and cash rebates than price discounts. *Discount* = merchandise discount. Std. errs. in parens. OLS used for *ln(Sales)*; neg. bin. used for *Cust* and *Trans*; logit used for *Purchase*. Poisson model estimated for robustness. Control var. estimates suppressed. Signif. * = $p < 0.10$; ** = $p < 0.05$; *** = $p < 0.01$.

Figure A2. Merchant Segment Results



Note. We conducted segment subsampling based on merchant scores, votes, price levels, tenure and stores. We divided the dataset by the medians of the five variables, and estimated the merchant-level model using the sub-samples. The effects of card-based partnerships on merchant sales, traffic and transactions for different segments are shown next. (See A2.) The results show that card-based partnerships with merchants that had higher votes were likely to have had higher gains in merchant sales (Figure A2a, in log form), more customers (Figure A2b), and a larger number of transactions (Figure A2c). Pricier merchants also showed higher profitability and customer attraction capabilities than merchants who offered their products and services at lower-price levels. The results of segmentation analysis on score, merchant tenure and stores were negative, though the merchant partners that had lower scores, higher tenure and higher number of stores were better off.

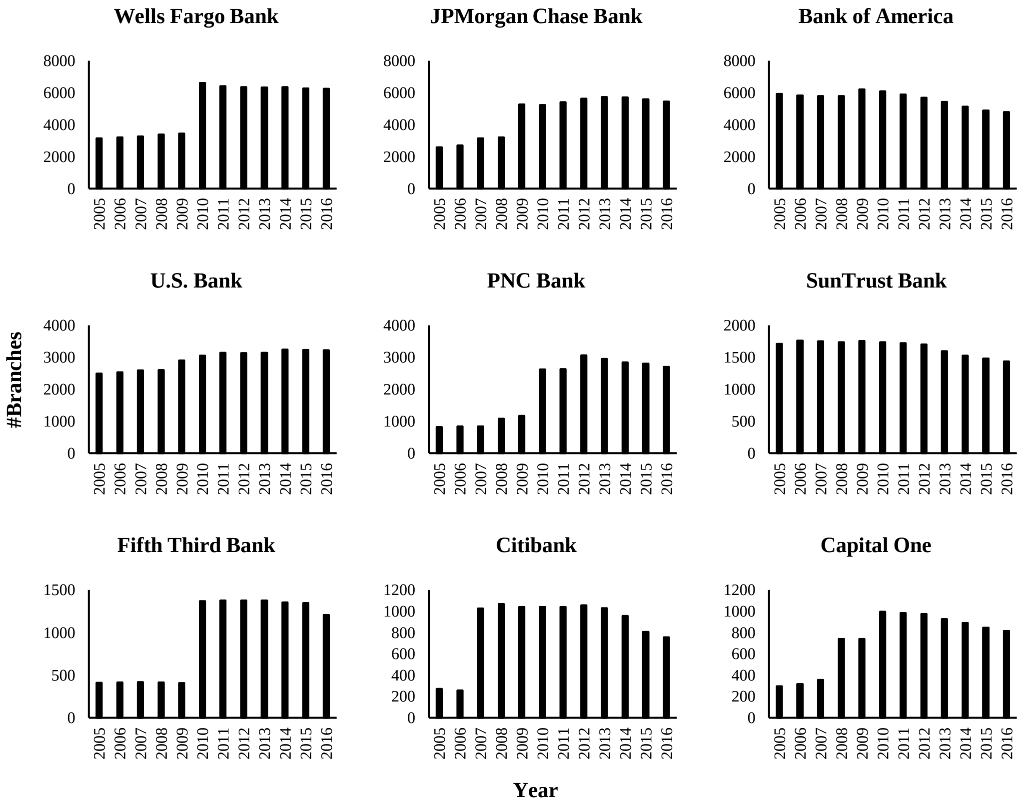
Figure A3. Customer Segment Results



Note. We looked into customer segments to explore the different effects of card promotions among customer groups. To understand consumer spending behavior, we divided the sample based on customers' average monthly spend in the business sector and on all other industry sectors, as well as the spend percentage on the targeted business sector. These kinds of data were all available to us in anonymized form, and reflect the kinds of detailed information that makes big data analytics so interesting for understanding consumer behavior in retail financial services. We estimated the customer-level model using the subsamples, and show the between-groups results in Figure A3. The dark bars represent heavy spenders and light bars light spenders. The results based on the three measures consistently show that heavy spenders were less likely to react to credit card promotions, while the offers were more attractive to light spenders. This may have been due to different price sensitivities across customer groups, based on their experience and preferences.

Appendix B. When the Bank Comes to You: Branch Network and Customer Omni-Channel Banking Behavior

Figure B1. Branch Networks of Leading U.S. Commercial Banks

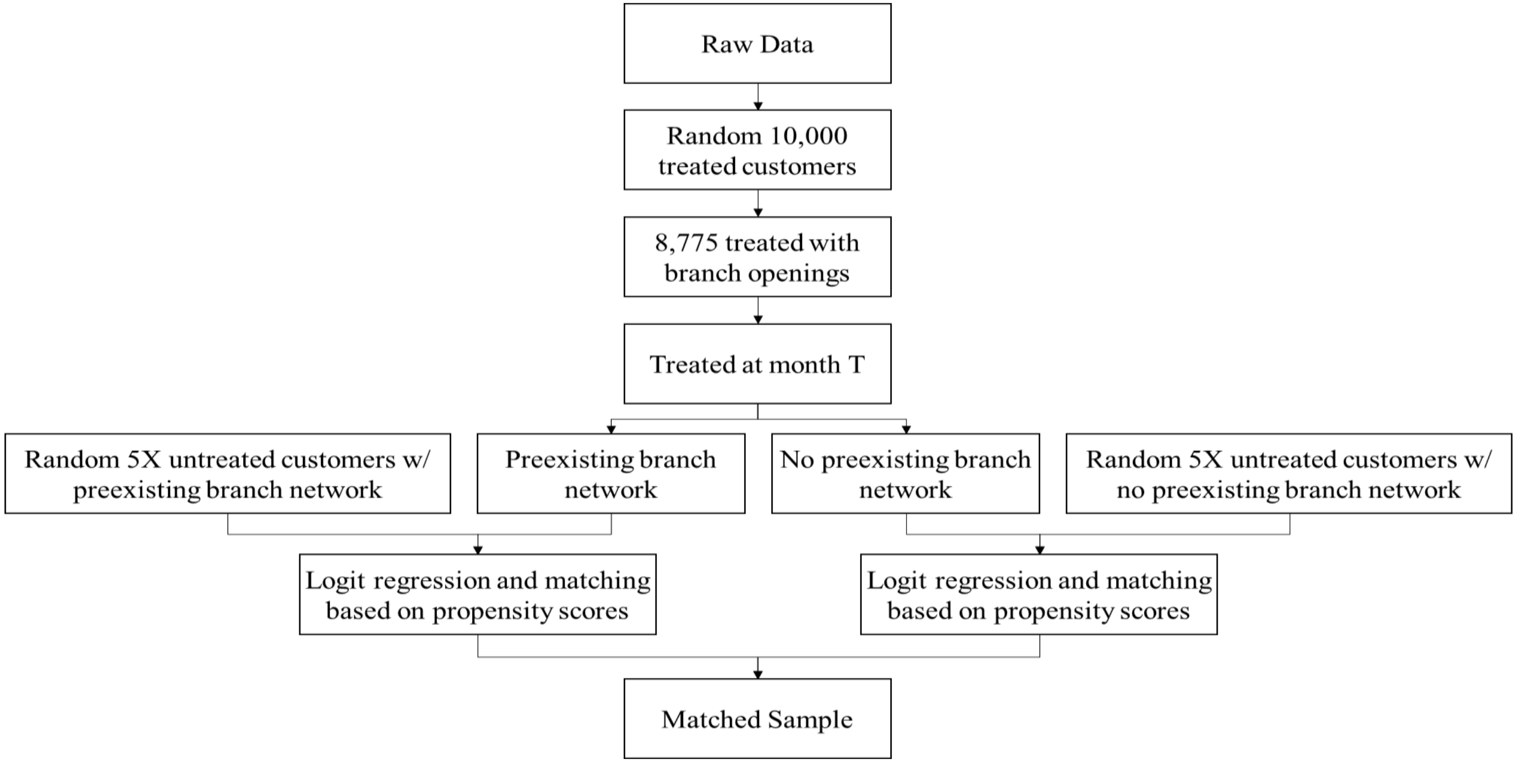


Data Source: Federal Deposit Insurance Corporation (FDIC)

Note. The U.S. banking industry was hit tremendously by the 2008 financial crisis and has operated since then under strict regulatory restrictions that curtail most banks from growing rapidly. The average efficiency ratio[10] of U.S. banks is close to 60% (BankRegData 2016)—much higher than the 40% to 50% ratio for typical Asian banks (The Asian Banker 2015). One reason for the high cost of retail banking is branch stores, which require substantial capital investment in physical operations and labor to set up and maintain. According to the CEB TowerGroup (2013), the average transaction costs of branches are approximately 20 times higher than those of mobile banking and 40 times higher than those of online banking. Thus, due to the current shift of consumer behavior in omni-channel financial services, banks have great opportunities to reduce operational costs and improve efficiency ratios by transforming branch networks and migrating transactions to digital channels (Mckinsey 2014). As Figure B1 shows, following the substantial bank consolidation and merger activities after the U.S. financial crisis, large banks, including Wells Fargo Bank and Bank of America, began to shut down more of their branches in 2010. This trend continued beyond 2012, as digital banking became more and more popular. In particular, Bank of America closed about 300 branches in 2013, followed by another 148 in 2014. Overall, banks in the U.S. shut down 2,599 branches and opened 1,137 in 2014, resulting to a net decline of 1,462 (1.5%) branches (CNBC 2014). Meanwhile, banks are experimenting with new branch models. They have made efforts to further reduce operational costs by retaining the flagship branches to showcase their featured products and improve their consultative services, while setting up many more-compact stores that have fewer tellers and more self-service kiosks for routine transactions.

[10] Efficiency Ratio = Operating Expenses / Revenue, which measures how well a company uses its assets and liabilities to generate revenue. A lower percentage is better, representing a company's capability to produce equivalent earnings with lower expenses.

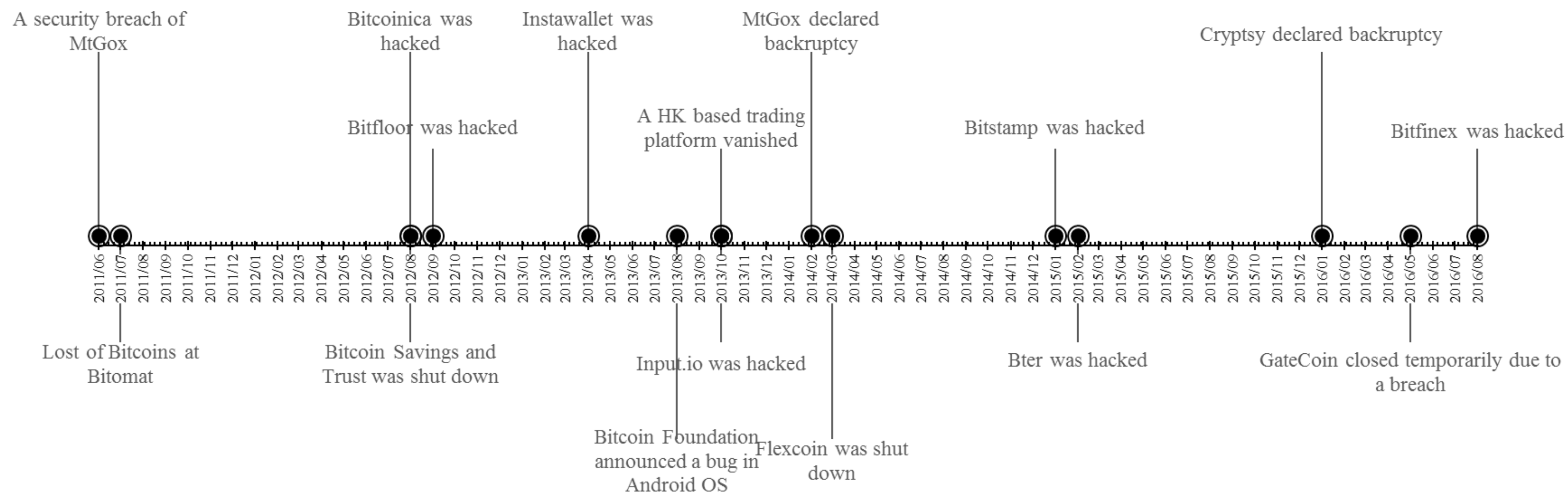
Figure B2. Propensity Score Matching Process



Note. The figure depicts detailed steps of matching for branch openings. A similar method is applied for matching branch closures. Based on each time point and whether there were prior established branch networks of the bank within the customer's residential zipcode location, we randomly select a control group, in which customers experienced no branch openings or closures throughout the study period but have the same local branch networks of the bank as those in the treated group. The number of customers in the control group is five times that of the treated group. Control variables including the average transaction and account data within six months prior to the treatment for each customer are acquired and used to estimate a logit model at the individual level. Based on the predicted propensity scores, we match one treated customer with one customer from the control group using the nearest neighbor (NN) algorithm and with no replacement, and we create a final sample that consists of 25,727 customers for further analysis.

Appendix C. Bitcoin's Global Penetration as A Spatiotemporal Effect of Security Events

Figure C1. A Brief History of Bitcoin Exchange Theft and Shutdowns



Notes. The sources for the data are 99Bitcoins.com and Wikipedia (2017)

Table C1. Variables, Definitions, and Data Sources

VARIABLE	DEFINITION	DATA SOURCE
Transactions	Daily buy-sell trade transactions of a country, date-stamped.	Mt.Gox
Date	Date of a bitcoin's trade transaction.	Mt.Gox
BTCATMs	Number of Bitcoin ATMs installed in a country for our data.	Coin ATM Radar
Inflation	Country inflation rate, last change in annual *consumer price index*.	World Bank
ShadEcon%	Size of shadow economy of country, estimated as a % of its GDP.	Elgin and Oztunali (2012)
AvgRemit$	Average USD remittance amount for a country.	World Bank
MIPenetrRate	Technology penetration in a country, measured by average of *mobile and Internet* (*MI*) subscriptions, per 100 people.	World Bank
R&D	Research and development expenses as a % of GDP in a country.	World Bank
Crises	Number of financial crises in a country between 1970 to 2011.	IMF
Restrictions	Number of bitcoin restrictions in a country that have been reported.	IMF
LegalStatus	Bitcoin legality in a country, for whether it is permissive and assenting, contentious and prone to disputes, hostile to bitcoin, or has no status.	BitLegal.com

Notes. Additional regulatory details, including tbasic transaction rights, taxation, and other regulation and official guidance. Other information was provided by BitLegal.com. We used four basic *LegalStatus* bitcoin environment variables in our model: permissive (*Open*), contentious (*Warnings*), hostile (*Hostile*), and no designated status (*Unknown*). We took logs of the *i*ndependent variables *Transactions* and Avg*Remits* for model estimation to resolve their right-skewed distributions.