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Decision modeling and empirical analysis of mobile financial services

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by

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Abstract

The past twenty years have been a time of many new technological developments, changing business practices, and interesting innovations in the *financial information system (IS) and technology* landscape. As the financial services industry has been undergoing the digital transformation, the emergence of *mobile financial services* has been changing the way that customers pay for goods and services purchases and interact with financial institutions. This dissertation seeks to understand the evolution of the *mobile payments* technology ecosystem and how firms make mobile payments investment decisions under uncertainty, as well as examines the influence of *mobile banking* on customer behavior and financial decision-making.

Essay 1 examines recent changes in the payment sector by extending the research on *technology ecosystems and paths of influence* analysis for how mobile payments technology innovations arise and evolve. Three simple building blocks, *technology components*, *technology-based services*, and the *technology-supported infrastructures*, provide foundations for the related digital businesses. I focus on two key elements: (1) modeling the impacts of competition and cooperation on different forms of innovations in the aforementioned building blocks; and (2) representing the role that regulatory forces play in driving or delaying innovation. I retrospectively analyze the past

two decades of innovations in the mobile payments space, and identify the industry-specific patterns of innovation that have occurred, suggesting how they have been affected by competition, cooperation and regulation.

Innovations involving IT provide potentially valuable investment opportunities for industry and government organizations. Significant uncertainties are associated with decision-making for IT investment though. Essay 2 investigates a firm's mobile payment technology investment decision-making when it faces significant technological risks and market uncertainties. I propose a new option-based stochastic valuation modeling approach for mobile payment technology investment under uncertainty. I analyze a mobile payment system infrastructure investment on the part of a start-up, and report on several sensitivity analyses and the use of least-squares Monte Carlo valuation to demonstrate some useful management findings.

Essay 3 examines the impact of the mobile channel on customer services demand across banking digital channels, and investigates how the use of the mobile channel influences customer financial decision-making. My findings suggest that the use of the mobile channel increases customer demand for digital services. The mobile phone channel serves as a complement to the PC channel, and the tablet channel substitutes for the PC channel, and the mobile phone channel and the tablet channel are complementary. In addition, my analysis indicates that customers acquire more information for financial decision-making following the use of the mobile channel. Compared to the PC-only users, mobile phone and tablet users are less likely to incur overdraft and credit card penalty fees. This study has implications for banks' managers related to the design and management of service delivery channels.

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1 Introduction

The history of the financial services industry has witnessed several waves of innovations for products and services delivery that have changed the ways customers interact with financial institutions. Advances in *information communication* and *technology* (ICT) have played an important role in initiating, driving and shaping these innovations (Hatzakis et al. 2010). As smartphones and tablets have been widely adopted and mobile apps have come into ubiquitous use, mobile devices have increasingly become new tools that consumers use for banking, payments, budgeting, and shopping. *Mobile financial services* include *mobile banking* that allows customers to obtain financial account information and conduct transactions with their financial institutions, and *mobile payments* (*m-payments*) that allow consumers to make payments, transfer money, or pay for goods and services. According to the survey conducted by Federal Reserve Board (2015) in 2014 in the U.S., 33% of all mobile phone owners have used mobile banking, while 17% have made an m-payment.

Since the 1950s and 1960s, the automation of banking products and processes by computers and through networks has led to improvements in the efficiency and effectiveness of financial intermediation-related activities in the economy (Montgomery 2012). Although the use of mobile financial services has increased rapidly in the past years, innovations in mobile payments are relatively invisible to consumers and industry practitioners. After 2011, companies and partnerships such as Square, Softcard, Google, PayPal, and Apple expanded their efforts to create and bring m-payments service innovations, built upon *near-field communication* (NFC) contactless chips, cloud servers and third party apps, to the marketplace.

Investments in m-payments technology innovations have offered high potential benefits (Etherington 2013), but significant uncertainties have also been associated with m-payments investment decisions (Liu et al. 2015b). The investments involve intensive network development that will take a long time to implement and achieve network effects. In addition, various cross-industry stakeholders with distinct organizational backgrounds, operational models, IT capabilities, and business goals will employ different investment strategies. Furthermore, there is no clear regulatory direction, ownership of the customer relationship, and technology standard for m-payments yet, nor an effective revenue-sharing model (Kauffman et al. 2015b). These uncertainties make *decision-making under uncertainty* (Dixit and Pindyck 1994) a useful theoretical perspective for evaluating a firm's flexibility to choose an appropriate time to invest, as decision-relevant information arrives and uncertainties are resolved over time.

Before the 1970s, customers experienced the branch network of a bank as a single touchpoint. But after the successful adoption and diffusion of automatic teller machines (ATM) and Internet banking in the 1990s and 2000s, customers became used to interacting with banks' self-service channels at lower transaction costs for their everyday financial service needs. The adoption of self-service channels has reduced banks' costs, reallocated demand for services across multiple channels, and increased customer profitability and loyalty (Xue et al. 2011). In the 2010s, major banks launched mobile banking channels, providing several kinds of competitive advantage, such as better security, easier access, various apps for smartphones and tablets, and location-based services. Customers have started to take advantage of the multi-channel approach but the multiple channels of the banks are acting independently.

Financial institutions are attracted to the omni-channel strategy and are moving to embrace mobile channels for transaction migration, online interactivity, and payment solutions, so customers experience banking services as a unified whole with a complete set of services, instead of a single channel with limited services capabilities within a bank (Broeders and Khanna 2015). Meanwhile, large banks are scaling back their physical channels by shrinking their branch and ATM networks and shifting to digital channels. For example, in the two years to 2015, Bank of America steadily closed about 10% of its branches and reduced about 2% of its non-bank-located ATMs (Egan 2015). Despite the advanced functionalities provided by mobile banking services, the customer's most common use of the mobile channel has been to check their account balance and recent activities, and to transfer money between their own accounts (Federal Reserve Board 2015). One of main reasons people decided not to use a mobile channel was that their financial needs were largely met by existing self-service channels (e.g., ATM and Internet banking) and full-service channels (e.g., branches and call centers). The limited size of most mobile phone screens has also restricted the usefulness of the mobile channel (Ghose et al. 2013, Kim et al. 2011).

This dissertation contains three essays that examine the impact of mobile financial services innovations on firm's technology investment decision-making and customer behavior in omni-channel banking services.

Essay 1 examines recent changes in the payment sector in financial services, specifically related to m-payments that enable new channels for consumer payments for goods and services purchases, and other forms of economic exchange. I extend the *technology ecosystems* and *paths of influence* analysis for how industry-centered technology innovations arise and evolve. I explore the extent to which the m-payment innovations can be understood through the lens of several simple building blocks, including *technology components*, *technology-based services*, and the *technology-supported infrastructures* that provide foundations for the related digital businesses. I focus on two key elements: (1) modeling the impacts of competition and cooperation on different forms of innovations in the aforementioned building blocks; and (2) representing the role that regulatory forces play in driving or delaying innovation in the larger scope of my modeling approach. I retrospectively analyze the past two decades of innovations in the m-payments space. The results identify industry-specific patterns of innovation that have occurred, and suggest how m-payments innovations have been affected by competition, cooperation and regulation.

Essay 2 proposes a new *option-based stochastic valuation modeling approach* for m-payments technology investment under uncertainty that incorporates a mean reversion process to capture cost and benefit flow variations over time. I analyzed the infrastructure investment of the Square mobile payment system on the part of a start-up. The analysis supported the evaluation of m-payments technology investment under uncertainty, and I was able to offer some illustrations about the kinds of managerial insights that can be obtained. I also report on several extensions that demonstrate how the creation of useful management findings can be supplemented with project value sensitivity analysis and simulation-based least-squares Monte Carlo valuation. The findings are useful to assess the investment timing of m-payments technology.

Essay 3 examines the relationship among the mobile phone, tablet and PC banking services channels, and assesses how the use of the mobile channel influences customer financial decision-making. I acquired access to a large-scale dataset of customer-level transactions from a financial institution in the U.S. for this study. My findings suggest that the use of the mobile channel increases customer demand for digital services. The mobile phone channel serves as a complement to the PC channel, and the tablet channel substitutes for the PC channel, and the mobile phone channel and the tablet channel are complementary. So banks can understand the customer channel usage pattern, and target the customer segments that are more active and profitable. In addition, my results indicate that customers acquire more information for financial decision-making following the use of the mobile channel. Compared to the PC-only users, mobile phone and tablet users are less likely to incur overdraft and credit card penalty fees. This essay provides insights for bank managers related to the design and management of service delivery channels.

The remainder of this dissertation is laid out as follows. Chapter 2 proposes the concept of a financial IS and technology ecosystem to examine recent changes in the payments sector. Chapter 3 develops a stochastic decision-making model of IT investment value under uncertainty, and presents my analysis of an m-payments sector case. Chapter 4 presents my empirical analysis of the impact of the mobile channel in omni-channel banking services. Chapter 5 concludes the dissertation and discusses limitations and future research.

2 Understanding the Evolution of the Mobile Payments Technology Ecosystem

2.1 Introduction

The past twenty years from 1994 to 2014 have been a period of high innovation in the development of payments technologies and solutions. The first big wave of innovations emerged when Microsoft attempted to acquire Intuit to enter the Internet banking sector in 1994 (Fisher 1994). There was an intense period of experimentation that occurred in parallel with Microsoft's and other firms' investigation of electronic bill payment and presentment, and these things supported the growth of industry-wide interest in online payments. The subsequent rise of the online payment services provider, PayPal, and the emergence of online brokers further stimulated the growth of non-cash payments. The growth of money market funds and other investment vehicles in the *shadow banking system* – non-bank financial intermediaries that do not operate subject to the regulations of depository institutions – along with other problems with asset-backed securities, derivatives and ineffective accounting practices contributed to the financial crash in 2008 and the subsequent global financial crisis. After the market downturn years of 2008–2011, companies such as Square, Softcard, Google, PayPal, and Apple Pay expanded their efforts to create and bring m-payments technology and service innovations to the marketplace.

A formal definition of an *m-payment* is any payment in which some kind of a mobile device is used to initiate, authorize and confirm an exchange of financial value in return for goods and services (Karnouskos 2004). Conceptually, an m-payment is a new form of value transfer, similar to other payment instruments that consumers can use, but that relies more on the advanced features of mobile devices and the *tokenization* of a consumer's financial credentials (Pandy and Crowe 2014).

This study analyzes the evolution of mobile payments technology innovations in the past two decades with respect to technological changes, market competition and cooperation, and government regulation.[1] Financial services professionals and analysts have had a difficult time to predict the arrival of new technological developments, estimate the extent of their impacts, and forecast their future status. Hence, there continues to be a strong need to understand how highly impactful technology-based financial innovations were initiated and developed, and then evolved over time. I address two fundamental research questions. What are the major forces that drive the evolution of technology-based innovations, such as mobile payments, in financial services? What are the roles played by market competition, cooperation, and regulation in shaping the observed paths of evolution and the changing pace of technological transitions?

To answer these questions, I propose a financial IS and technology ecosystem approach that extends Adomavicius et al.'s (2008a) *technology ecosystem paths of influence model*. I consider the issues that financial services decision-makers and analysts face, as they think through what will drive the major changes in the technology ecosystem in the financial IS and technology landscape. I categorize innovations in three levels: the technology component level, the technology-based service level, and

[1] Two earlier articles in the present research stream were published in *Electronic Commerce Research and Applications* (Liu et al. 2015b) and *Technological Forecasting and Social Change* (Kauffman et al. 2015a). Earlier versions were presented at the 2013 Innovation for Financial Services Conference in Singapore and the 2014 Pacific Asia Conference on Information Systems in Chengdu, China.

the technology-supported business infrastructure level.[2] The technology ecosystem perspective only considers technology supply-side forces for innovations though. In this research, I offer an extended view that incorporates market-side competition, co-operation and regulation among a range of stakeholders in financial services as important forces that jointly shape the evolution of technology innovations.

I incorporate the effects of competition, cooperation, and regulation as a means to explore technology evolution in the payments sector. This sector has a highly regulated yet competitive marketplace with extensive interactions among the innovators, adopters, and regulators. To understand the recent developments in services, the influence of related technology innovations, and the resulting structural changes in the payments industry, it is important to analyze the historical changes in the payments technology ecosystem.

I will argue that market competition, cooperation, and regulation act as key accelerators or decelerators of industry changes, while new m-payments innovation has the potential to transform it. Some accelerators include the adoption of co-opetition strategy by key stakeholders for business infrastructure innovation, new capabilities that arise from innovations in technology components, the outcome of differentiation strategies for new technology services innovations, and the emergence of new strategic thinking from high-tech firms that become financial institutions themselves. On the other hand, the decelerators arise from the defensive behavior of existing firms in the market, the increased complexity and uncertainty when multiple firms offer dif-

[2] Adomavicius et al. (2007, 2008a, 2008b) constructed three key building blocks, including components, products and applications, and infrastructures, and focused on the general IT landscape rather than the financial services sector, as is done here. I adapt their approach to emphasize the services innovation perspective instead of the product innovation perspective.

ferent technology solutions in the absence of regulatory guidance and technology standards, and a lack of understanding by investors who fund new and potentially high-risk ventures as to how technologies will evolve. These are likely to lead to market entry deterrence to prevent innovators from participating, and damage due to fierce competition that can impair the health of the payments sector in the financial services industry.

The ecosystem view recognizes multiple factors affecting the evolution of mobile payments technology innovations, and identifies several patterns behind the process by which one core technology for payment services seems to replace another over time. I connect technology evolution thinking to financial innovations, and propose a new perspective to master the complex relationship between them in the evolutionary process of technology-based financial innovation. The application of my extended analysis approach to m-payments technology evolution contributes to research in the domain of electronic and mobile payments. Unlike prior research, I focus on payments innovations from an evolutionary perspective, rather than a technical or a managerial perspective (Karnouskos et al. 2008). I collected data on key events that have occurred during the past two decades in the payments industry. I coded them, analyzed the underlying forces that drove their occurrence, and identified their evolutionary patterns. The results validate the need to consider market forces, in addition to technology forces (Zmud 1984).

2.2 Theoretical Background

This study draws upon several streams of research on technology innovation and financial services, technology ecosystems and paths of influence, and market competition, cooperation, and regulation.

2.2.1 Technology Innovation and Financial Services

There is a rich literature on technology innovation, including Kondratiev's (1925) innovation waves, Schumpeter's (1939) S-curve innovation cycles, Drucker's (2007) seven sources of innovation, and Rogers' (2010) diffusion of innovation. However, relatively little work has focused on categorizing different innovations and studying their interactions. Zmud (1982) first characterized the differences between new product and service innovations and process innovations. Robey (1986) then differentiated among three types of *organizational innovations*: new product or service innovations, administrative innovations, and technical innovations. Swanson (1994) proposed a tri-core model for IS innovations: innovations confined to the IS task; innovations supporting administration of the business; and innovations embedded in the core technology of the business. Lyytinen and Rose (2003) further considered base IT innovations, service innovations and system development innovations. Though these studies primarily offer an organizational instead of evolutionary view of innovations, they can be used as a basis for us to classify technology innovations at different levels.

Innovation in financial services has been recognized as an engine of economic growth, generating market gains for the innovators and adopters (Tufano 1989), improving welfare for society (Frame and White 2004), and leading to revolutionary changes in the structure of the financial market and institutions (Merton 1995). On the other hand, financial services innovations can be a double-edged sword – they have a veiled relationship with catastrophic events and financial crisis (Diaz-Rainey and Ibikunle 2012, Thakor 2012). Most studies on technology-based financial innovations have focused on their diffusion paths, the characteristics of adopters, and the consequences of innovations for firm profitability, social welfare and economic performance (Kavesh et al. 1978, Merton 1992b, Miller 1986). The literature rarely has concentrated on understanding the origins of innovations and how they evolve though (Lerner and Tufano 2011). My work attempts to fill this research gap by analyzing past innovations and prospectively assessing future innovations, where there are opportunities for firms to take advantage of investment and market opportunities.

2.2.2 Technology Ecosystem and Paths of Influence

How technologies evolve is an important research topic. Prior work suggests that *technology evolution* is a process of continual improvement in the performance of a technology through novel recombination and synthesis of existing technologies (Henderson and Clark 1990, Foster 1986). Sood et al. (2012) showed that technologies evolve along step functions with multiple crosses as the capabilities emerge, and there are huge spikes in performance after periods of long dormancy (Tellis 2008). I adopt path dependence (David 2007, Arthur 1994) and new growth (Romer 1994) thinking to understand the dynamic process of financial IS and technology evolution. The evolution of technology innovations can take various paths within a technology ecosystem, so understanding technological changes requires an integrated view of the continuous path that the change process traces over time (Boland et al. 2003).

Motivated by the lack of depth of insight available from Gartner's *hype cycle perspective* (Fenn et al. 2000), Adomavicius et al. (2007) first proposed a *technology ecosystem view* to represent temporal development of innovations associated with different clusters of technologies. They defined an *IT ecosystem* as a subset of ITs in the technology landscape that are interrelated to one another in a specific context of use (Adomavicius et al. 2008b). An ecosystem represents three distinct groups of technologies with specific *technology roles*: components, products and applications, and infrastructures. Driven by technological changes, innovations happen in different technology roles, resulting in cross-level effects – *paths of influence* (Adomavicius et al. 2008a). Adomavicius et al. (2012) validated the existence of cross-level effects and identified several patterns of technology relationships in the context of data on wireless networking, using econometric forecasts of the technology changes.

2.2.3 Firm Strategy and Market Regulation

The impact of market competition on technology innovation remains controversial among researchers (Sood et al. 2012). Does competition spur and speed up innovation, or does it block and slow down its evolution? Some positive effects have been identified in the literature. Given that technological innovations are critical for the survival and success of firms (Anderson et al. 2006, Banker et al. 1993), and that a firm's returns from innovation at the margin are significantly larger in an oligopolistic than a monopolistic market (Fellner 1961, Scherer 1967), large firms tend to devote a massive amount of time, equipment, money and personnel to technology innovation. Competitive pressure encourages new innovations and improvements in products and services. In addition, competitive necessity (Goh and Kauffman 2013) and compulsive sequences involving known and observed patterns of problem-solving that lead, step-by-step, to innovations (Rosenberg 1969) encourage firms to fully realize the benefits from innovations and trigger further breakthroughs that enhance their value. Furthermore, the strategic entry of firms that aim to pre-empt the market and the co-opetition strategy emphasizing cooperative alliances among rival firms will also spur the discovery of new opportunities and capabilities, as well as promote faster progress with technological change and service improvement (Brandenberger and Nalebuff 1996, Teece 1992).

Negative effects of competition have been documented too. Several competitive strategies will likely result in the deceleration of the development of technology innovations, and increase uncertainty related to technology investments (Dixit and Pindyck 1994, Mason and Weeds 2010). Examples include: an incumbent's defensive strategy in response to the innovations brought by new market entrants (Katz and Shapiro 1987); the emergence of multiple technology solutions and standards that increase the market uncertainty (Kauffman and Li 2005); and cooperative defense and resistance when innovations generate new technical problems causing potential risks or change the market's competitive *status quo* (Ferrier et al. 1999). In addition, the leading firms in the industry often possess a large amount of resources, which put them at an advantage for being successful with innovations. This often allows them to continue to grow and dominate the next generation of technology platforms, and has resulted in monopolistic market power that tends to deflect and de-power the efforts and incentives of other innovators (Arrow 1962). However, a lot of real-world examples demonstrate that wealthy firms are not always able to maintain leadership, and sometimes they are even unable to survive the next generation of innovation (Tellis 2008). For example, leadership in the mobile phone market moved from Motorola, Blackberry and Nokia to Google, Apple and Samsung.

Regulation regarding competition policy, pricing, market entry, natural monopoly and public utilities also plays an important role in shaping technology and innovation evolution (Blind 2012, Stewart 2010). The impact of regulation on innovation and competitiveness in the market has attracted considerable research interest. Swann (2005) investigated a number of British companies and showed that regulation can either nourish or obstruct innovation activities. Prior studies also found a negative correlation between the intensity of product market regulations and the intensity of R&D expenditures in some countries (Bassanini and Ernst 2002). Stricter regulations seem to have had a negative influence on services innovation in certain industry (Prieger 2002). In the financial services sector, financial institutions are closely connected to consumer welfare, so regulators are extremely cautious about how disruptive technological innovations may change the market (Dewatripont and Tirole 1994). Silber (1983) analyzed financial innovations and showed that about 30% were induced by regulation. Going forward though, regulators may find it more and more difficult to keep up with the pace of technological innovation and market changes. When they do get a handle on it, it is likely that they will have lagged effects to slow down the pace of technology evolution and innovation (Stigler 1971). In some key sectors, regulators often caution market participants that technology innovations might create hidden dangers, or send misleading signals about the health of the market. Warren (2008) indicated that the inflexibility of financial regulations could hinder truly beneficial innovations. On the other hand, when regulation supports a technology standard in some way, or provides a roadmap for a specific technology innovation, market uncertainty will be diminished and its development will be accelerated.

2.3 Financial IS and Technology Ecosystem

I next introduce the technology ecosystem approach for analyzing the paths of influence for mobile payments technology evolution, and integrate it with the extended competition and regulatory analysis.

2.3.1 Modeling Concepts

Technology ecosystem. The *technology ecosystem model* proposed by Adomavicius et al. (2008a) emphasizes the nature of technology change and evolution in the underlying technologies themselves, a supple-side perspective. An *ecosystem* consists of a population of interrelated technologies with specific roles and overlapping hierarchies. These things represent a complex system of determinants for the evolutionary outcomes that are commonly observed in technology product and service settings. Rapid technology innovation and the uncertain outcomes associated with competition contribute to the difficulty of predicting future technology evolution.

Context of use. Following the concept of a technology ecosystem and considering the unique features of financial services, the idea of a *financial IS and technology ecosystem* ought to be considered. It includes a set of interdependent financial IS and technologies that work together in the operation and production of a specific financial service. To define such a financial IS and technology ecosystem requires the identification of a relevant set of technologies within a specific context of use though. For example, since I am interested in analyzing electronic payments solutions to deliver *electronic funds transfer* (EFT) services to customers, the related EFT technology ecosystem will then include technologies such as telecommunications, cyber security, credit cards, electronic banking kiosks, and so on.

Financial IS and technology innovation at three levels. Technology innovation will happen at three levels within a financial IS and technology ecosystem: the *component* level, the *service* level, and the *business infrastructure* level. Table 2.1 summarizes the definitions, descriptions and examples for such innovations at each level.

The difference between component and service innovations is that the former acts as a sub-unit or sub-system of the latter. Innovators recombine or integrate existing component innovations, or modules involving multiple components, into service innovations to address customers' needs. For example, credit cards originally were an innovation at the service level for many EFT services vendors. Credit cards also consist of a set of component innovations though, including: the magnetic stripe; Europay, MasterCard and VISA (EMV) chips; and connectivity with an automated clearing house (ACH) for transactions. As such, identifying the context of use and defining the scope of the financial IS and technology ecosystem should be an important first step.

The distinction between business infrastructure innovation and component innovation is that business infrastructure innovation creates the basis but is not necessary for the provision of services to customers. For example, market-wide *value-at-risk* (VAR)-based risk management tracking systems, which enable firms and regulators to oversee trading activity risks effectively, are must-have infrastructure capabilities, and one can hardly imagine any firm in the market operating without them today. Other examples of technology-supported business infrastructures in the EFT ecosystem include short message services (SMS) and email capabilities. They are not operationally necessary for *electronic bill payments* (EBP) and card-holder-initiated transactions, though they may be helpful for communication between customers and financial services providers for mutual informedness and account security.

Table 2.1. Three Levels of Financial IS and Technology Innovation

Innovation Levels	Definitions	Descriptions	Examples
Component	Technology innovations that create the most basic building blocks of financial services.	Technology innovations at this level are necessary for financial services to be offered and to perform their functions in ways that create a *service focus* and *customer centricity*.	The Internet, ATMs, and credit cards innovations in the EFT context. The Square "dongle" that makes it possible to use a mobile phone for credit and debit card transactions.
Service	Technology innovations that directly interact with customers, and provide access to a spectrum of financial services.	Technology innovations at this level include a *focal technology* innovation and *competing technology* innovations that may directly compete in the delivery of financial services.	Focal innovation: electronic bill payments (EBP) in online banking. Competing innovations: wire transfers, cardholder-initiated transactions, third-party money transfers, and electronic checks.
Business Infrastructure	Technology innovations that add value to the functionality or performance of financial services, and create a product or service delivery platform.	Technology innovations at this level create a basis for services provision, extend functionalities and provide other value-added capabilities and services to customers.	Short message services (SMS) and email capabilities for EFT. Electronic communication networks (ECNs) for electronic trading. Value-at-risk (VAR) metrics tracking systems for financial risk management.

Note: Even if various technology innovations (e.g., a PIN, a security token, a computer chip, etc.) seem to be at the component level for online banking, only certain innovations may be necessary in the EFT context (the Internet, ATMs, credit cards, etc.).

Paths of influence. Paths of influence are used to represent the impact of technology-based financial innovations across different levels in a financial IS and technology ecosystem. Technology innovation that happens at any level can affect the subsequent innovations across the other levels. For example, the success of the global adoption of smartphones and mobile apps has helped to drive the development of mobile financial services innovations, such as mobile banking, mobile payments, and peer-to-peer money transfers. This illustrates how a technology innovation at the component level – from feature phones to smartphones – can influence the development of new services technology innovations at other levels.

I will use *C*, *S*, and *I* to represent the present state of technology innovation at the *component level*, *service level*, and *business infrastructure level*. An asterisk (*) represents the future state of a technology innovation. In this way, I can analyze interdependencies among technology innovations over time, address the complexity of their relationships, and identify trends with how technology innovations evolve.

2.3.2 Impacts of Competition, Cooperation, and Regulation

A financial services ecosystem is affected by multiple factors related to technology, market, society, and institutions (Hekkert et al. 2007, Markard and Truffer 2008). As a result, modeling technology-driven paths of influence alone is insufficient to tell the full story. Including the impact of firm strategy and market regulation on technology innovation, a set of new artifacts that affect the technological changes is defined: competitive forces that are spurring or stalling innovations, and regulatory forces that are driving or delaying innovations. These forces often result in changes in both observable and unobservable facets of value from innovations, including profit, social welfare, expenses, beneficial network effects, and goodwill (Au and Kauffman 2008).

Innovation-spurring competition. *Innovation-spurring competition* influences the evolution of innovations in multiple ways. In an oligopolistic market, a number of competing firms invest in R&D, resulting in faster technology innovations and service performance improvement. A leading firm's efforts with innovation may create a basis for further breakthroughs in the related areas or facilitate faster and wider adoption of the innovation. Competition will encourage firms to pursue preemption or co-opetition strategies, creating new opportunities and capabilities in some important aspects of financial services.

Innovation-stalling competition. *Innovation-stalling competition* demonstrates the negative side of competition. To maintain market power and leadership, an established incumbent firm may employ a defensive strategy to prevent others from adopting, accessing or making use of a specific technological innovation, slowing down or even blocking the evolution of the innovation. With a differentiation strategy, competing firms tend to invest in different technology solutions, resulting in the appearance of multiple similar innovations in the market at almost the same time. Though differentiation increases new product and service variety, the lack of a recognized standard creates uncertainty and limits mass adoption of a specific innovation. In addition, high competitive pressures sometimes give firms an incentive to push immature technologies into the market, increasing the possibility of innovation failure and market risks. These all will negatively affect the adoption and diffusion of a truly valuable innovation.

Regulation-driven innovation. *Regulation-driven innovation* occurs when regulators set rules to ensure that firms achieve minimum revenues, and reduce their risks and compliance costs. They may try to motivate firms to enhance their productivity, avoid imitation and achieve innovation. Regulators may also wish to liberalize and privatize markets that have been dominated by public organizations. Hence, they may make decisions that unintentionally support the adoption of a specific kind of technology innovation, which potentially will result in the emergence of a future technology standard and lead to technology evolution (Blind 2012). These are likely to be by-products of working with industry leaders, so new services in an area of technology innovation become more valuable. Regulators are unlikely to consciously favor one technology over another, though it may be the case that they block some technology innovations from diffusing because they are viewed as being potentially damaging, or actually have damaged competitiveness, or amplified the risk associated with operating in a specific area of the market.

Regulation-delayed innovation. *Regulation-delayed innovation* occurs when the actions of regulators restrict cooperation between companies for R&D, and thus discourage innovation activities. Market entry regulations also put up barriers for innovators to enter a specific market. In addition, regulators' actions may change the conditions in the marketplace, on purpose or unintentionally, so it becomes unattractive for firms to adopt or use specific technological innovations (Aghion et al. 2005, Blind 2012). These post hoc regulatory restrictions lower the impetus for technological progress (Averch and Johnson 1962), limit innovation in financial services, and slow their implementation. Typically, the purpose of regulation is not to directly interfere with innovations and delay their development. Instead, it is to mitigate potential negative effects associated with disruptive technology innovation, and to ensure security, stability, efficiency, and fairness in the related marketplace.

2.4 Paths of Influence for Mobile Payments Technology

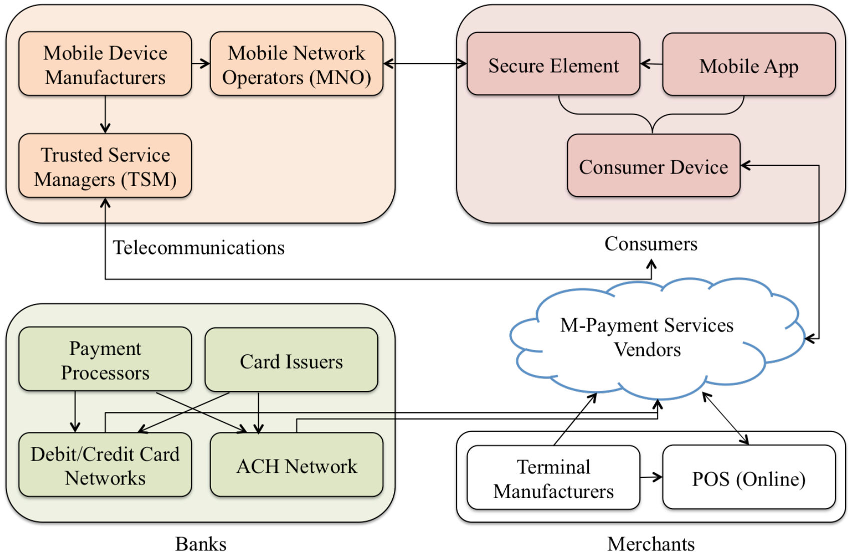
M-payments are widely viewed as the next revolution in payments to support store-based bricks-and-mortar selling. Huge potential benefits are associated with successful adoption for firms that are able to get the technology innovation right

(Etherington 2013). The investment and adoption decision-making for m-payments technologies involves significant uncertainties though. These consist of technological risks, changing consumer demand and expectations, competition in the marketplace, and ill-defined technology standards (Kauffman et al. 2013). Various technology solutions will emerge when industrial standards are not provided, generating uncertainty for potential adopters. In addition, the m-payments technology ecosystem demonstrates complexity in its structure, spanning multiple sectors, including banking, payments, telecoms and retailing. Its success thus also depends on the efficacy of collaboration among stakeholders in multiple related industries across the underlying innovation network. Such collaboration is typically very hard. All these contribute to the difficulty of m-payments investment and adoption decision- making. As a result, it is critically important for senior managers to understand the patterns of technological changes and the paths of innovation development. It will help them estimate the sustainability of certain innovations, and what is likely to be the future state of the m-payments market, and eventually to make the right investment decisions. I will next analyze the paths of influence for the m-payments technology ecosystem.

2.4.1 The M-Payments Technology Ecosystem

I first offer an overview of current mobile payments services and define the m-payments technology ecosystem. Figure 2.1 shows the generalized near field communication (NFC)-enabled m-payments technology platform that represents the most recent business model innovations, such as Softcard, Google Wallet, and Apple Pay (Contini et al. 2011).

Figure 2.1. The NFC-Enabled M-Payments Technology Platform



In this business model, each sector takes on different responsibilities. Mobile network operators (MNOs) and mobile device manufacturers equip the smartphones with a Secure Element (SE) and an NFC chip for safe memory and execution operations. Banks control the payment terminals and issue specialized credit, debit or prepaid cards. Merchants install new NFC-enabled *point-of-sale* (POS) terminals. And *trusted service managers* (TSMs) and gateway services providers transmit, process, and secure the transactions and provide additional services to merchants and consumers (de Reuver et al. 2015).

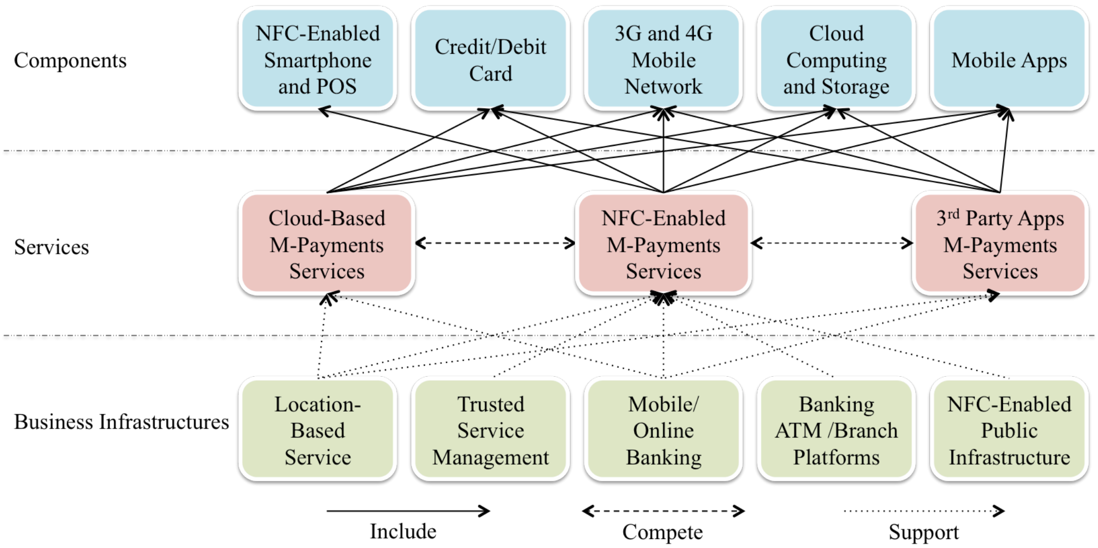
M-payments satisfy customers' cashless payment service demand, relying on the prevalence of mobile phones and the tokenization scheme. The tokenization of customers' payments credentials significantly reduces the risk of and impact from data breaches, so customers are better protected from fraud and other kinds of disruptions. There is a new regime for risk management that is possible with mobile payments, and an extension to the instantaneous credit provision capabilities of the standard credit card for merchants and customers through new devices. The digitalization of m-payments process, reduced financial risks and lower transaction costs will also support peer-to-peer payments among individuals, as the sharing economy expands.

Understanding the scope of the participants and the business process will help us to know what technology innovations are likely to influence the development of m-payment services, and how they will fit into my extended paths of influence model. Following the four steps offered by Adomavicius et al. (2007), I identify the related technology innovations occurring at three levels in the m-payments technology eco-system. Step 1 involves the identification of the focal innovation and context of use. Step 2 covers the identification of competing service innovations. Step 3 is for the identification of technology innovations at the component level. And finally Step 4 is for the identification of technology innovations at the business infrastructure level. Figure 2.2 illustrates the interrelationships among technology innovations at three levels – component, service, and business infrastructure – for m-payments. It serves as a basis for interpreting how the market has developed and how it will further evolve.

2.4.2 Paths of Influence Analysis for the M-Payments Technology Ecosystem

I next offer a first step toward an explanation of the technology evolution process in the m-payments ecosystem, by discussing my methods in greater detail. I collected information on when m-payments-related technology innovations occurred. My second step was to understand how competition and regulation add to our understanding of the evolutionary patterns, which I will explain shortly.

Figure 2.2. The Relationships among Mobile Payments Technology Innovations



Qualitative analysis method. Since the first m-payment service emerged in the late 1990s, a number of significant technological changes have occurred in the m-payments technology ecosystem. The development process has involved many different related technology innovations that occurred at the component, service, and business infrastructure levels. Hence, the ecosystem is an ideal setting to illustrate the nature of the changes that have occurred in the related financial IS and technologies. Also, the payments marketplace with intense competition, cooperation, and regulation among stakeholders, is ideal for me to map the analysis to the new constructs.

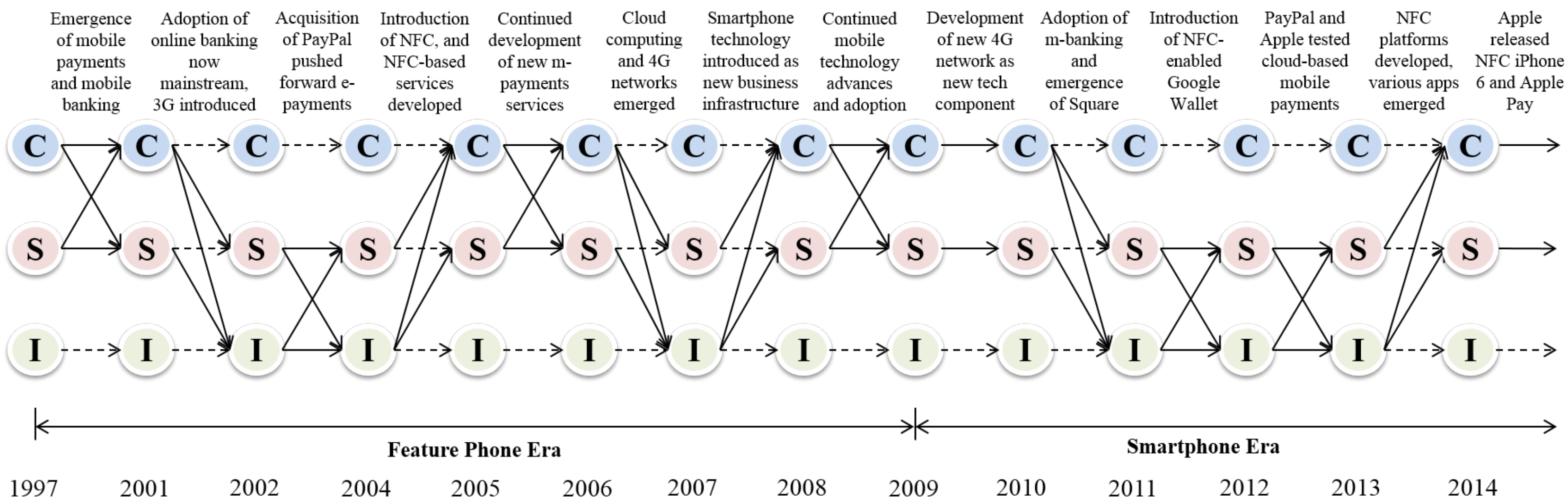
Given the complex structure of the m-payments ecosystem and limited sources of quantitative data, I adopted a qualitative analysis approach (Miles and Huberman 1994, Sarker et al. 2013, Strauss and Corbin 1998), following guidelines described by Hevner et al. (2004). I collected data involving m-payments technology-related events over eighteen years between 1997 and 2014. I used news and industry announcements, government reports and surveys, publicly-available historical documents, Internet search tools, and also interviews with industry practitioners. In total, I tracked innovations on approximately twenty related technologies in the m-payments technology ecosystem. The changes in m-payment technology and the associated events are reported in Appendix A, which are organized in chronological sequence. I applied the procedure for identifying an ecosystem, as described earlier, for different points in the timeline that my data cover. The coding and analysis procedure is similar to what is described in Kauffman et al. (2015a).

Paths of influence and patterns of evolution. I coded the events occurring in the evolution of m-payments technology at the component, service, and business infrastructure levels, and identified different patterns of technological change based on the paths of influence across different levels. I adopted a state transition diagram to visualize the paths of influence over time and to depict patterns in the ecosystem's development trajectory. (See Figure 2.3) Technology evolution involves entrepreneurs and organizations that contribute to the path-dependent nature of the process, which makes it seem random.

The arrows in Figure 2.3 represent the paths of influence that reflect changes in the three kinds of innovations across fourteen time periods. The collection of arrows in each period represents the various evolutionary patterns of m-payments technology. M-payments technology evolution started with the introduction of SMS-enabled m-payments in 1997; and it exhibits five different patterns that are summarized in Table 2.2. I noted the similarities to the patterns presented by Adomavicius et al. (2008a).

Most of the recent innovations in the m-payments ecosystem have started with new components and services that allowed for more advanced performance and new

Figure 2.3. M-Payments Technology State Transition Diagram, 1997-2014



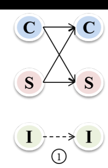
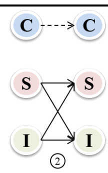
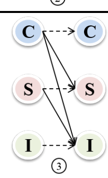
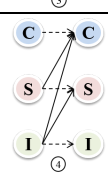
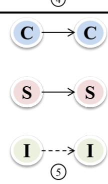
functionality. For example, the vendors of various mobile wallets (Google Wallet, Apple Pay, and Softcard) now offer services that permit swiping a mobile phone to make a payment. They are also providing the ability to collect detailed data about where consumers are transacting and what they are buying – as well as more information about where they are, and how they are moving. This information can be analyzed to understand and predict consumers' purchase behavior. It also allows merchants to send real-time targeted advertisements and perform *location-based services* (LBS), by taking advantage of existing components (the global positioning and accelerometer components of smartphones, cloud servers and storage, and high-speed mobile networks) and business infrastructures (mobile banking, location-based systems) (Groenfeldt 2014, Liu et al. 2013).

2.4.3 The Effects of Competition, Cooperation, and Regulation

Some of the patterns that I have observed are a by-product of competition and cooperation that have occurred among the different stakeholders in the m-payments ecosystem. I previously noted that, among the drivers of changes in the financial IS and technology ecosystem, innovation-spurring and innovation-stalling competitive forces played an important role in the observed developments.

When the first two SMS payments-enabled Coca Cola vending machines were installed in Finland in 1997 (Montgomery 2012), few people were truly aware of the capabilities of mobile devices to initiate, authorize and confirm the exchange of financial value in return for goods and services supplied. By 2001 though, the introduction of 3G mobile networks enhanced their connectivity and capability for data transmission among mobile phones, and the competition for the central roles in the mobile marketplace had begun. The component-based innovations of the early 2000s were stimulated by competition among mobile market participants, and created a strong push-forward force for m-payments-related technology innovations. Since that time, the collaboration and cooperation strategies have come to characterize much of the additional development of the market, especially when firms such as Google, MasterCard, Citibank, First Data Corporation and Sprint from different industry sectors worked together to create Google Wallet. Their cooperation accelerated the development of NFC-enabled m-payments technology solutions, resulting in a service and infrastructure alignment pattern that I have observed in our sketch of m-payments technology evolution in its ecosystem (Aspan and Saba 2011).

Table 2.2. Evolutionary Patterns for the M-Payments Technology Ecosystem

NAME	PATTERN	DEFINITIONS AND COMMENTS	EVENTS
1. Services development		All of the technology innovations observed are clustered at the component and service levels; technologies at component and service levels are refined and gain greater attention over time.	Emergence of m-payments and mobile banking; continuous developments of new m-payments services; the further adoption of smartphones.
2. Service and infrastructure alignment		The observed innovations occur at the levels of service and business infrastructure.	Innovation-spurring competition by PayPal, Google Wallet and Apple; eBay's acquisition of PayPal.
3. Feed-forward		Involves innovations so that new services become possible in the presence of a new component innovation, or a new infrastructure innovation that is desirable to have because of already-developed components and services	Introduction of 3G networks, cloud computing and Square; the wide adoption of Internet and mobile banking
4. Feed-back		Involves new services motivated by the development of a new business infrastructure that enables it, or a new component that will be possible due to development of business infrastructure and services	Introduction of NFC standards, smartphones, and smartphones that support NFC as new components and business infrastructures
5. Incremental		New component innovations support subsequent component innovations; new services beget subsequent service innovations; and for business infrastructures	Development of 4G networks and the NFC platform; carrier-backed m-payments emerged; launch of Apple Pay, and iPhone 6 and iPhone 6 Plus

Complementary and countervailing forces. I now shift gears to do a richer assessment of how some of the other events that are present in the timeline of the evolution of m-payments technologies played out, when there is evidence of the concomitant effects of regulation. Sometimes financial IS and technology providers benefit when they are able to anticipate regulatory actions to minimize the risks, so it is possible for them to harmonize their actions to push forward the adoption and diffusion of an innovation. Otherwise, they may encounter countervailing forces from the market or the regulators. This represents a setting in which *competition spurs innovation while regulation drives or delays it* – in other words, in settings where there are *complementary* or *countervailing* forces at work to some degree. I recognize that it may be difficult to identify the exact extent to which each force is at work, but it nevertheless is possible to identify the outcomes associated with their co-occurrence.

When there are active vendors whose interests align with the regulators' interest on new technology-based services, this will increase the likelihood of the success of technology innovation and help to push its evolution forward faster. Elements of this kind of behavior on the part of market participants can be observed with the success of M-Pesa in Kenya and other countries in East Africa, and the transformation of the consumer payments process there (Graebner 2014). A large segment of the population in these countries has long been unbanked, and generally under-served by financial services organizations, which have struggled to achieve profitability in markets with low-income consumers (Deloitte 2012). The success of M-Pesa since 2007 has been due to its close collaboration with the Central Bank of Kenya, which provided its expertise to help M-Pesa's management to mitigate key systemic risks and offered it room to innovate rather freely (Bishko and Chan 2013). Collaboration between the national central banks and mobile financial services entrepreneurs in that region also facilitated a valuable and direct dialogue (Nyaga 2014).

More recently, the dialogue has emphasized the negative impacts of M-Pesa's near-monopoly power though, such that the regulators are now interested in shaking up the financial network infrastructure of the economy, by permitting the entry of new *mobile virtual network operators* (MVNOs), such as Finserve Africa, Mobile Pay, and Zioncell Kenya (Heinrich 2014). This process aids in identifying the inappropriate aspects of the highly-concentrated network operational and financial risks related to financial technology innovations for payments (The Economist 2013).

Digital convergence, competition and innovation. When large and powerful Internet firms have turned their attention to the payments marketplace – the traditional territory of large financial institutions, the competition, risk, and market uncertainties have all been affected. Changes in competition driven by digital convergence (Yoffie 1997) involve a somewhat different impetus for innovation. Instead of having existing market participants to develop new innovations, other players – start-ups, technology firms, telecoms and Internet giants – have entered the m-payments marketplace because the expected returns for successful firms there are so high (Ernst and Young 2014).

Examples of digital convergence are occurring all around us. Accenture (2012) has pointed to instances of digital convergence, such as Square and iZettle, which have been expanding the capability of mobile phones as POS checkout devices to support consumer purchases. Despite the new technologies, the payments scheme is still similar in its underlying operations, since banks dominate the payment authorization, clearing and settlement processes. However, there is now greater transparency in the payments process, new segments of payments services for under-banked and unbanked customers are being served, and new ways to accomplish risk management now become possible. The digital convergence process exhibits that next generation technologies seem to be inheriting somewhat amplified characteristics that were acquired during the prior generation.

Fragmented markets and uncertain standards. In other settings where there is a more fragmented market, for example, characterized by the lack of an accepted technology standard, or conflicting strategic objectives across different business networks, there may be innovation-stalling competition, as well as regulation-driven effects. Regulations, in some cases, pave the way for the market to understand how the emergence of innovations may proceed.

The history of m-payments, based on my empirical observations, suggests that almost all of the initiatives in the 2000s failed. After 2011, the m-payments standard competition between online independent payment service providers, such as PayPal and Alipay, and the new technology platforms, such as Google Wallet and Softcard (Arthur 2014), as well as more recent developments around Apple Pay (CardNotPresent.com 2014), created uncertainties for stakeholders' adoption decisions and network formation (Zalubowski 2014). This slowed down the pace of m-payments services innovations, as market leadership was still a major issue that needs to be sorted out. In 2012, a U.S. Senate (2012) hearing was convened to assess the development of a framework for mobile payments and identify the major roadblocks for m-payments infrastructure and services development.

Financial stability, risk management and government regulation. Government agencies that deal with the market for financial services also have considered the stability and risks of current banking and payment systems in light of competition around technological innovations (World Bank 2012). Some have noted that m-payments innovations may be detrimental to the operation of well-functioning financial services in an economy (Khiaonarong 2014), and that they also may cause severe security issues (Dobos 2013, ISACA 2011). For the most part though, the purpose of regulation is not to interfere with innovation-spurring competition in the m-payments arena, but instead to facilitate a more successful payments regime, maintain financial stability, monitor the risks, and build an efficient payment process.

In January 2010, the Federal Reserve Banks of Atlanta and Boston convened a set of key players in the U.S. mobile payments ecosystem to create the Mobile Payments Industry Workgroup (MPIW). The purpose was to identify the barriers, potential risks and opportunities for the development of a robust mobile payments environment. In addition to suggesting the fundamental elements for success, the MPIW has been trying to understand the appropriate regulatory oversight model that will enhance safety and integrity in payments systems. New regulations regarding the risk management and instantaneous credit capabilities of m-payments have begun to address consumer protection issues also, such as identity management, consumer privacy, cyber security and how prepaid mobile phone accounts are handled (Contini et al. 2011).

A notable example of regulation-delayed effects related to m-payments technology innovation occurred in China in March 2014. The People's Bank of China (PBC), China's central bank, promulgated innovation-stalling regulations that slowed down the initiatives of Tencent and Alibaba to roll out virtual credit cards (Zhao and Xie 2014). The central bank was especially concerned about these companies' use of quick-scan QR codes that support m-payments innovations. The problem was a perceived lack of security with respect to the transaction verification process that uses QR code-based technology. It expressed concerns about the potential risks that new payment mechanisms may create, especially for the stability of the banking and credit card industries, although others have alleged that the pull-back on third-party m-payments could be based on the concern that there would be lost revenues and fees for banks, and conflicts with NFC-based initiatives that UnionPay promoted (Hernandez 2014).

Vendor competition, solution success, and the specter of regulatory intervention. During the past five to ten years, large firms in financial services have competed intensely to produce innovations that will transform the traditional processes related to payments services. Such competition may decelerate the development of new services since the related investments may involve greater uncertainty. This will affect the patterns of technology evolution, possibly causing a shift in the observed patterns going forward. In contrast, some firms have been able to push a technological innovation forward by obtaining strong support, and by partnering and making alliances with other firms to gain advantage and accelerate the development of new services (Dai and Kauffman 2004).

I observed this in the timeline of m-payments ecosystem events most recently, when Apple announced its cooperation with VISA, MasterCard and American Express at the business infrastructure level, in the rollout of Apple Pay mobile payments via smartphones used at contactless POS outlets (Townsend 2014). Most merchants and banks supported Apply Pay shortly after its initial launch, which brought a new set of capabilities and installed base of consumers to the m-payments market. According to recent estimates, about 800 million people have access to iTunes (Arora 2014), although many fewer have an iPhone 6 or similar mobile handset. This nevertheless was an astonishing development in terms of the potential network effects that Apply Pay may eventually be able to project in the m-payments ecosystem. Some large U.S. retailers, however, including Wal-Mart, CVS, and Rite Aid, have refused to commit to Apple, since they have contracts with rival payments systems that will punish the stores for adopting Apple Pay (Wells 2014).

Apple's extraordinary success as a newly-entering m-payments services vendor, according to Webster (2014), is that "Apple Pay was the kick in the pants that everyone in the ecosystem needed to get the mobile payments flywheel focused and moving in high gear." The untested aspect of the Apple Pay launch is whether Apple will be able to build strong network effects with merchants, who will recognize that adopting Apple Pay is an essential part of doing business – again, a *hook-up-lose-out value proposition*, based on the long-standing argument of Clemons and McFarlan (1986). Adoption may ensue on multiple sides of the m-payments platform around Apple's solution – current iPhone 6 and next-generation users, banks, as well as merchants and stores – because the functionality and convenience are high-value solutions. Antitrust issues in the market may arise around such a powerful technology services vendor, just as Microsoft, when it seemed like the dominant and unchallenged force in the Internet browser and office software suite market niches, was alleged to have inappropriately tied the distribution of Microsoft Windows to Internet Explorer and the Microsoft Office software suite (Liebowitz and Margolis 2001). Apple's market capitalization of US$724 billion as of mid-March 2015 is now about 114% greater than Microsoft's at US$338 billion, so there may be future issues with regulation that Apple will face (Watts 2014).

2.5 Discussion and Implications

Organization-level internal factors such as firm heterogeneity and competitive strategy, and industry-level external factors including government regulation and technology standards, jointly contribute to shaping the evolution of m-payments innovation. They have encouraged and supported, or stalled and delayed the adoption and diffusion of specific m-payment-related technologies. I next discuss m-payments technology evolution at the organization level, and provide some recommendations to firms about how to increase their firm-level returns on investment (ROI) after committing to m-payments.

I claim that first-mover advantage and network effects are positively associated with the success of a firm's investments in technology innovations. Gaining the first-mover position and obtaining network effects will help to accelerate the pace of evolution of a technology, especially when the investment decision can be made flexibly or delayed to manage its risks.

The development of the m-payments market supports this statement. The m-payments services market has been highly fragmented since it emerged. Many competing technology solutions have coexisted in the market; different stakeholders have invested in and shepherded their development. There have been no widely-accepted technology standards so far though. This has made firm-level m-payments adoption decisions difficult for many market participants. On the other hand, in spite of the market uncertainties that are present, there still are advantages and benefits associated with the early adoption of a truly valuable technology innovation that will become a standard later on (much like EMV chips in credit cards). David (1985) noted that first-to-market technology innovations can become entrenched, such as QWERTY keyboards or Microsoft Windows, and sometimes inferior standards can persist because of the installed base they have built up. This will give firms an incentive to preempt the rest of the market with their early adoption and full commitment (Dai and Kauffman 2006). When the uncertainties associated with technology innovations are substantial and the investment is at least partially irreversible, firms will value flexibility. They can benefit, for example, through having the flexibility to defer adoption (Dixit and Pindyck 1994). This may affect the opportunities that firms have to leverage first-mover advantage though: deferring for too long a time may eliminate the flexibility for a firm to benefit from timing adoption to achieve high ROI (Mason and Weeds 2010).

Another issue is network effects in financial services, which affect decision-makers' choices in two ways. First, strong network effects will induce them to make investment decisions at a little earlier rather than a later time (Kauffman et al. 2013, 2015b). Second, they will tend to make similar rather than different investment decisions. An analogy is that stores have an incentive to geospatially cluster (Krugman 1991). When there are enough stores to form a business hub, competitors located elsewhere will be at a disadvantage. As a result, they may eventually move to the hub, further increasing its relative attractiveness. This is precisely the story that I have seen play out with Apple Pay and the banks. Clearly, the strong network effects associated with Apple Pay will hasten the decisions of banks to adopt and speed up innovation, while consecrating the value of the first-movers' choice to become involved.

Firm differences are also important when I consider these issues. In practice, a firm's willingness and ability to commit and participate in cross-industry collaborations for payment-related technology innovation will vary. Some have the spare resources; others do not. The lack of uniform willingness to commit may also be due to the individual views that firms have of the risks of future technological changes, market uncertainties associated with consumer and merchant responses to new technologies, as well as other firm-specific factors, such as different market shares, nuanced and contrasting technology capabilities, and competing strategic objectives.

It is unlikely that all firms will make unanimous adoption decisions and take actions all at once in most technology adoption settings, because senior managers must make the "right" decisions in the absence of perfect information or a full and sophisticated decision-making capability (Au and Kauffman 2003). The firms are also different in terms of their ability to acquire and process information from the market, and even when they are able to acquire similar information, they still may process it differently. In previous research in different domains, Au and Kauffman (2005, electronic bill presentment adoption), Li and Kauffman (2012, public transit systems pricing mechanism adoption), Li et al. (2014, inefficient herd behavior in a world of rational decision-makers) and Ma and Kauffman (2014, software-as-a-service adoption) noted that firms go through a process of *adaptive learning*. They may eventually align their rational expectations about the business value of a technology they are evaluating, and whether and when to adopt – or they may not.

The lack of harmonized firm actions in the market typically will result in an observable time-wise distribution of their adoption decisions, as opposed to *clustered adoption* that occurs more or less all at once (Au and Kauffman 2001, Au et al. 2009). I conclude, therefore, that one firm's decision, including which m-payments technology innovation to invest in, when to adopt, and how heavy the investment should be, will impose undesirable externalities on other firms. The firms which are early adopters of a specific technology innovation may impose *competitive externalities* on other non-adopters, for example. High competitive externalities can potentially delay adoption and slow down the pace of a specific technology innovation, because other rival firms may commit to competing technology innovations. These things will make it harder for firms to align their collective interests, to make mutually-beneficial adoption decisions based on their rational expectations of what is likely to come out in the market.

Competitive externalities are external penalties that affect other competitors if one firm's adoption of a specific technology innovation has the potential to affect and change market-wide profitability (Seidmann and Wang 1995). An early adopter typically can obtain higher profits from the new services and increased transactions that become available with the new technology. Since one firm's profitability from adopting a technology innovation critically depends on its transactions volume, relative market share, and the number of other competing adopters, the firm's incentive for adoption will decrease as more and more rival firms adopt. When adoption becomes less and less attractive due to too many adopters, as Bakos and Brynjolfsson (1993) and Dai and Kauffman (2006) have shown for electronic procurement market participation, it eventually will drive latecomers to reconsider their strategies. If this occurs with respect to technology innovation, firms are more likely to turn to competitive differentiation strategies, since this will mitigate head-to-head market competition among them. An example in the m-payments domain is PayPal, which left NFC capabilities in its m-payments solution to achieve differentiation in comparison to Google Wallet and Softcard in 2011 (Pymnts.com 2012). Such strategic interactions among firms, thus, are likely to delay the diffusion of a specific type of innovation and decelerate its evolutionary pace. This is also true for their competitive interactions when they are mostly influenced by the uncertainties in the market of a given technology solution or standard. I view this as another kind of competitive externality: an *indecision externality*. This term makes sense, because it is clear in such cases that the entire market bears the social costs of stalled adoption. Indeed, any movement in the market to the "next" equilibrium involving new technology will be beneficial, especially in terms of the value for firms to learn what is necessary to succeed for a given m-payments technology innovation.

Competition itself in the financial services industry and the payment services segment also demonstrates unique features. Decades ago, banks and other financial institutions bore the heavy financial weight of initial fixed costs in building the foundations for today's payments system. As a reward, they gained dominant positions in the industry and have enjoyed oligopolistic market power for years. With the high entry barriers in the financial services market, it has been difficult for new entrants to enter and succeed, unless some portion of the market becomes *newly vulnerable*: easy to enter, attractive to attack, and difficult to defend (Clemons 1997, Granados et al. 2008). An example is the trading segment of the financial markets, which has experienced great technological innovation (McGowan 2010, Menkveld 2013), and the emergence of issues that made new oversight and regulation a reality (Gould 2011).

Things have changed with m-payments though, especially in terms of what Weber (1995) has called *digital bypass*. Many current financial services, inclusive of m-payments, heavily rely on the success of underlying technology innovations, rather than any firm's historical position in the marketplace. For example, some m-payments solutions are able to digitally bypass the offline payments networks in banking with direct access to the ACHs and the card networks. This disintermediation capability created a technology-based vulnerability. It also provided opportunities for new entrants to be involved and compete with existing market players. Due to competitive pressures, the latter have had to adjust their strategies. For example, they now are forced to invest to reduce customers' transaction costs and improve service quality, with little hope for additional profitability. The investments they make will be more a matter of strategic necessity than strategic advantage (Goh and Kauffman 2013). These, in turn, will result in a new wave of competition for payments services, eventually leading to gains in consumer welfare and economic efficiency (Laffont and Tirole 1990, 2001), such as have been seen in the past with ATMs (Bernhardt and Massoud 2002, McAndrews 1998, Wright 2004).

These analyses allow me to conclude that the payments sector is a *newly vulnerable* market, in large part due to the rise of m-payments. So I expect that competition in this market will be much more intense than in other traditional markets – at least for a while. Since competition may impose two opposite effects on technology innovation – an innovation-spurring or innovation-stalling effect, there are two questions that need to be asked. (1) Which effect will dominate and drive the outcome? (2) And what can be done so the more positive innovation-spurring effects will be fully expressed, while the more negative innovation-stalling effects are minimized?

My answer is this: the level of uncertainty that exists in the market will play a key role in this process. Both technological and business-related uncertainties in the m-payments market will impact the effects of competition. If such uncertainties can be mitigated, there is a higher likelihood that incentive-compatibility and value co-creation among different stakeholders can be achieved without destabilizing the existing market structure. As a result, competition is more likely to accelerate technological advances, spur the creation of valuable innovations, and benefit the m-payments ecosystem.

Newly-vulnerable markets, such as has been occurring in the payments sector, tend to have relatively unstable institutional structures. Many new firms are likely to be entering and pursuing digital convergence strategies or alliance strategies, with some of them – including existing market participants – failing and exiting the market. This creates high business-related uncertainties for participants, so that decision-making related to m-payments adoption, in particular, is likely to be difficult. The decision process is made even harder in light of the high switching costs and technology lock-in power that are present in a technology-intensive industry (Farrell and Shapiro 1989), like the financial IS and technology ecosystem. In addition, the m-payment market is fragmented in terms of its underlying infrastructure technologies, and thus is viewed as having high technological uncertainty as well (AFP 2014, Kim 2012). No industry observers, consultants or university researchers have expressed an ability to foresee what is likely to happen in the future, though many have offered insightful predictions. Instead, firms mostly are experiencing a "learning-by- doing" process. The existence of various incompatible technology solutions indicates their lack of agreement with respect to expectations on what the relevant technology standard will be and which business models are likely to be suitable for m-payments (Hayashi and Bradford 2014).

In the presence of significant uncertainties, it is likely that competition will harm the health of the m-payments market. Competition brings along a lot of new things, attracting new firms, producing new products, enabling new strategies, and introducing new technologies. The fact is that not all of them are able to offer true value though. Some new market entrants will be operating inefficiently and will not create real business value. Some technology innovation-based strategies will be myopic in maximizing short-term profitability, and will fail to achieve sustainable returns in the long-term. And some innovations are not mature enough to be implemented and create much value. These are like noise in the market that will delay the adoption and evolution of more valuable innovations. They also represent a loss in social welfare due to the inappropriate investments of some participating stakeholders. Market uncertainties can be mitigated through standardization in the underlying payments technologies, in order to have competition result in the beneficial innovation-spurring effect though.

Finally, it is important to note that m-payments technology solutions require a high level of consumer data-sharing. Thus, financial services firms are often reluctant to make commitments that may compromise their separate commitment to customer data privacy. I expect that, over time as the market gradually reaches a consensus on appropriate technology solutions and business infrastructures that are likely to become the actual standards, firms will see that some m-payments technologies achieve critical mass across a large installed base of users. Once this happens, concerns in the marketplace will be diminished among consumers, banks, and the regulators about the technology adoption aspect, though they will continue to express concerns about data privacy, and identify theft and payment fraud.

2.6 Concluding Remarks

M-payments services have been under development for years, though few initiatives by individual or groups of stakeholders have reached critical mass and market-wide adoption. Based on my competitive and regulatory analysis in the m-payments technology ecosystem, I suggest that establishing a clear understanding of the direction of industry competition and related regulatory policies can accelerate services development and facilitate successful adoption of technology components and business infrastructures. Open dialogue and collaboration involving central banks, commercial banks and m-payments services vendors related to the mitigation of risks and uncertainties are crucial for fostering a new business model for m-payments without damaging the payments system, as it currently operates. New competition policies are needed to enable new entrants to compete with large existing players. The latter may have insufficient incentive to be innovative in reducing costs and improving service quality, as new entrants may have (Laffont and Tirole 2001).

The convergence of e-commerce and m-commerce requires new payment methods to take advantage of mobile, Internet, social networks and data analytics capabilities. M-payment technologies bring the capabilities of the traditional payments system to the online world, while supporting bricks-and-mortar businesses in the offline world. This has been featured as *offline-to-online* competition. It provides new opportunities for traditional businesses to compete with online businesses, and is enabled by the digital intermediation of third-party digital payers, such as PayPal and Alipay (Russell 2013). This competition will revolutionize how people make payments in the e-commerce and the bricks-and-mortar world, and touch all aspects of their everyday lives. It also has the potential to spur significant financial services innovations that will increase social welfare by transforming the brick-and-mortar store payment process to match the new capabilities for m-commerce (Bishko and Chan 2013).

Admittedly, even though IT-enabled financial innovations have been talked about for years, the pace of technology innovation in some important niches of financial services has been slow due to various reasons. Since technology providers such as Apple, Google, Alibaba and Facebook have entered the financial services world, regulators may consider refining the related policies to provide new room for innovation. Coordination of financial regulation and competition policy may benefit the future marketplace for m-payments. It is important that the gains arising from technology innovations can be fully realized and passed to various stakeholders, which in turn will offer them incentives to further innovate. Finally, national infrastructural level and consumer demographic characteristics also play roles in the development process and outcomes of m-payment services in the cross-national technology ecosystem.

3 Technology Investment Decision-Making under Uncertainty

3.1 Introduction

Large-scale IS and IT investments are high-risk and potentially high-return commitments that can offer strategic and competitive advantage for organizations that take calculated risks with them. The U.S. Department of Commerce's Office of the CIO (2014) views *major IT investments* as those that require attention due to their "sensitivity, mission criticality, or risk potential, or that includes $25 million or more in development, modernization, and enhancement costs over the life of the project." McKinsey and Co. defines *large-scale IT projects* as those that exceed $15 million (Bloch et al. 2012, p. 1). They note: "large IT projects often run 45% over budget and 7% over time, while delivering 56% less value than predicted."

Many technology investment initiatives fail to deliver the promised benefits though, and some have caused dramatically large losses (Nash 2000, Widman 2008). Senior managers struggling with how to create IT-driven business value would like to control the risks associated with their investments. The practical problems that technology-related stakeholders grapple with require an effective risk management framework to hedge the risks and respond to market changes that affect technology investments (Benaroch et al. 2006a). A promising approach is to manage the timing of commitment to an IT solution by evaluating new information that is continuously arriving from the market, deferring investment decision-making, and only making a commitment when the critical uncertainties are resolved (Kauffman and Kumar 2008, Kauffman and Li 2005).

The common uncertainties with technology investments are due to factors that affect the firm's ability to successfully appropriate business value (Duliba et al. 2000, Teece 1986), including an organization's internal technical capacity to complete a difficult IT project, and input cost uncertainties that arise due to external issues, such as changing costs of inputs and government regulations that affects costs and benefits in different ways (Pindyck 1993, Schwartz and Zozaya-Gorostiza 2003). The firm's ability to fund a long-term capital-intensive investment, and the alignment of the targeted application with stakeholders are additional risk factors for investments by an organization (Benaroch 2002). Others include: future customer demand for technology products and services (Benaroch and Kauffman 2000); fast clock-speeds of different industries that affect operational and technology investment practices (Mendelson and Pillai 1999) and recognition of the necessity of cooperation and alliances (Teece 1992); product performance, project schedules and market requirements (Huchzemeier and Loch 2001); and updated information on competition among technology standards, and competitors' preemptive moves (Kauffman and Li 2005).

Real option methods to manage IT investment risks have drawn the attention of many IS and technology management researchers over the years, including Benaroch and Kauffman (1999), Dai et al. (2007), Dos Santos (1991), Fichman (2004), Tallon et al. (2001), Taudes (1998), Yang et al. (2012) and Zhang and Babovic (2011). Option-based risk management for IT projects, proposed by Benaroch (2002), helps decision-makers distinguish between embedded *implicit option*s (deferral and abandonment) and *explicit options* (pilot and staging) in their decision-making process. Deferral options permit technology investments to be postponed for different lengths of time, as senior managers learn about the potential outcomes of their investments prior to committing to them.

This study uses financial economics thinking for decision-making under uncertainty and real option methods to model a firm's technology investment decision-making process for major and large-scale IT projects, considering uncertainty about the cost and benefit flows represented by a *mean reversion process*.[3] I will address this research question: How can the timing of a firm's commitment to a specific technology project be analyzed using an approach that considers the mean reversion property of uncertain benefit and cost flows, as decision-relevant information being revealed over time?

The literature on real option methods has mostly focused on determining when real options should be exercised, based on updated information acquired from completed projects. In this research, I adopt a different strategy though. I focus on option exercise that involves dynamic information updating, based on the observation of current benefit flows and costs at any point in time. I also model uncertainty for costs and benefits that vary according to the mean reversion property for IT investments. This is something that researchers in some other fields have attempted to do – for example, Jaimungal et al. (2011) used the *mean reversion stochastic process* to model the value of option-bearing projects – but IS researchers have not done it this way. This is because there are known problems with the tractability of various real option

[3] An earlier article in the present research stream was published in *Information Technology and Management* (Kauffman et al. 2015b). Earlier versions were presented at: the 2012 International Conference on Electronic Commerce in Singapore; the 2013 Hawaii International Conference on System Sciences (Kauffman et al. 2013); the 2013 China Summer Workshop on Information Management in Tianjin, China; and the 2014 AIS-Journal Joint Author Workshop at the Pacific Asia Conference on Information Systems in Chengdu, China.

models, with the result that closed-form solutions cannot be computed. Most of them assume the uncertain cost and benefit flows follow a *geometric Brownian motion* process, which ignores that both have a tendency to revert to equilibrium levels of spending and value (McDonald and Siegel 1986, Harmantzis and Tanguturi 2007, Singh et al. 2004). This research contributes the first approach for the IS literature that models costs and benefits in mean reversion terms for the context of IT investments.

I will present an application for a mobile payment systems infrastructure project. The application shows how my method can yield actionable valuation and adoption timing knowledge for management of technology projects, investments, infrastructure and services. The application of my method to a case involving mobile payments system infrastructure demonstrates the upside potential of financial IS and technologies with strong network effects, as well as the high uncertainty in the trigger phase of the technology hype cycle (Fenn et al. 2000). I will develop a dynamic decision rule based on newly-updated information; which enhances management's capability for effective decision-making when there is lack of historical information and experience with new technologies. I will also illustrate how to use a simulation-based *least-squares Monte Carlo* (LSMC) valuation approach in technology investment projects. The method overcomes the shortcomings of directly applying a financial option pricing model for IT investments in a way that leads to overvaluation, which is caused by restrictive assumptions (Banker et al. 2010).

3.2 Literature

There are a number of different perspectives for assessing technology investments. I will review four that are relevant to the present research: financial economics and decision-making under uncertainty; real option methods; technology investment timing; and finally numerical methods for analyzing specific technologies and contexts to obtain realistic valuation estimates.

3.2.1 Decision-Making under Uncertainty

The literature on *decision-making under uncertainty* (Dixit and Pindyck 1994) offers a useful theoretical perspective based on financial economics for evaluating a firm's flexibility to choose an optimal time to invest. Technology investment decisions share three important characteristics with other types of investment decisions under uncertainty. First, they usually involve large-scale infrastructure development, personnel and training costs that are partially or completely irreversible. Second, there is uncertainty, including technological uncertainty and market uncertainty, over the future benefits and costs of the investment. Third, decision-makers have the flexibility with investment commitment timing to diminish their uncertainty to an acceptable level as information arrives over time. My framework builds on the theoretical foundations for investment under uncertainty.

The technology investment decision-making process is one that involves managing the balance among value, cost and risk. McDonald and Siegel (1986) argued that the benefits from an irreversible project investment follow a continuous-time stochastic process. Schwartz and Zozaya-Gorostiza (2003) further contributed a cost-benefit diffusion methodology for different kinds of IT investment decision-making, when the investment costs and benefits are subject to stochastic changes over time. The stochastic process most commonly used is geometric Brownian motion (Taudes 1998, Benaroch and Kauffman 1999, 2000). Applying this stochastic process involves making a trade-off between a desirable and tractable closed-form solution and the inappropriateness of its assumption of continuously increasing mean and variance of the cost and benefit flows over time against the reality of market competition and the product life cycle (Bollen 1999, Heinrich et al. 2013). Schwartz (1997) proposed the use of the *mean reversion stochastic process*, also known as an Ornstein-Uhlenbeck process, to reflect that investment costs and benefits tend to revert to their long-term equilibrium values. This process is appropriate for evaluating projects when the real option approach results in recommendations of investing too late when the costs are high. Sarkar (2003) showed that the assumption of mean reversion has an impact on investment decisions, and that using geometric Brownian motion to approximate a mean-reverting process may be problematic. Given the limitations of the geometric Brownian process, I will model uncertainty for costs and benefits using variants of mean reversion process in evaluating technology investment projects.

3.2.2 Real Option Methods in IT Investment

Fichman (2004) argued that, when uncertainty and irreversibility are high, real option analysis should be used to structure the evaluation and management of IT project investment opportunities. IT investment risk can be evaluated using a family of financial risk management methods. Benaroch (2002) and others (Kim and Sanders 2002, Alvarez and Stenbacka 2007) identified various IT investment options, including deferral, staging, exploration, scale alternation, outsourcing, abandonment, leasing, compound, and strategic growth options. Benaroch and Kauffman (1999, 2000) examined electronic banking network expansion, and demonstrated the development of realistic models for decision-making under uncertainty to enhance senior management's capabilities to formulate effective strategies. They applied a variant of the Black-Scholes-Merton framework to evaluate the flexibility of deferring a bank's ATM network infrastructure investment. Other applications to IT include 3G networks in the wireless industry (Harmantzis and Tanguturi 2007), application services providers in IT services (Singh et al. 2004, Techopitayakul and Johnson 2001), and data warehousing systems in the airline industry (Benaroch et al. 2007).

The limitation of applying the Black-Scholes model to IT investments is the assumption that the exercise price is known in advance, and that American options can be replaced with a portfolio of European-style options to represent the investment opportunities. Schwartz and Zozaya-Gorostiza (2003) applied a different investment option exercise strategy that addresses some shortcomings of the Black-Scholes model. They determined the investment exercise timing when a critical cash flow triggers the *optimality rule*, rather than specifying the exercise time based on updated information. This way, managers are able to make decisions by observing benefit and cost flows over time. Another criticism is the overvaluation problem associated with the use of financial option pricing approaches for IT investment evaluation. Benaroch et al. (2006b) and Banker et al. (2010) examined the capabilities of the Black-Scholes model for the valuation of IT projects, and showed that its restrictive assumptions on traded assets may result in overvaluation, in spite of the fact that the logic of the approach has been widely touted as being helpful in supporting strategic thinking. Here, I adopt a dynamic strategy for option exercise rather than determining the time for exercise in advance, so that the aforementioned shortcomings of applying the Black-Scholes model in IT investment projects are addressed.

3.2.3 The Timing of New Technology Adoption

Time plays an important role in investment decision-making. Prior studies have pointed out many factors that affect a firm's adoption of a new technology at a given time: when information acquisition (Jensen 1988, McCardle 1985), information spillovers (Mariotti 1992), and strategic interactions occur (Reinganum 1981). Uncertainties about the future benefits and development costs will cause them to be perceived by decision-makers as fluctuating over time – sometimes higher and sometimes lower. They depend on decision-makers' expectations of what it will take to implement, and what level of demand such products and services will garner in the market once they have been deployed. IT investments often have high-upside potential, but also high uncertainty and indirect returns (Lucas 1999), which makes timing an important factor that must be taken into considerations in decision-making. An important thread in this literature has been using analytical models to study and support investment timing strategy for firms when they must decide whether to adopt one of two incompatible technologies, in light of evolving expectations about future competition (Kauffman and Kumar 2008, Kauffman and Li 2005). This offers a basis for a decision model related to technology investments, where uncertainties about the investment will be resolved over time. My approach contributes by modeling the timing strategy for a firm's decision-making for IT investment subject to uncertainty about the costs and benefits.

3.2.4 Numerical Methods in Option Pricing

In option pricing, finance researchers choose among different numerical methods to trade off between simplicity and generality in practice, based on their use of different formulas and approximations (Stein and Stein 1991, Fouque et al. 2000), lattice and finite difference methods (Parkinson 1977, Brennan and Schwartz 1977, 1978), Monte Carlo simulation (Boyle et al. 1997, Glasserman 2004), and other specialized methods (Andersen 2000, Longstaff and Schwartz 2001). Merton (1992a) showed that the price of an American option is given by a complex mixed differential equation that is difficult to solve. To overcome this problem, I will adopt Longstaff and Schwartz's (2001) LSMC method for technology investment option valuation. It combines simulation and advanced regression methods to develop an approximation for a set of conditional expectation functions. Stentoft (2004) showed that various approximations of option prices using LSMC converge to a meaningful price under certain conditions. The numerical methods for option pricing offer a useful foundation for examining IT investments value and key elements related to the decision-making process that I wish to study.

3.3 The Model

I next present a real option framework that enables a firm's decision-making process for technology adoption under uncertainty. Various risks and uncertainties related to technology investments are represented by multiple stochastic processes, for investment costs, future benefits, and other factors associated with the IT investment project that will affect its value over time.

Suppose a firm is risk-neutral. A manager will have an option to wait until an appropriate time to invest in order to maximize the firm's returns and hedge the related risks. The manager can decide whether and when to invest I dollars, signing contracts with technology providers or setting up technology systems infrastructure, for example. (See Table 3.1 for my modeling notation.) The investment decision is irreversible; it will be hard for the firm to unwind payments to contractors or employees and the development of technology infrastructure.

Table 3.1. Modeling Notation and Definitions

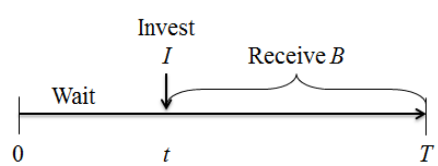
MATH	DEFINITION	COMMENTS
V, B	Investment value, benefit flow at time t	PV of future benefit flows B, that fluctuate over time
I, ROV	Firm's investment cost I, real option value	For technology investment, for the deferral option
$\bar{B}, \bar{I}$	Long-term mean benefit, investment cost	B, I tends to revert to the level of $\bar{B}$, $\bar{I}$ in the long term
α_B, α_I	Speed of mean reversion for benefits, costs	Subject to the exponential mean reversion process
σ_B, σ_I	Standard deviation of B, I	Affects volatility of benefit flows, investment costs
g, d	Mean benefit growth rate, decay rate	Subject to the mean benefit growth curve and decay rate
ρ_{BI}	Correlation between B and I	$\rho_{BI} = 0$, equates with uncorrelated cost-benefit
r_f	Risk-free discount rate	Discounts future benefits and costs
dz	Wiener increment	Defines a standard mean reversion process
t, T	Time; maximum deferral time, or # periods in which cash flows occur	dt is a small increment in time; bounds option's exercise time; cash flows can be benefits or costs for firms
L	Length of technology lifecycle	Capture the length of period the technology is available
λ	Mean # of jumps per unit of time	In dt, probability that a jump will occur is λdt
B_{max}, $\overline{B_L}$	Maximal mean benefits, mean benefit at L	The expected maximal benefits, mean benefit level at L
Y	Δ value, random variable	Measures after-shock change in value
dq	Shock-led value jump process	Changes in value of dq follow a Poisson process

Technology innovation happens fast. Technology-based products and services are subject to a quick lifecycle with rapid development, market uptake, and early obsolescence. Ignoring the lifecycle often leads firms to make significant errors in the valuations of technology investment projects (Bollen 1999). In this research, I assume the investment opportunity lasts over time [0, T], when the cost and benefit flows from investing in the technology system occur. Thereafter, the investment opportunity related to it will expire. The firm can invest at any time up until T, the maximum time for deferral. The current cost of the investment is known, but future changes will be uncertain. The investment cost is modeled as $I = \exp(x_t)$, where x_t follows a *geometric mean reversion process*, with $dx_t = \alpha_I(\theta - x_t)dt + \sigma_I dz$. Here dz is a standard Wiener process, α_I is the speed of reversion parameter, σ_I is the standard deviation affecting the volatility, and θ is the long-run mean level to which x_t tends to revert.[4] I utilize the exponential value of x_t to ensure a positive investment cost *I*. In other words, I assume the investment cost's natural logarithm follows a geometric mean reversion process. Applying Itō's Lemma with $I = \exp(x_t)$ gives $dI = \alpha_I \left[(\theta - \ln I) + \frac{\sigma_I{}^2}{2\alpha_I}\right] Idt + \sigma_I Idz$. Transforming it via $\bar{I} = \theta + \frac{\sigma_I{}^2}{2\alpha_I}$ yields $dI = \alpha_I(\bar{I} - \ln I)Idt + \sigma_I Idz$ (Changes in Investment Cost).

The mean reversion process is strictly positive with a distribution skewed to the right, and is characterized by a fat tail for large positive values (Brigo et al. 2007). The conditional expected value of investment *I* at time *t* is $E(I_t) = \exp[\bar{I} + (\ln I_0 - \bar{I})e^{-\alpha_I t}]$ (Expected Value of Investment Cost), where I_0 is the investment cost at time 0 with certainty. The conditional variance is $V[I_t] = \sigma_I{}^2/2\alpha_I\,(1 - e^{-2\alpha_I t})$. As *t* becomes large, the expected value of I_t converges to $\exp(\bar{I})$ and the variance converges to $\sigma_I{}^2/2\alpha_I$. This means that the investment cost will finally converge to the equilibrium price of technology in the market as time goes by.

After it has made an investment, the firm will receive benefits until time *T*. (See Figure 3.1.)

Figure 3.1. Investment Timeline



I assume that once the investment decision is made, the system will be installed and begin to function, and the costs of operation, marketing, and maintenance will

[4] I thank an anonymous reviewer of the related journal article for suggesting the mean reversion process, instead of the geometric Brownian motion process due to its lognormal distribution, with a time-dependent mean and variance, and for pointing out the relevance of the technology product lifecycle.

either be negligible, or will have been added to the initial investment cost. In practice, the decision-makers will always incorporate these costs occurring during the development stage into the initial investment. Some technology projects may take an uncertain amount of time for the investment until completion. And there is always a lag from when the investment began to the receipt of the first flow of benefits. There will be no effect on the valuation of costs and benefits that determine investment decision-making though. Also the benefits received before the completion of investment are usually small. So I assume the investment is implemented at one point in time, with no lag between the completion of investment and receipt of the first flow of benefits.

Let B denote the stochastic benefit flows arising from the investment, with $dB = \alpha_B(\bar{B} - \ln B)Bdt + \sigma_B B dz$ (Stochastic Benefit Flows), which is modeled similar to the investment costs. Here, α_B represents the *speed of reversion* parameter and σ_B is the constant standard deviation of the cash flow described by a standard Wiener process. The mean benefits, $\exp(\bar{B})$, can be time-varying according to a deterministic model, which can take into account factors such as network effects, growth rate, customer learning curve, or decay in product value at the end of lifecycle. I further assume that no other competitors offer similar technology or systems, or enter the market in [0, T]. And there is no correlation between the stochastic changes in the investment cost and benefit flows, so $\rho_{BI} = 0$.

The value of an investment at time t is the expected present value of the stream of future benefits, adjusted for the corresponding costs at time t. Present value can be assessed based on the discounted benefit flows from time t when the firm makes the investment decision to the latest deferral time, T, with $V = E_t\left[\int_t^T \exp\,(B(\tau)e^{-r_f(\tau-t)})d\tau\ \right]$ (Discounted Investment Value). E_t is the expectation conditional on information available at time t, r_f is a risk-free discount rate, and τ is the time period over which discounting occurs. The result of integrating Discounted Investment Value from t to T depends on the model for the mean benefits $\exp\,(\bar{B})$.

The decision to invest at time $0 \leq t \leq T$ is equivalent to exercising a financial option before its expiration date T. Let $F\,(B, I, t)$ denote the value of this investment opportunity at time t. Since B and I do not involve traded assets, but are the expected values of a pair of random variables, they will have risk premia associated with them. The net present value of this investment opportunity with an embedded deferral option is $NPV\ = max\ [(V - I), 0]\ +\ ROV\ = F(B, I, t)$ (Investment NPV with Deferral). The related option value is $ROV = min\ [F(B, I, t) - (V - I),\ F(B, I, t)]$ (Real Option Value). Substituting the Discounted Investment Value and Expected Value of Investment Cost Equations for the risk-neutral measure into the Real Option Value Equation gives: $ROV = \min\left[F(B, I, t) - E_t\left[\int_t^T \exp\,(B(\tau)e^{-r_f(\tau-t)})d\tau\ \right] + \exp[\bar{I} + (\ln I_0 - \bar{I})e^{-\alpha_I t}]\ ,\ \ F(B, I, t)\right]$. I then apply Itō's Lemma to obtain the *differential real option value* for the investment:

$$dROV = \frac{\partial ROV}{\partial t}dt + \frac{\partial ROV}{\partial B}dB + \frac{\partial ROV}{\partial I}dI + \frac{1}{2}\frac{\partial^2 ROV}{\partial B^2}dB^2 + \frac{1}{2}\frac{\partial^2 ROV}{\partial I^2}dI^2 + \frac{1}{2}\frac{\partial^2 ROV}{\partial B \partial I}dBdI$$

Substitution of the Changes in Investment Cost and the Stochastic Benefit Flows Equations, along with the expression for $dROV$ into the Bellman Optimality Equation, $r_f ROVdt = E(dROV)$, with $\rho_{BI} = 0$, yields the following second-order differential equation: $\frac{1}{2}{\sigma_B}^2 B^2 ROV_{BB} + \frac{1}{2}{\sigma_I}^2 I^2 ROV_{II} + \alpha_B(\bar{B} - \ln B)B\ ROV_B + \alpha_I(\bar{I} - \ln I)I\ ROV_I + ROV_t - r_f ROV = 0$. The solution to this equation must satisfy two boundary conditions. First, the value of the real option must be 0 at time T: $ROV(B,I,T) = 0$. This is because the decision to make the investment cannot be deferred any longer at time T. Second, at any other time, $0 \leq t < T$, the real option value of the investment opportunity will always be non-negative: $ROV(B,I,t) \geq 0$ for all $0 \leq t < T$.

I apply dynamic programming to find critical values for the benefit flow that will trigger the exercise of the investment option. The Bellman Optimality Equation states that the value of a state under the optimal policy − in this case, the value of the investment opportunity − must equal the expected return for an action associated with that state. At optimality, the real option value is zero, which means there is no incentive to wait while the value of the investment opportunity remains positive. The benefits that are available at that time are critical: our assessment of benefits is based on all of the information available in the market. The corresponding action is the exercise of the real option. This will yield the optimal decision rule. When $V - I > 0$ and $ROV(B, I, t) > 0$, the best decision for the firm is to wait, as long as waiting is possible. When $V - I < 0$, and $ROV(B, I, t) \geq I - V > 0$, the firm should also wait for the cost flows to decrease or for the expected value to increase. If waiting is not possible, the project should be abandoned. Only when $ROV(B, I, t) = 0$ and $V - I > 0$ will it be the optimal time to invest.

3.4 M-Payments Project Valuation Illustration

I next will apply variations of the technology investment decision-making model to a real-world case. I illustrate the application of my approach to showcase how it enables decision-makers to consider benefit and cost uncertainty. I assessed a new IT investment project to demonstrate a *prospective application* of the method. Although I did not have access to all aspects of the data through direct project participation, there nevertheless is enough publicly-available information to instantiate my approach. As is the typical case in IT investment valuation work, it is necessary to make estimates when information on some of the key variables is not available, or when a modeling process differs from how managers think about how it works in practice. I will adapt the technology investment model to fit the specific setting of Square's (squareup.com) m-payment system development project, and evaluate the decision-making problem for a generic case of investment in representative m-payment systems in the market.

3.4.1 Background

After 2011, a number of companies and industry partnerships announced new m-payment technology solutions built on NFC contactless chips, cloud servers and card readers that plug into mobile devices (Romann 2014). The launch of Google Wallet in the United States provided a "tap and go" NFC m-payment solution in 2011 (Gustin 2011). Its primary competitor, now called Softcard (gosoftcard.com), developed by a consortium involving Verizon, AT&T and T-Mobile, launched an NFC application in 2012 (Perez 2013b). Also in 2012, Apple was awarded a U.S. patent for its iWallet, and at that time, its m-payments strategy mostly involved observing the market and waiting for things to develop further (Webster 2013). Other technology and process innovations were taking advantage of third-party apps on smartphone platforms, enabling merchants to process card payments.

3.4.2 The Square M-payment System

Square, a company that offers an application on the iOS and Android platform, serves as a virtual terminal with a pluggable reader into smartphones for authorization and settlement of merchant and consumer card transactions. The company was founded in 2009 with an initial investment of $10 million, and launched its first application and services in 2010 (Rusli 2011). Since 2011, Square's innovation in m-payments has been drawing widespread attention in the market with its rapid growth. In August 2012, Starbucks invested $25 million in Square, and its technology was used to process all credit and debit transactions in 7,000 of Starbucks' U.S. stores (Griffith 2014). However, the Starbuck deal led to large losses of more than $20 million in 2013, which reflected the risks and uncertainties that arise with IT investments and Internet start-ups (Barr et al. 2014). As of 2014, Square was processing about $30 billion in transactions annually, which puts its annualized gross profit at about $300 million and its market value in excess of $5 billion (Wilhelm 2014).

3.4.3 Irreversible Investments, Uncertainty and Timing

The commitment to mobile payments systems has three characteristics that distinguish it from other types of technology investments: irreversibility, uncertainty and timing. They also make the investment in mobile payments systems an option-like project (Dixit and Pindyck 1994). The investment in m-payments technology solutions involves intensive network development and will typically take a long time to implement and achieve network effects. To succeed, firms need to build new industry-wide infrastructure, by making specific but partially-reversible IT capital commitments on their own or through participating some cross-industry alliance (Hughes 2014, Pymnts.com 2014). Substantive uncertainties are associated with these kinds of investment behavior, including both technological risks and uncertain market responses (Kauffman et al 2013). In addition, in the m-payments ecosystem, various cross-industry stakeholders with distinct organizational backgrounds, operational models, IT capabilities, and business goals will employ different investment strategies. Typically, industry "giants," such as large banks, leading telecom operators, joint-venture trusted-services managers or independent services providers are likely to be first-movers. Many other firms will stand back and wait until these leaders have demonstrated the desirability and operability of a certain m-payment system business model and technology solution, and then jump on the bandwagon. As a result, firms time their investments somewhat differently. They will prefer to have the flexibility of implementing and committing to an m-payment technology as free riders in a later stage, or purchasing the technology investment opportunity in advance as an active early-stage developer (Montgomery 2012).

3.4.4 Model Specification and Estimation

I assume the time-varying mean benefit of an m-payment technology investment $\exp(\bar{B})$ changes according to $\bar{B} = B_{max} \times (1 - e^{-gt})$ (Mean Benefit Change). Here g is the mean benefit growth rate, which is derived from the growth of transaction volume over time, and $\exp(B_{max})$ is the intrinsic maximum benefit from transactions.

The mean benefit growth curve reflects customer learning and network effects. The benefit flows were estimated using Square's reported annual processing run-rates, and full-year figures for 2013 and 2014 for credit and debit card swiping, online sales and manually-entered payments.

Since I assume a constant growth rate of the number of transactions processed, g can be computed using transaction volumes for any two consecutive years: $\frac{\ln \bar{B}_t}{\ln \bar{B}_{t+1}} = \frac{1-e^{-gt}}{1-e^{-g(t+1)}}$, so I get g = 0.61. The benefit per transaction, treated as a fixed value at 0.94%, can be derived from the transaction fees that Square charges users, excluding the interchange cost that banks charge and assessment costs from VISA, MasterCard and Discover.[5] Table 3.2 shows investment costs, estimated transactions volumes and benefit flows of the investment project, from *Techcrunch* in 2014 (Wilhelm 2014). Figure 3.2 compares the mean benefit growth curve and the value of benefit flows over time, when I assume that B_{max} = \$162,755,000.

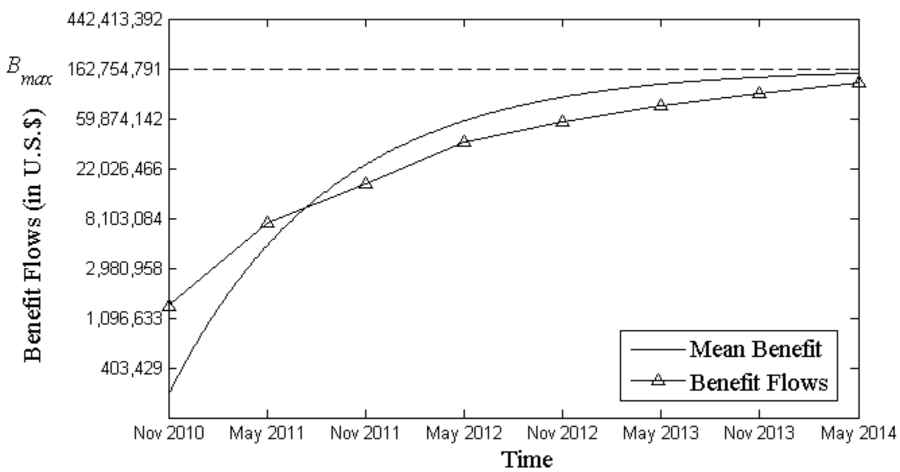
I estimated the volatility of expected benefit flows to be 50%, similar to what Benaroch and Kauffman (2000) used to compute the investment opportunity in their electronic banking research. Their decision was based on extensive senior management interviewing. I considered an investment time horizon of 5 years.

Figure 3.3 shows how the model in Section 3.3 can be adjusted to evaluate m-payment system development projects like Square's. The lag from initial investment to the initial flow of benefits is one year, reflecting the fact that Square took one year from November 2009 to November 2010 to start to develop its application and net-

[5] Square priced at a flat rate of 2.75% per swipe, and 3.50% plus a \$0.15 fee per manually entered transaction as of July 3, 2014 (squareup.com/pricing). I adopted a fixed rate of 0.94% after excluding other costs.

work before it received its first benefit flow. I will eliminate the lag τ in my investment analysis to adapt it for the real option framework.

Figure 3.2. Mean Benefit Growth and Value Flows



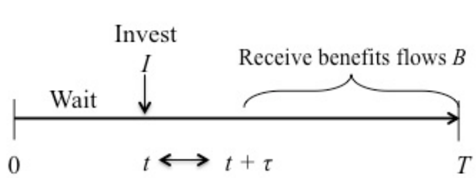
Note: Benefit flows labels are based on their natural logarithm values, representing their rapid growth over time.

Table 3.2. Transactions, Investments and Benefits

PERIOD	DATE	DOLLAR VALUE OF TRANSACTIONS	BENEFIT RATE	BENEFIT FLOWS	NATURAL LOG	INVESTMENTS
1	Nov 2009	-	-	-	-	$10,000,000
2	May 2010	-	-	-	-	-
3	Nov 2010	$150,000,000	0.94%	$1,410,000	7.25	-
4	May 2011	$801,000,000	0.94%	$7,529,000	8.93	$27,500,000
5	Nov 2011	$1,725,300,000	0.94%	$16,218,000	9.69	$100,000,000
6	May 2012	$4,028,910,000	0.94%	$37,872,000	10.54	$3,000,000
7	Nov 2012	$5,959,350,000	0.94%	$56,018,000	10.93	$200,000,000
8	May 2013	$8,278,200,000	0.94%	$77,815,000	11.26	-
9	Nov 2013	$10,488,480,000	0.94%	$98,592,000	11.50	-
10	May 2014	$12,944,250,000	0.94%	$121,676,000	11.71	-

Note: All dollar amounts are stated in U.S. dollars. The original Series A funding of Square was due to angel investors, including Khosla Ventures, Esther Dyson, Marissa Mayer of Yahoo!, Napster founder Shawn Fanning, Foursquare founder Dennis Crowley and others (Cutler 2010). The May 2011 Series B funding was due to Sequoia Capital and VISA. The Series C funding came from Kleiner Perkins Caufield & Byers in November 2011, and in May 2102 from Virgin Atlantic entrepreneur, Richard Branson. Series D funding involved investments from Citi Ventures at $50 million, Starbucks at $25 million, and Rizvi Traverse Mgmt. and CrunchFund for the remainder. I do not consider the April 2014 $100 million debt financing by J.P. Morgan Chase, Morgan Stanley, Goldman Sachs, Silicon Valley Bank, and Barclays Capital (Crunchbase 2014).

Figure 3.3. The M-Payment System Development Project



The initial investment cost I_0 is the sum of the discounted value of the capital investments raised from the Series A, B, C and D rounds of financing: I_0 = \$278,073,000. The initial investment to develop the network is stated inclusive of the relevant operational and marketing costs. I further assume that the long-run mean investment cost is based on the initial investment level. The volatility of the cost change is estimated to be 50%, and I use a risk-free annual discount rate of 7%. The mean reversion speed for the benefit and cost changes is assumed to be 0.1. Applying the Mean Benefit Change equation to Discounted Investment Value, the value of the system is: $V = \frac{B_{max}[e^{-r_f t}(g+r_f-r_f e^{-gt})-e^{-r_f T}(g+r_f-r_f e^{-gT})]}{r_f(g+r_f)}$. Table 3.3 summarizes the parameter values for the base case in the m-payment infrastructure investment project.

Table 3.3. Parameter Values for the M-Payment Investment Analysis

	DESCRIPTION	VALUE		DESCRIPTION	VALUE
I_0	Initial investment cost	\$278,073,000	σ_B	Benefit flow volatility	50%
α_I	Cost reversion speed	0.10	σ_I	Cost flow volatility	50%
α_B	Benefit reversion speed	0.10	r_f	Risk-free discount rate	7%
B_{max}	Maximum mean benefit	\$162,755,000	f	Transaction fee benefit	0.94%
T	Investment horizon	5 years	g	Mean benefit growth rate	0.61

Note: Dollar figures are stated in U.S. dollars. Transaction fee benefit and mean benefit growth rates are estimated with current data on Square's transaction pricing and transaction growth (Crunchbase 2014). The cost and benefit flow volatilities are estimated based on Benaroch and Kauffman (2000). I computed the simulated results with thousands of dollars, and a natural logarithm value of 12 for maximum mean benefit, which is \$162,755,000. The mean benefit growth parameter g was computed using Square transaction volumes for any two consecutive years based on $\frac{\ln \bar{B}_t}{\ln \bar{B}_{t+1}} = \frac{1-e^{-gt}}{1-e^{-g(t+1)}}$, which resulted in a value of 0.61.

Table 3.4 shows the results of my evaluation of the m-payment system infrastructure project at the beginning of each period. These values were obtained by solving the corresponding partial differential equations. After eliminating the one-year lag, I only considered eight periods in the decision-making process. The values of the investment opportunity and the NPV were computed using the expected and realized values of benefit flows adjusted by the discounted investment cost. The NPV reached its maximum value in November 2011, so it was optimal to invest in the project at that time. By evaluating this investment with my approach, I can deliver decision-relevant insights on the firm's commitment to this large-scale IT investment project.

Table 3.4. Value of the Investment Opportunity, NPV, Cost and Benefit Flows

PERIOD	EXPECTED *B*	EXPECTED *I*	OPPORTUNITY *V*	*B*	NPV
Nov 2010	$1,000	$278,073,000	$80,824,000	$1,410,000	$70,085,000
May 2011	$240,000	$268,670,000	$90,227,000	$7,529,000	$78,078,000
Nov 2011	$4,709,000	$259,584,000	$99,081,000	$16,218,000	**$79,889,000**
May 2012	$23,743,000	$250,806,000	**$103,463,000**	$37,872,000	$73,528,000
Nov 2012	$57,186,000	$242,325,000	$90,529,000	$56,018,000	$47,851,000
May 2013	$92,198,000	$234,130,000	$48,889,000	$77,815,000	$7,229,000
Nov 2013	$119,517,000	$226,213,000	-$20,821,000	$98,592,000	-$50,372,000
May 2014	$137,615,000	$218,563,000	-$110,398,000	$121,676,000	-$122,927,000

Note: All dollar amounts are stated in U.S. dollars. Bold fonts indicate maximum values, and gray cell backgrounds indicate negative values for the respective variables.

3.5 Model Extensions

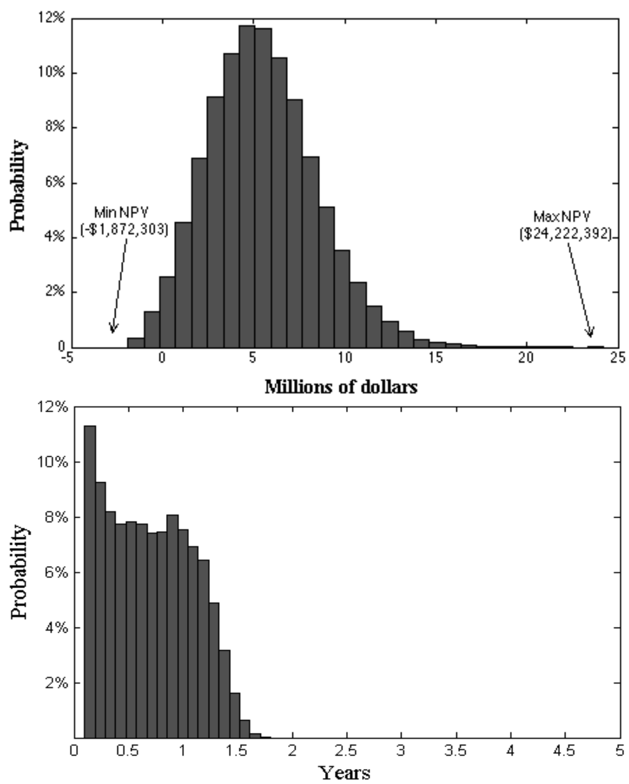
I next will evaluate the performance of my modeling approach with two extended analyses, and interpret the implications from them. I first will simulate a firm's optimal investment timing strategy and the best obtainable payoffs considering the effects of benefit and cost uncertainty from an IT project, and then perform an extensive sensitivity analysis with respect to the key parameters of the model. Then I will employ the *least-squares Monte Carlo* (LSMC) valuation method to handle the scenarios in which an unexpected event may occur during the diffusion process.

3.5.1 Simulation and Sensitivity Analysis

I simulate a base case. One firm is considering adopting a technology, and in its decision-making, the firm knows the values of the key model parameters, as well as the extent of the uncertainty it must endure related to some of them. Appendix B provides the parameter values and simulation procedure.

Figure 3.4 shows the estimated NPV distribution and the optimal investment timing distribution for positive payoffs derived from this base case. The expected NPV is around $5,483,000 with a maximum of $24,222,000 and a minimum of -$1,872,000. The resulting value is sufficiently high for managers to appropriately make a “go” decision for this investment. It also indicates the high risk to realize the expected benefits from the implementation.

Figure 3.4. NPV and Optimal Investment Timing Distributions for the Base Case



Discussion. I used a stochastic process to simulate cost and benefit changes over time. It allows the value of the investment opportunity to change continuously as new information arrives. In practice, the estimation of investment value raises the issue of *rational expectations*. The managers may not be able to assemble the information they need for decision-making all at once. There are costs and frictions associated with sorting out what information is meaningful and action-relevant. Information processing is difficult because managers will act based on interactions with other stakeholders and uncertainties in the market. Their information processing is complicated, which may lead to inappropriate expectations and cause their action to be different from the model-recommended investment strategy.

I offer the following:

- **Observation 1 (Deferring Technology Investments with Payoff-Relevant Information Revelation).** *A firm's senior managers will benefit by being able to defer technology investment decisions based on appropriate expectations as information is revealed over time about future trends regarding technology standards and market conditions, as well as the volatility of investment costs and benefits.*

Another important managerial consideration is that a firm may wish to invest in technology at an early stage to gain first-mover advantage. Once a specific technology solution has been successfully developed and adopted, it is likely to achieve strong network effects, as has been observed in the past couple years with Square's add-on device to make payment card swiping possible via a mobile phone. The first-mover will be rewarded with high payoffs from developing the network. First-mover advantage will inevitably decrease though, and may even eliminate the flexibility that a firm may benefit from in dealing with uncertainty. Moreover, strong network effects tend to drive decision-makers toward making investment decisions earlier. Thus, the combination of first-mover advantage and strong network effects may hasten the decision-making process of senior managers, and lead to pre-emptive investment strategies that run the risk of an unexpected large value change occurring that may be disadvantageous (Clemons and McFarlan 1986, Kauffman and Kumar 2008, Mason and Weeds 2010).

To get to a deeper understanding of the insights that my modeling approach produces, I perturbed some key parameters and analyzed their impacts on the investment valuation and decision timing. (See Appendix C for a summary of the results of a comprehensive sensitivity analysis.)

Effects of investment horizon *T*. To see if the investment horizon makes any difference on the best payoff and optimal timing distributions, I repeated the computations when the investment time horizon is shortened to 4 years or extended to 6 years from 5 years in the base case. (See Figures 3.5 and 3.6.) When T = 4 years, the expected best payoff is around $1,464,000, and the investment timing distribution tends toward an earlier optimal time compared to the base case. In contrast, if the investment opportunity expires in 6 years, the expected payoff will increase to around $8,933,000, and the investment timing will be more evenly distributed in the first 2 years.

When there is a longer decision-making period, the manager has more deferral time and flexibility to piece all the decision-relevant information together and process it for effective decision-making to achieve a higher payoff. In addition, it also extends the duration of perceiving benefit flows from the technology adoption and investment cost reversion to the long-term market level. My results suggest:

- **Observation 2 (Effects of Investment Horizon).** *When there is more flexibility with the investment decision horizon, the firm is more likely to defer the technology investment decision for a longer period to create the potential to achieve a higher payoff.*

On the other hand, when the firm has to make decision with a shorter investment horizon, it reduces the benefits for dealing with the uncertainties and the flexibility for the manager to make a value-maximizing decision. The pressure that arises due to the shorter decision horizon also hastens the firm's time to adopt the technology.

Figure 3.5. NPV and Optimal Investment Timing Distributions, *T* = 4 years

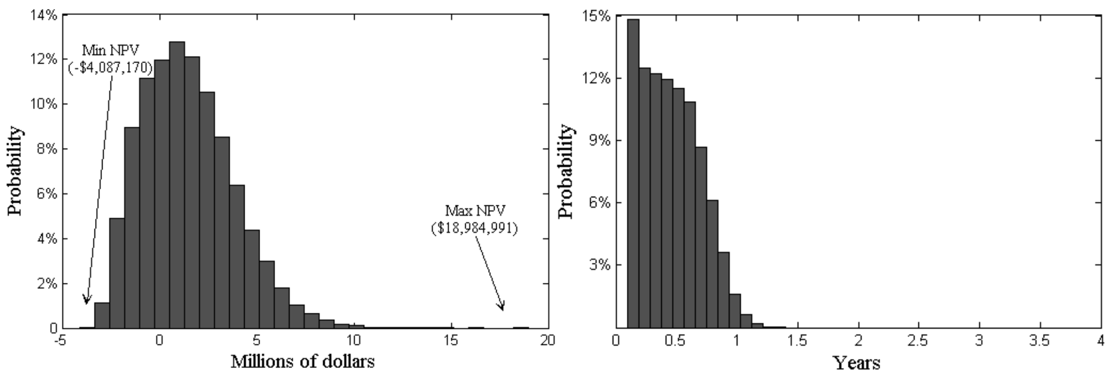
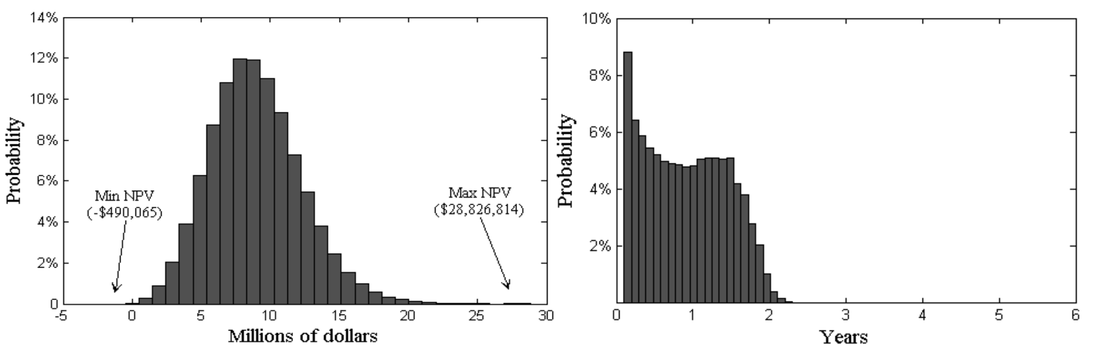


Figure 3.6. NPV and Optimal Investment Timing Distributions, *T* = 6 years



Effects of benefit volatility σ_B. The effects of benefit volatility on the payoff and timing distributions are illustrated in Figures 3.7 and 3.8 for two volatility levels, σ_B = 25% and 75%, compared to 50% for the base case. When σ_B = 25%, the expected payoff is around $5,051,000 with a lower maximum and higher minimum compared to the benchmark. When σ_B = 75%, the payoff distribution exhibits a longer tail at the higher end, and the expected payoff will be around $6,233,000 with a higher maximum of $51,501,000 and more negative value of minimum of -$2,789,000. The timing distribution, however, is not affected by the volatility of benefit flows. The results suggest:

- **Observation 3 (Effects of Benefits Volatility).** *When there are higher risk and volatility associated with future benefits from technology adoption, the firm will be able to achieve a higher return on investment, but there will be a greater likelihood of a large loss.*

High-risk technology projects can generate large benefits and returns for the investing firm due to improvement with decision analytics, process efficiency, and customer engagement. On the other hand, large-scale IT commitments involve high monetary and personnel investments that cannot be reversed if the implementation fails to achieve expected performance and user acceptance in the market. This may result in large losses and a negative return on investment.

Figure 3.7. NPV and Optimal Investment Timing Distributions, σ_B = 25%

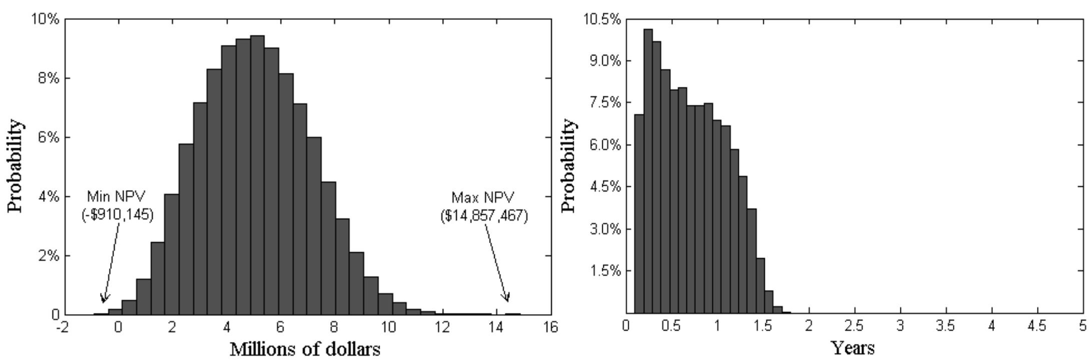
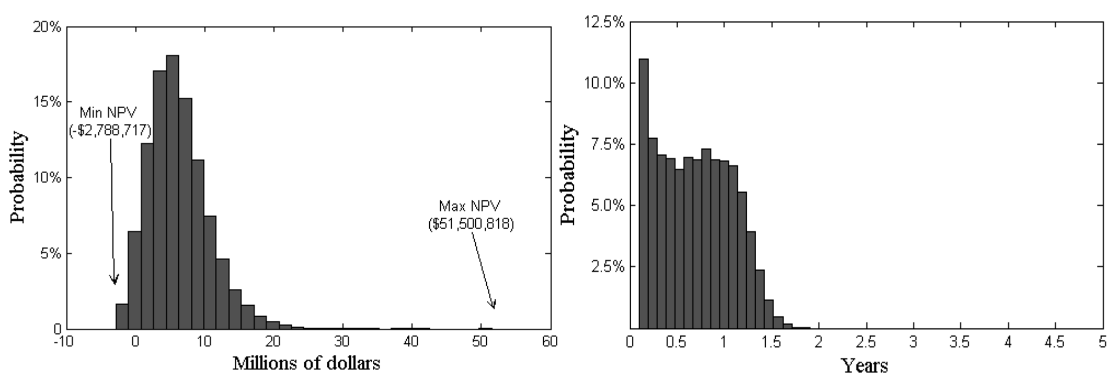


Figure 3.8. NPV and Optimal Investment Timing Distributions, σ_B = 75%



Effects of speed of benefits reversion α_B. I further examined the impact of the mean reversion property on valuation and investment timing by adjusting the speed of benefit reversion. Figure 3.9 shows that when $\alpha_B = 1.2$, the expected payoff is around \$2,416,000, which is less than half of that of the base case, and the distribution is more skewed to the positive side with a longer tail. When $\alpha_B = 1.8$ in Figure 3.10, the corresponding expected payoff will increase to around \$7,770,000 with higher maximum and minimum. The resulting NPV distribution and the unchanged investment timing distribution motivate:

- **Observation 4 (Effects of Speed of Benefits Reversion).** *When the benefit flows revert to the equilibrium level at a faster speed, a higher return will be achieved from the investment.*

Figure 3.9. NPV and Optimal Investment Timing Distributions, $\alpha_B = 1.2$

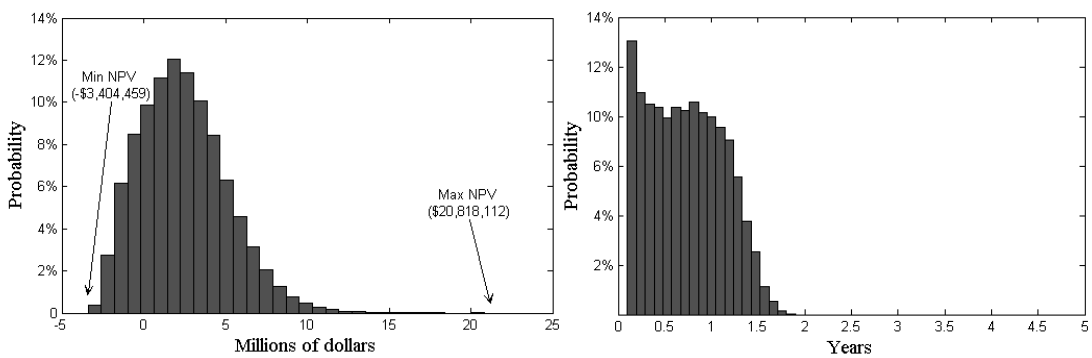
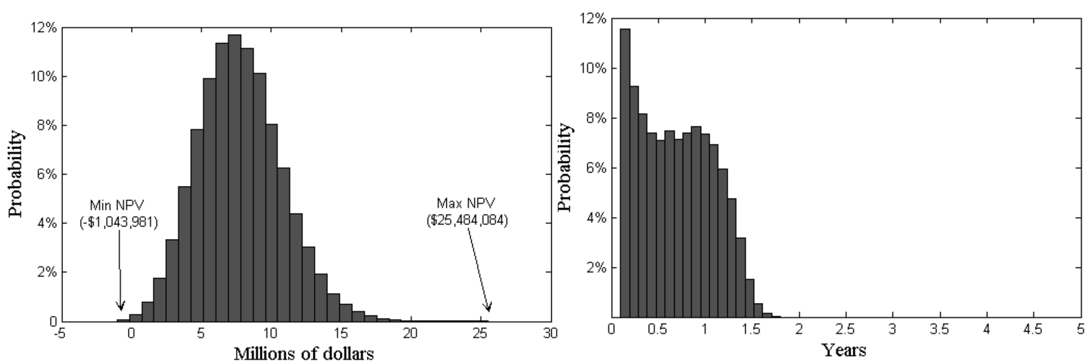


Figure 3.10. NPV and Optimal Investment Timing Distributions, $\alpha_B = 1.8$



As a new technology infrastructure gains acceptance by market stakeholders and the installed base of users reaches critical mass, the firm will begin to see flows of various benefits from the technology investment. The faster the benefit flows reach the equilibrium level, the higher will be the total returns on investment can be achieved within a certain time horizon. This is what has occurred for venture capital-supported start-ups related to IT and companies that use initial public offerings of stocks for fast growth, such as Square's exponential increase in transaction volume after multiple rounds of funding in the U.S. The sooner that firms acquire the needed capital and resources to build their customer base and market share, the greater returns they will generate for their investors and shareholders. The mean reversion property of benefit flows from the technology investment thus appears to have a significant impact on the investment returns.

3.5.2 Least-Squares Monte Carlo (LSMC) Valuation

The Black-Scholes-Merton framework assumes no external competitive or regulatory impacts on the benefit flows and future payoffs from the IT investment. Next, I will adopt Merton's (1976) *jump-diffusion* thinking to extend my approach. This will allow me to incorporate a process that supports the inclusion of external impacts on future payoffs. A Poisson process is useful to represent the unexpected occurrence of rare events that will change the benefit flows drastically, causing the investment payoffs to jump. The benefit from the investment at time $t + dt$ will be $B(t + dt) = B(t) + (Y - 1)\, B(t)dq$, given that a jump occurs between t and $(t + dt)$, where $(Y - 1)$ is a random variable for the percentage change in investment value if the jump event occurs. The term dq will have the value of 0 with probability $1 - \lambda dt$, and the value of 1 with probability λdt, with λ as the mean number of jumps per unit of time: the *value jump rate*.

The difficulty in applying the Black-Scholes model is that there is no obvious and objective value for the underlying project, nor does the option value based on this model include a trend term in its solution. Also, the use of a *twin security* that mimics the discounted cash flow value of the underlying asset has been advocated to estimate the volatility of its value. To obtain a good proxy for the objective value of a project, it is appropriate to replicate the characteristics of a non-traded IT investment with something that is traded. An alternative way to do this is to construct a *replicating portfolio* of traded securities whose value and volatility also approximate those of the underlying asset.[6]

The simulation-based LSMC method enables me to estimate the volatility of the project's value, as well as to approximate the option value of the investment opportunity. This also allows me to estimate the optimal stopping rule for the investment option. If the value of the IT investment in the next period is greater than the value for the current period, then the firm should defer investing; otherwise, it should execute its technology investment project immediately. Similarly, LSMC also can be applied using a more complex jump-diffusion process. See Appendix D for the numerical solution procedure.

The results of my numerical valuation are around \$3,202,000 for the case when there is no value jump $\lambda = 0$, and around \$3,690,000 when a value jump occurs with

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[6] This perspective has been best articulated by Robert Merton (1988, p. 326), in the 1998 *American Economic Review* article on the occasion of his December 1997 receipt of the Alfred Nobel Memorial Prize in Economic Sciences: "My principal contribution to the Black-Scholes option-pricing theory was to show that the dynamic trading strategy prescribed by Black and Scholes to offset the risk exposure of an option would provide a perfect hedge in the limit of continuous trading. That is, if one could trade continuously without cost, then following their dynamic trading strategy using the underlying traded asset and the riskless asset would exactly replicate the payoffs on the option. Thus, in a continuous-trading financial environment, the option price must satisfy the Black-Scholes formula or else there would be an opportunity for arbitrage profits." This is a useful perspective since it means that whether one uses a twin security or an equivalent portfolio of market-traded securities, the result will be the same: the characteristics of a non-securitized asset can be represented well enough and in a manner that is similar to what happens with real markets for assets that are thinly traded or lack liquidity (Amram and Kulatilaka 2000).

the probability $\lambda = 0.05$. Thus the value of the investment opportunities is higher with a possibility of a value jump, holding fixed the expectation that the value jump magnitude will be 0 across the different cases. This means that if a jump does not occur, the investment opportunity will be less likely to be deep in the money, and thus, the investment option will not be worthwhile to exercise when $\lambda = 0$. In the presence of the occurrence of a positive jump in value, the investment will be much more valuable than it would have been otherwise. My results imply that a gain to the firm from dealing with uncertainty in the value of the investment still may not offset the overall effects of value jumps over time (Kauffman and Walden 2001). So a firm will have less incentive to keep the investment opportunity open and may wish to adopt a more aggressive posture with an early investment strategy. My simulation bears out this intuition.

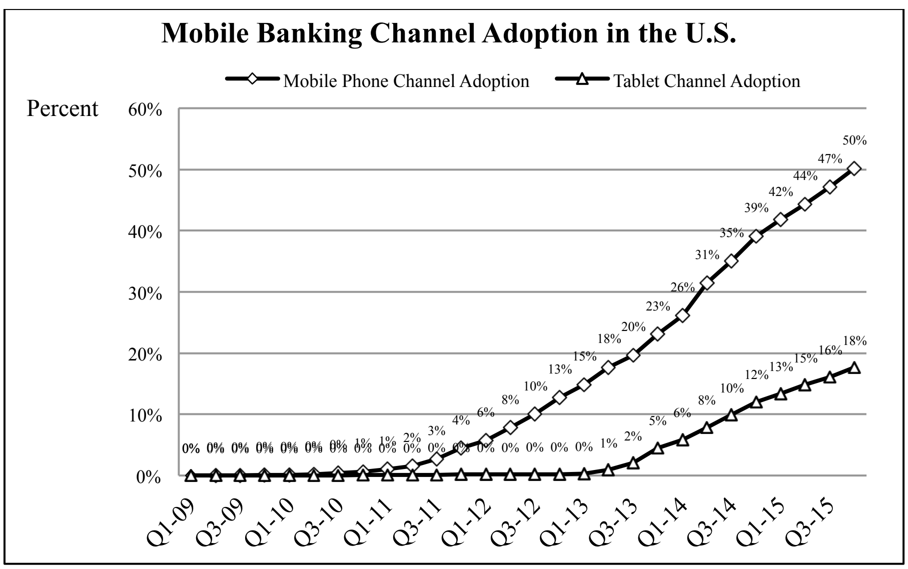
4 Impact of the Mobile Channel in Omni-Channel Banking Services

4.1 Introduction

Given the rapid adoption of smartphones and tablets, and the widespread use of mobile banking apps, mobile devices have become the new tools of choice for customers performing financial transactions. *Mobile banking* is a service that involves customers using a mobile device (e.g., smartphone, tablet, etc.) to obtain financial account information and conduct transactions with financial institutions. According to the Federal Reserve Board (2015), 87% of the U.S. adult population had a mobile phone and 71% of mobile phones were smartphones, while 39% of all mobile phone owners with a bank account made use of mobile banking in 2014. A survey by A.T. Kearney (2014) reported that 85% of banking executives viewed mobile banking as the cornerstone of their digital strategy going forward, and the mobile channel had become the customers' first touchpoint for banking. Figure 4.1 indicates that 50% of financial institutions regulated by the Federal Deposit Insurance Corporation (FDIC) in the U.S. had adopted a mobile phone services channel, and 18% had launched a channel for tablet-based services as of the last quarter of 2015.

The impact of the mobile channel on customer transactions in an omni-channel context for banking services remains an unexplored but important empirical setting. The omni-channel banking is a multi-channel approach that seeks to provide the customer with seamless banking services whether the customer is banking from a PC or mobile device, by ATM, or in a branch. (See Figure 4.2 for an illustration of omni-channel banking services). First, it is vital to understand how an omni-channel strategy affects customer service demand. It is not only a strategic advantage but also a competitive necessity for banks to understand customer cross-channel transaction behavior for providing a more robust customer experience and managing channels effectively. The *complementarity* and *substitution* patterns among the mobile phone, tablet and PC channels have not yet been documented in the context of financial services (Bell et al. 2015, Xu et al. 2016). Second, the mobile channel provides customers with an additional touchpoint for acquiring financial account information, allowing them to be the architects of what information they would like to receive and when they would like to receive it (Corbat and Kirkland 2015). As a result, customers obtain more information about relevant service offerings and attributes, and exhibit different banking behaviors equipped with more information for financial decision-making (Li et al. 2014).

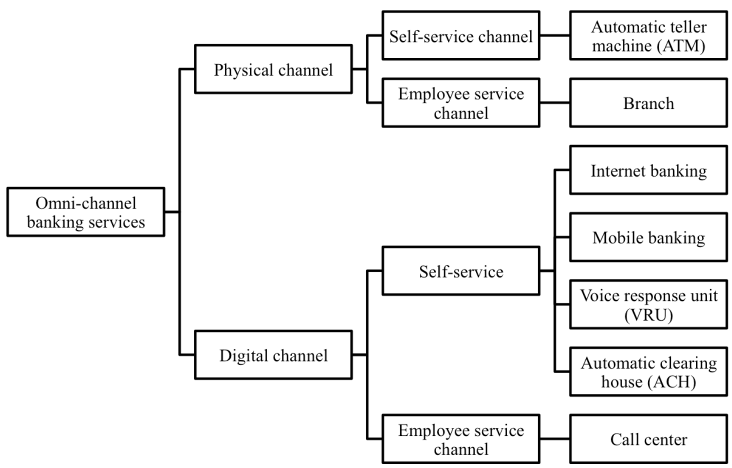
Figure 4.1. Mobile Banking Channel Adoption in the U.S.



Source: Apple iTunes App Store and Federal Deposit Insurance Corporation (FDIC). Percentage was calculated based on 6,589 financial institutions that represent all the members of FDIC in the U.S. Data as of December 31, 2015.

I acquired access to a large-scale dataset of customer-level transactions from a financial institution in the U.S. My goal was twofold: (1) to document the impact of the mobile channel on customer service demand across the digital channels, and (2) to assess the change in customer financial decision-making that arose from the use of the mobile channel.[7] In particular, I utilized customer transaction records through the mobile phone, tablet and PC channels to examine the complementarity and substitution among different digital channels, and explore the relationship between the use of the mobile channel and financial charges related to customers' demand deposit and credit card accounts. To reduce selection bias, I applied a propensity score matching approach to construct control and treatment groups of customers with a similar propensity to adopt a mobile device.

Figure 4.2. Omni-Channel Banking Services



Note: The classification of banking service channels is based on Xue et al. (2007). Mobile banking channels include both the mobile phone and tablet channels.

I ascertained the effect of the use of the mobile channel on increasing customer demand for services through digital channels. Second, customers who lived in an area with a lower density of ATMs and a higher density of branches had higher services demand through all of the digital channels. Third, I found that the mobile phone

[7] An earlier version of this study was presented at the 2015 International Conference on Mobile Business in Texas (Liu et al. 2015a).

channel complemented the PC channel, the tablet channel substituted for the PC channel, and the mobile phone channel and the tablet channel were complementary to one another. Such insights enable banks to understand customer channel usage patterns, and target those customer segments that are more active and profitable. My results indicated that customers acquired more information for financial decision-making following the use of the mobile channel and also that, compared to PC-only users, mobile phone and tablet users were less likely to incur overdraft and credit card penalty fees.

This study contributes to the literature on banking services in two ways. First, I conducted this research in the omni-channel context of financial services, including all of the digital and physical channels (Hernando and Nieto 2007, Patrício et al. 2003). The research on mobile banking has mostly been made up of survey-based studies on the factors that influence customer adoption and usage, such as customer intention to use, trust and risk perceptions, and service- and firm-specific attributes (Kim et al. 2009, Lee and Chung 2009, Luarn and Lin 2005, Luo et al 2010, Zhou et al. 2010). Without actual observations of customer transactions, survey-based data analysis may introduce measurement error and limit the results to what is perceptible to customers (Xue et al. 2011). This study overcomes the challenge of the lack of reliable and multi-channel transaction data to examine customer service demand and measure how the use of the mobile channel influences transaction migration across channels.

Second, I explored how the mobile channel affected customer financial decision-making. Overdraft and credit card penalty fees act as important sources of revenue in retail banking. Customers paid fees of $32 billion on automatic overdraft loans in 2012 in the U.S. (Oldshue 2013). Customers seem only to pay *limited attention* to their financial information due to the high cost of monitoring (Card et al. 2011), and their *rational inattention* to their account balances, payment due dates or credit lines may result in financial charges for overdraft on their accounts, paying fees late, or overspending on their credit card accounts (Sims 2003). Customers are utilizing multiple screens to monitor their account balances and activities, and making payments through multiple devices. Given that customers perform more inquiries following the adoption of the mobile channel, this ability to easily access and evaluate complete financial information will better inform their financial decision-making (Stango and Zinman 2014). By examining changes in overdraft and credit card penalty fees that customers incurred, I was able to investigate how the use of the mobile channel influenced customer financial behavior.

4.2 Prior Literature

4.2.1 Channel Complementarity and Substitution

A related stream of research in e-commerce and advertising has investigated the *substitutive* and *complementary* patterns between digital and physical retail channels (Ansari et al. 2008, Bell et al. 2016, Brynjolfsson et al. 2009, Forman et al. 2009, Kumar et al. 2014, Weltevreden 2007). When a bricks-and-mortar store opens near where customers live, and the new physical channel provides additional utility, customers will substitute away from online purchasing. Forman et al. (2009) explained that the disutility costs of purchasing online are significant and that offline transportation costs matter. Goldfarb and Tucker (2011) also identified a substitutive pattern between online and offline advertising. However, Kumar et al. (2014) argued that the opening of a physical store reduced customers' store access costs and resulted in: a higher number of store purchases and returns; a higher number of, more diverse, and more expensive online purchases; and a higher number of net total purchases through all the channels combined. Bell et al. (2015) further showed that putting a showroom into a market induced customer migration and had a significant impact on channel sales and operational efficiency.

Among the digital channels, there is either a complementary or substitutive relationship when customers are exposed to multiple sources of information (Xu et al. 2016). Yang and Ghose (2010) examined the impact of search engine advertising on consumers' responses in the presence of organic listings of the same firm, and suggested that the click-throughs on organic listings had a positive effect on the click-throughs on paid listings, and vice versa. Ghose et al. (2013) attributed the difference in browsing behavior between mobile phones and PCs to the higher search costs of using mobile phones. Ghose et al. (2015) argued that the complementarity between web and mobile advertisements simultaneously improved web click-through rates, mobile click-through rates and web conversion rates, but negatively influenced the mobile conversion rate.

An emerging stream of literature has examined the impact of mobile channel introduction on omni-channel retailing. Bang et al. (2013) argued that the performance impact of mobile channel introduction depended critically on product characteristics and the fit between channel and product. Xu et al. (2016) quantified the economic impact of tablet introduction on sales volumes and revenues, and the results suggest that the tablet channel acted as a substitute for the PC channel and a complement to the smartphone channel. The literature on banking service channels primarily has focused on the complementarity and substitution between digital and physical channels (Campbell and Frei 2010, Hernando and Nieto 2007). I contribute by demonstrating the relationship among mobile phone, tablet, and PC channels in the omni-channel context of banking services, which will deliver significant implications for bank's IT investment and channel management.

4.2.2 Impact of Channel Adoption in Banking Services

There is a rich literature on the impact of online banking adoption on customer's service demand and channel usage. Hernando and Nieto (2007) argued that the online channel acted as a complement to, rather than a substitute for physical branches. Geng et al. (2015) provided evidence for customer channel migration. They found that branch closures increased customer transactions through online channels, but decreased customer transaction-making through other physical channels. Campbell and Frei (2010) argued that customer adoption of online banking was associated with: (1) substitution for more costly self-service channels (ATM and voice-response unit); (2) augmentation of service consumption through the full-service channels (branches and call center); (3) a substantial increase in total transaction volume; (4) an increase in service cost; and (5) a decrease in short-term customer profitability.

Prior research has focused on the impact of self-service channel adoption on customer profitability, loyalty, and cross-selling opportunities in retail banking (Campbell and Frei 2010, Xue et al. 2011). Hitt and Frei (2002) explored the difference in characteristics or behavior between customers who used electronic service delivery channels and those who used conventional channels, and argued that online banking users tended to use more products and were more profitable. Xue et al. (2007) further explored channel usage and suggested that higher *customer efficiency* in self-service channels was associated with greater profitability and had a complex relationship with customer retention and product utilization. Xue et al. (2011) studied the determinants and outcomes of Internet banking adoption, and argued that customers who had greater service demand and higher efficiency, and lived in the areas with a greater density of online banking adopters, were faster to adopt Internet banking. In addition, customers increased their banking activities, acquired more products, and conducted more transactions in the post-adoption stage. I continue in the same vein of analyzing customer-level transaction data to measure the actual use of the mobile channel in retail banking.

4.2.3 Customer Financial Decision-Making

Information and communications technologies enable electronic service delivery channels for financial services and provide greater *information availability* (Clemons 2008, Li et al. 2014). Following their adoption of the mobile channel, customers will obtain more information in the presence of lower search costs (Bakos 1997). Prior research suggests that *limited attention* would hinder individuals from acquiring and using the available information for financial decision-making (DellaVigna 2009, Hirshleifer et al. 2009, Hong and Stein 1999). In addition, decision-makers' *rational inattention* makes them choose which information to attend to carefully, and which information to ignore (Lee et al. 2009, Sims 2003, Wiederholt 2010). Stango and Zinman (2014) showed that paying fees is affected by customer attentions that contained no information about recent behavior or the structure of fees for a particular customer type. Karlan et al. (2016) suggested that informative reminders might increase savings in deposit accounts and be more effective if they increased the salience of a specific expenditure. It is essential to understand how greater information availability following mobile channel adoption affects customer behaviors towards paying fees.

There is a dearth of empirical research explaining why customers overdraft on their accounts, make late credit card payments, and overspend their account limit, resulting in penalty charges (Agarwal et al. 2008, Liu et al. 2015c). Stango and Zinman (2014) stated that decision-making without full information and limited attention could explain customer overdraft behavior. Liu et al. (2015c) suggested that mobile alerts might help customers to avoid balance perception errors and to prevent overdraft fees incurred by making fewer low-balance debit transactions and cancelling automatic recurring withdrawals. Agarwal et al. (2008) studied credit card cash advance, late payment, and over-limit charges, and found that consumer learning through paying a fee was effective in avoiding the triggering of future fees. Stango and Zinman (2009) suggested that customers who used different cards at the point of sale and repaid credit card debt with the available checking balance could largely avoid over-limit and late payment charges.

4.3 Development of Hypotheses

I next develop hypotheses related to the impact of the mobile channel on customer service demand and financial decision-making.

4.3.1 Service Demand

The digital channels in banking services enable customers to access account information, transfer money between accounts, and make payments using PCs and mobile devices. Transactions made through mobile phones, tablets, and PCs are all digital banking transactions. Some of the related literature used customer account, transaction, demographic, profitability, retention, and channel density information to investigate the drivers of Internet banking adoption (Campbell and Frei 2010, Xue et al. 2011). The findings suggest that Internet banking adoption has a substantial *augmentation effect* for the adopters. In e-commerce, Xu et al. (2016) showed that the introduction of a new tablet channel enhanced Taobao's sales volumes, and customers tended to transact more when a tablet was used with a PC, a smartphone, or both. Given that mobile devices have been widely adopted, and mobile networks have become ubiquitous, customers can access their bank accounts using mobile phones or tablets anytime and anywhere, and thus I suggest:

- **Hypothesis 1 (Augmentation Effect of the Mobile Channel).** *The total number of transactions through all of the digital channels increases following the use of the mobile channel.*

4.3.2 Channel Complementarity and Substitution

In the past several decades, banks bore heavy financial costs for developing their physical and electronic banking networks (Kauffman et al. 2015b). Prior research suggests that convenience was the main motivator for customer use of a new channel (Lichtenstein and Williamson 2006, Cheng et al. 2006), and the relative inconvenience of alternative channels may have promoted new channel usage (Ramsay and

Smith 1999). Previous studies found that greater branch density was associated with more online banking activities due to greater awareness and customer engagement, and greater product use following online banking adoption (Xue et al. 2007, Xue et al. 2011). Forman et al. (2009) argued that the offline density of physical locations affected customers' online activities. When the cost of a customer travelling to a physical location is much higher than accessing the same service using a mobile phone, tablet, or PC, the availability of ATMs may influence customer use of digital banking channels (Kumar et al. 2014).

The mobile phone channel offers ubiquitous network access, provides instantaneous banking account access, and facilitates immediate interactions (Xu et al. 2016, Jung et al. 2014, Venkatesh et al. 2003). Thus the mobile phones are often used for banking while customers are on the move. The two-factor authentication approach using short message services (SMS) also makes the mobile phone channel a complement to the PC channel for acquiring account information and conducting financial transactions. However, the typical small screen size of mobile phones limits navigation and input capability (Chae and Kim 2004). The larger screen size of most tablets compared to mobile phones and the higher portability compared to PCs may suggest that tablets may substitute for the PC channel. When a customer has access to both a PC and a tablet, they may regularly use the tablet channel for mobile banking services. Thus, I propose the following:

- **Hypothesis 2A (Influence of Physical Channel Density).** *Customers who live in an area with a lower density of ATMs and a higher density of branches have higher service demand through all of the digital channels.*

- **Hypothesis 2B (Channel Complementarity and Substitution).** *The mobile phone channel complements the PC channel, and the tablet channel* *acts as a substitute for the PC channel.*

4.3.3 Customer Inquiry

Most banks have already launched mobile banking apps and mobile alerts to support increased information monitoring and active account management by their customers (Campbell and Frei 2010). The mobile channel provides an additional touchpoint for customers, and increases *information availability* (Granados et al. 2012, Li et al. 2014). This facilitates more inquiries about account balances, monthly statements, financial charges, payment due dates, and available credit. I measured how much customers knew about their financial status using the number of inquiry transactions. I examine the following:

- **Hypothesis 3 (Mobile Channel and Customer Inquiry).** *The use of the mobile channel increases a customer's inquires about their accounts.*

4.3.4 Customer Financial Decision-Making

Overdraft and credit card penalty fees are important sources of revenue for banks. But lenders face the challenges of how to mitigate customer dissatisfaction and anger. In the U.S., an overdraft occurs when money is withdrawn from a bank account by check, by ATM, or by debit card at the point of sale, resulting in a negative account balance. The main reasons for customer overdrafts include the customer's intentional decision to take a short-term loan at a higher price than might otherwise be available, and negligence with respect to check payments and other electronic funds transfers and automated payments. Liu et al. (2015c) argued that customers who were uncertain about their current balance might accidentally overdraft on their accounts. So given the greater information availability from the mobile channel, I assert:

- **Hypothesis 4 (Mobile Channel and Overdraft Frequency).** *Use of the mobile channel reduces a customer's overdraft frequency.*

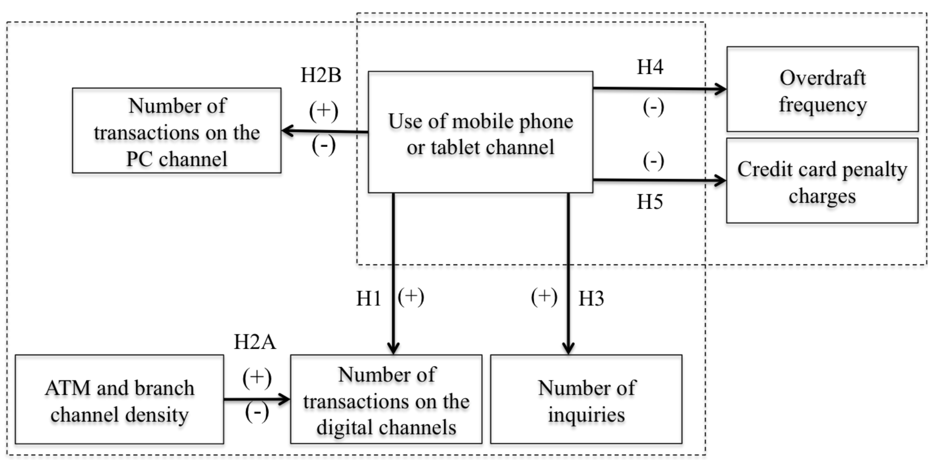
Easier access to information may affect customer financial decision-making following mobile banking adoption, so I expect that customers who use the mobile channel will be less likely to incur credit card penalty fees. An *over-limit fee* is charged when a customer's monthly credit card balance exceeds its credit limit, and a *late payment fee* is charged to a cardholder who misses making the minimum payment by the payment deadline.[8] Thus, I assert the following:

- **Hypothesis 5A (Mobile Channel and Over-Limit Charge).** *Customers who use the mobile channel are less likely to incur over-limit charges.*

- **Hypothesis 5B (Mobile Channel and Late Payment Charge).** *Customers who use the mobile channel are less likely to incur late payment charges.*

The hypotheses are summarized in Figure 4.3.

Figure 4.3. Conceptual Framework



[8] Definitions are available at CreditCards.com: http://www.creditcards.com/glossary/term-overlimit-fee.php and http://www.creditcards.com/glossary/term-late-payment-fee.php.

4.4 Research Context, Data and Preliminary Evidence

I next provide an overview of my research context and data, and preliminary evidence of the impact of the mobile channel on customer multi-channel transactions.

4.4.1 Research Context and Data

I acquired access to a large-scale anonymized dataset of customer-level transactions from a financial institution in the U.S. that serves customers throughout the country via branches, ATMs, and digital service delivery channels, such as telephone banking, Internet banking, and mobile banking. It provides a variety of banking products and services to meet customer financial needs, and is among the first financial institutions to have invested in Internet banking and mobile banking innovations. The institution launched mobile banking and personal financial management mobile apps to support its business, and made them available via the Apple and Android online app stores to assist customers who wanted to make more transactions and avoid unnecessary fees.

I collected data for more than 190,000 customers who made at least one banking transaction through digital channels from April to June 2013. On average, each customer performed 73.9 digital transactions per month, including *inquiry*, *service*, *external transfer*, and *maintenance* transactions. In this sample, approximately 22.6% and 12.0% of customers conducted at least one transaction using a mobile phone and a tablet, respectively. In total, customers cumulatively performed more than 43 million transactions in three months, of which only 3.4% were through mobile phones and 1.9% through tablets.

The anonymized data contained basic customer demographic information, such as on-file date, income level, residential zip code, etc. I operationally defined *physical channel density* as the number of bank branches and ATMs within each of nearly 25,000 zip code areas. I obtained information on demand deposit and credit card accounts for the monthly customer overdraft frequencies, and the charges of over-limit and late payment fees. In the sample, nearly 16.0% of customers incurred at least one overdraft penalty, while only 0.7% and 3.6% of credit card customers had an over-limit charge or a late payment charge, respectively. Most customers only overdraft on their accounts less than three times per month. Other information included customer current and historical deposit account balances, credit card statement balances, lines of credit, minimum payment amounts, average number of transactions, etc. Table 4.1 provides a detailed description of the main variables in my analyses.

4.4.2 Propensity Score Matching and Preliminary Evidence

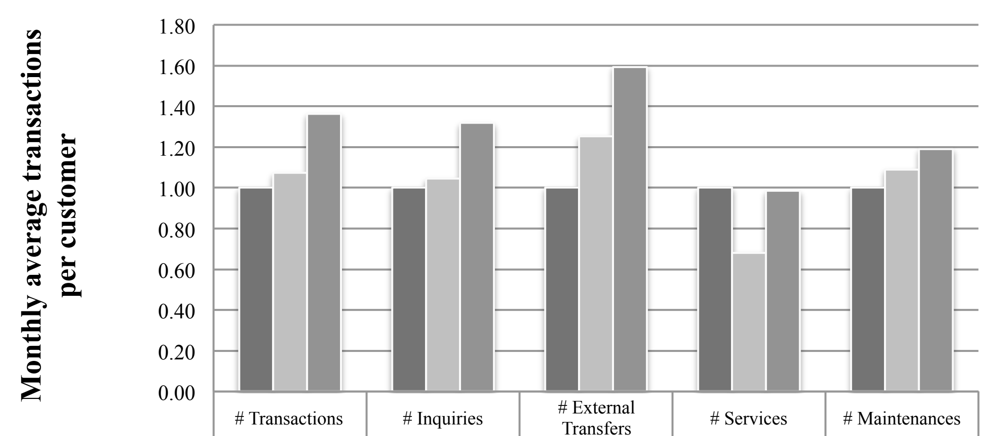
I view the use of a mobile device as the treatment that the customer receives, and assume a customer's decision to use a mobile phone or a tablet is based on the person's characteristics, such as demographics and income level, availability of alternative physical channels, and historical banking behavior. However, mobile banking users may be more tech-savvy and likely to use mobile devices for banking, and have higher digital service demands. Thus, when comparing the differences in customer behavior between users and non-users, self-selection to adopt a mobile device might result in biased estimates of the impact of the mobile channel. To control for the potential selection bias, I applied a one-to-one static propensity score matching method to select a pair of treated and untreated customers with a similar probability of receiving a treatment from the same state of the U.S., based on their individual characteristics (Kumar et al. 2014, Mithas and Krishnan 2009, Rosenbaum and Rubin 1983, Smith and Telang 2009). (See Appendix E for the detailed matching procedure and results).

Table 4.1. Variable Definition and Summary Statistics

VARIABLE	DEFINITION	NO. OF OBS.	MEAN	STD. DEV.	MIN	MAX
# Transactions	Total number of monthly transactions through mobile phones, tablets and PCs	583,488	73.91	143.75	1	38,435
Mobile	1 if a mobile phone is used in a month, 0 otherwise	583,488	0.15	0.36	0	1
Tablet	1 if a tablet is used in a month, 0 otherwise	583,488	0.08	0.27	0	1
# Inquiries	Number of monthly inquiry transactions	583,488	66.37	133.72	0	38,435
# External Transfers	Number of monthly external transfer transactions	583,488	2.60	5.11	0	242
# Services	Number of monthly service transactions	583,488	4.92	16.30	0	927
# Maintenance	Number of monthly maintenance transactions	583,488	0.02	0.15	0	17
# Mobile	Number of monthly transactions through mobile phones	583,488	2.48	11.66	0	917
# Tablet	Number of monthly transactions through tablets	583,488	1.37	9.03	0	857
# PC	Number of monthly transactions through PCs	583,488	70.05	141.45	0	38,430
Current Balance	Balance on deposit account at the end of a month (in thousands)	583,488	14.64	64.77	-8.98	16,863.83
Average Balance	Average balance on deposit account in the previous 12 months (Apr 2012-Mar 2013) (in thousands)	194,493	12.50	65.74	-2.22	26,948.76
Average # of Transactions	Average number of transactions through digital channels since the customer came on file	194,493	53.30	60.98	1	14,818.23
Tenure	Number of years since the customer came on file	194,493	12.51	10.87	0	113.42
Low Income	Identifier of low income customer	194,493	0.13	0.34	0	1
Branch Density	Number of branches in a zip code area (end of month)	583,488	1.26	1.14	0	6
ATM Density	Number of ATMs in a zip code area (end of month)	583,488	10.81	12.89	0	173
Overdraft Frequency	Number of overdraft transactions in a month	583,488	0.16	0.69	0	18
Over-limit Charge	1 if a customer incurred an over-limit charge in a month, 0 otherwise	129,902	0.007	0.083	0	1
Late Payment Charge	1 if a customer incurred a late payment charge in a month, 0 otherwise	129,902	0.029	0.167	0	1
Last Statement Balance	Balance for the last credit card account statement (in thousands)	129,902	2.51	4.03	-13.00	61.72
Last Statement Min Payment	Minimum payment for the last credit card account statement (in thousands)	129,902	0.22	1.16	0	37.91
Credit Line	Line of credit for a customer's credit card account (in thousands)	129,902	12.83	11.28	0	254
# Cards	Number of credit cards a customer holds	129,902	1.33	0.51	1	11
Average Statement Balance	Average credit card statement balance in previous 12 months (in thousands)	129,902	2.61	3.69	-1.42	51.61

I next provide preliminary evidence for the impact of the mobile channel on customer service consumption through all of the digital channels. I compared the average number of total and different types of transactions among three groups of customers that were matched by the propensity scores of using a mobile phone: (1) customers who transacted through the PC channel only, (2) customers who transacted through the PC and mobile phone channels, and (3) customers who transacted through the PC, mobile phone, and tablet channels (Xu et al. 2016). Figure 4.4 shows that the average number of total transactions increased by 7% from Group 2 over Group 1 when a mobile phone was used, and increased by 36% from Group 3 over Group 1 when a mobile phone and a tablet were used. The differences in the numbers of total and different types of transactions among the three groups were all statistically significant at a 95% confidence interval, except the difference in numbers of service transactions between Group 1 and Group 3. To protect the confidentiality of customer banking information, I masked the actual numbers of transactions by normalizing the numbers in Group 1 to 1.

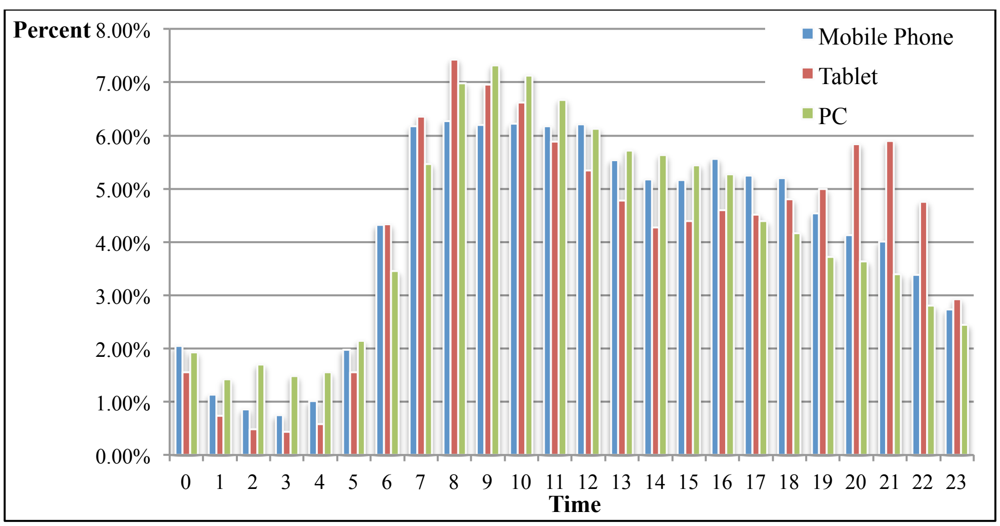
Figure 4.4. Monthly Average Transactions for Each Type



	# Transactions	# Inquiries	# External Transfers	# Services	# Maintenances
PC Only	1.00	1.00	1.00	1.00	1.00
PC+Mobile Phone	1.07	1.04	1.25	0.68	1.09
PC+Mobile Phone+Tablet	1.36	1.32	1.59	0.98	1.19

Figure 4.5 shows the hourly shares of transactions for each channel over the time span of a day (00:00 to 23:00 hours). I aggregated the number of transactions at each hour for each channel, and plotted the hourly shares of transactions through mobile phones, tablets, and PCs. The temporal difference in customer transaction-making using mobile devices suggested the ubiquity and portability features of the mobile channel compared to the PC channel. In Figure 4.5, the trend lines for the three channels moved in the same directions during working hours (8:00 to 16:00). During commuting hours (6:00 to 8:00 and 16:00 to 18:00), the share of mobile phone and tablet transactions steadily outweighed the share of PC transactions. When the customers were at home (18:00 to 21:00), the share of tablet transactions started climbing while the share of mobile phone and PC transactions continued to drop sharply, suggesting that customers tended to use tablets for banking while at home.

Figure 4.5. Hourly Shares of Transactions for Each Channel



4.5 Research Methodology

I use the matched samples generated by the procedure described in Appendix E to examine the impact of the mobile channel on customer service demand and overdraft frequency. Since not every customer had credit card accounts, I constructed a similar sample containing a subset of customers to test the Mobile Channel and Over-Limit Charge Hypothesis (H5A) and Mobile Channel and Late Payment Charge Hypothesis (H5B). The unit of analysis was customer-month.

4.5.1 Service Demand and Customer Inquiry

The basic approach to testing the Augmentation Effect of the Mobile Channel Hypothesis (H1), Influence of Physical Channel Density Hypothesis (H2A), Channel Complementarity and Substitution Hypothesis (H2B), and Mobile Channel and Customer Inquiry Hypothesis (H3) was to measure the extent to which the service demand and customer inquiry were influenced by the use of the mobile channel. I examined the impact of the use of a mobile device on the number of transactions through each channel and all three channels combined, as well as on the number of inquiry transactions through all of the digital channels. To examine the effect of physical channel density, I included in the regression models the counts of branches and ATMs within the same zip code of a customer's primary residence.

There are two key issues related to the econometric specification: (1) the number of transactions for a given customer was discrete and over-dispersed, with a variance larger than the mean; and (2) the unobservable heterogeneity across customers, such as different demographic characteristics and capabilities for accessing their banking information and accounts with mobile technology, needed to be controlled for (Campbell and Frei 2010). The negative binomial regression model is often used to deal with over-dispersed count data (Hilbe 2011). I performed a Hausman specification test for the null hypothesis that both of the fixed-effects and random-effects estimators were consistent, and I failed to reject the hypothesis. So I used a *random-effects negative binominal model* due to the high efficiency (Kauffman et al. 2012). I assumed individual customers differed randomly in a manner that was not fully accounted for by observed covariates. I modeled the probability of observing y_{it} transactions for customer i in month t as:

$$E(y_{it}) = exp(\beta_0 + \beta_1 Mobile_{it} + \beta_2 Tablet_{it} + \beta_3 Mobile_{it} \times Tablet_{it} + \beta_4 ATMDensity_{it} + \beta_5 BranchDensity_{it} + \phi X_{it} + \delta_i),$$

where δ_i is the customer-specific random effect. Also, X_{it} is a vector of time-varying control variables, including the customer's balance in the deposit account at the end of a month (*Current Balance*), the number of monthly transactions by type (*# External Transfers*, *# Services*, *# Maintenance*), binary variables indicating whether a certain type of transaction has been made within a month (*External Transfer*, *Service*, *Maintenance*), month dummies (*Apr*, *May*), etc. I added in the interaction term, *Mobile×Tablet*, to test that the effect of using one mobile channel is different if the other mobile channel was used. The coefficients β_1 to β_3 captured the effects of using a mobile phone or a tablet on service demand in the digital channels, and β_4 and β_5 captured the how the ATM and branch channel density affected customer transaction-making.

4.5.2 Overdraft and Credit Card Penalty Fees

I tested the Mobile Channel and Overdraft Frequency Hypothesis (H4) using a similar approach. However, the dependent variable, *Overdraft Frequency*, displayed more zeros than would be expected under a negative binominal model. To deal with these issues, I applied a *zero-inflated negative binominal model* for the observations that were generated by two possible processes. For a given customer *i*, one process generated zeros with a probability of φ_i, while the other process generated data from a negative binominal model with probability $1 - \varphi_i$. The probability φ_i depended on the characteristics of customer *i*, which was a vector of time-invariant zero-inflated variables, z_i, including *Tenure*, *Low Income*, *Average # of Transactions*, *Average Balance*, enrollment of overdraft protection (*Overdraft Protection*), etc. I tested H4 using the following specifications for the process that generated data from a negative binominal model:

$$
\begin{aligned}
E(OverdraftFrequency_{it}) \\
&= exp(\beta_0 + \beta_1 Mobile_{it} + \beta_2 Tablet_{it} + \beta_3 Mobile_{it} \times Tablet_{it} \\
&+ \beta_4 ATMDensity_{it} + \beta_5 BranchDensity_{it} + \beta_6 CurrentBalance_{it} \\
&+ \beta_7 \#Transctions_{it})(1 - \varphi_i)
\end{aligned}
$$

For the *Over-Limit Charge* and *Late Payment Charge*, I applied *logistic regression for rare events* to deal with binary dependent variables with dozens of times fewer ones than zeros (King and Zeng 2001). I tested H5A and H5B with:

$$Pr(OverLimitCharge_{it} = 1|\cdot) = F(\beta_0 + \beta_1 Mobile_{it} + \beta_2 Tablet_{it} + \beta_3 Mobile_{it} \times Tablet_{it} + \beta_4 LastStatementBalance_{it} + \beta_5 \frac{LastStatementBalance_{it}}{CreditLine_{it}} + \beta_6 \#Cards_{it} + \phi Z_i);$$

$$Pr(LatePaymentCharge_{it} = 1|\cdot) = F(\beta_0 + \beta_1 Mobile_{it} + \beta_2 Tablet_{it} + \beta_3 Mobile_{it} \times Tablet_{it} + \beta_4 LastStatementBalance_{it} + \beta_5 LastStatementMinPayment_{it} + \beta_6 \frac{LastStatementBalance_{it}}{CreditLine_{it}} + \beta_7 \#Cards_{it} + \phi Z_i),$$

where the *Last Statement Balance*/*Credit Line* captures a customer's monthly spending level, and Z_i is a vector of time-invariant control variables, including *Tenure*, *Low Income*, average monthly spending level (*Average Statement Balance*/*Credit Line*), etc.

4.6 Empirical Results

I estimated the regression models using a maximum (penalized) likelihood estimator.[9] I summarize the main results for the impact of using mobile phones and tablets in Table 4.2a and Table 4.2b.

[9] I used the TCOUNTREG and LOGISTIC procedures in SAS for the panel estimation of count and logistic regression models.

Table 4.2a. The Impact of the Mobile Phone Channel on Customer Behavior

	(1) # Transactions	(2) # Inquiries	(3) # PC	(4) # Tablet	(5) Overdraft Frequency	(6) Over-Limit Charge	(7) Late Payment Charge
Mobile	0.279*** (0.003)	0.308*** (0.004)	0.074*** (0.004)	0.149*** (0.015)	0.385*** (0.015)	-0.230* (0.138)	0.371*** (0.082)
Tablet	0.220*** (0.005)	0.283*** (0.006)	-0.018*** (0.006)		-0.057* (0.030)	-0.528** (0.263)	0.279** (0.141)
Mobile×Tablet	-0.061*** (0.008)	-0.081*** (0.009)	0.068*** (0.009)		0.109*** (0.042)	-0.342 (0.495)	-0.275 (0.214)
ATM Density	-0.003*** (0.000)	-0.002*** (0.000)	-0.002*** (0.000)	-0.010*** (0.001)	-0.001*** (0.001)		
Branch Density	0.014*** (0.002)	0.010*** (0.003)	0.014*** (0.003)	0.085*** (0.011)	-0.007 (0.011)		
External Transfer	0.401*** (0.003)		0.417*** (0.003)	0.284*** (0.015)			
Service	0.577*** (0.003)		0.634*** (0.003)	0.311*** (0.014)			
Maintenance	0.196*** (0.009)		0.204*** (0.009)	0.163** (0.046)			
# External Transfers		0.025*** (0.000)					
# Services		0.006*** (0.000)					
# Maintenance		0.160*** (0.006)					
log(*Current Balance*)	0.018*** (0.001)	0.039*** (0.001)	0.023*** (0.001)	0.104*** (0.004)	-0.270*** (0.003)		
log(*# Transactions*)					0.169*** (0.006)		
log(*Last Statement Balance*)						0.788*** (0.082)	-0.862*** (0.030)
log(*Last Statement Min Payment*)							1.520*** (0.030)
Last Statement Balance/Credit Line						14.628*** (0.533)	2.902*** (0.208)
Tenure					0.120*** (0.011)	0.051 (0.118)	0.166*** (0.060)
Low Income					-0.105*** (0.021)	0.404** (0.171)	0.246*** (0.104)
log(*Average # of Transactions*)					-0.008*** (0.001)		
log(*Average Balance*)					0.040*** (0.000)		
Overdraft Protection					0.081*** (0.016)		
Average Statement Balance/Credit Line						1.702*** (0.106)	-0.213*** (0.207)
# Cards						-0.493*** (0.165)	-0.473*** (0.094)
Apr	-0.096*** (0.003)	-0.072*** (0.003)	-0.100*** (0.003)	-0.134*** (0.013)	-0.118*** (0.014)	0.046 (0.156)	-0.038 (0.092)
May	-0.300*** (0.003)	-0.294*** (0.003)	-0.314*** (0.003)	-0.262*** (0.014)	0.216*** (0.014)	-0.029 (0.157)	-0.018 (0.091)
Number of Observations	244,118	244,118	244,118	244,118	244,118	129,902	129,902

Note: each column represents a separate regression, and the column header is the dependent variable. The dependent variables for regressions (1)-(5) are the count of customer monthly transactions, and the dependent variables for regressions (6) and (7) are binary indicators for incurrence of a credit card penalty fee in a month. Robust standard errors are in parentheses. Significance level: * p<0.1; ** p<0.05; *** p<0.01. I marked the estimates of zero-inflation variables with cells that have a gray background. *Last Statement Balance/Credit Line* and *Average Statement Balance/Credit Line* are percentage values. The unit of analysis is at the customer-month level.

Table 4.2b. The Impact of the Tablet Channel on Customer Behavior

	(1) # TRANSACTIONS	(2) # INQUIRIES	(3) # PC	(4) # MOBILE	(5) OVERDRAFT FREQUENCY	(6) OVER-LIMIT CHARGE	(7) LATE PAYMENT CHARGE
Mobile	0.340*** (0.006)	0.353*** (0.006)	0.148*** (0.006)		0.494*** (0.026)	-0.157 (0.241)	0.478*** (0.127)
Tablet	0.182*** (0.005)	0.228*** (0.005)	-0.069*** (0.005)	0.089*** (0.013)	-0.045* (0.027)	-0.026 (0.228)	0.005 (0.135)
Mobile×Tablet	-0.079*** (0.009)	-0.079*** (0.009)	0.042*** (0.010)		0.082** (0.042)	-0.698 (0.522)	-0.070 (0.224)
ATM Density	-0.002*** (0.000)	-0.002*** (0.000)	-0.002*** (0.000)	-0.003*** (0.001)	-0.004*** (0.001)		
Branch Density	0.015*** (0.003)	0.009*** (0.003)	0.013*** (0.003)	-0.002*** (0.009)	-0.013 (0.015)		
External Transfer	0.434*** (0.004)		0.449*** (0.004)	0.327*** (0.013)			
Service	0.608*** (0.004)		0.676*** (0.004)	-0.045*** (0.013)			
Maintenance	0.174*** (0.013)		0.170*** (0.014)	0.113*** (0.043)			
# External Transfers		0.028*** (0.000)					
# Services		0.006*** (0.000)					
# Maintenance		0.157*** (0.010)					
log(*Current Balance*)	0.007*** (0.001)	0.027*** (0.001)	0.013*** (0.001)	-0.162*** (0.003)	-0.312*** (0.004)		
log(*# Transactions*)					0.200*** (0.009)		
log(*Last Statement Balance*)						0.556*** (0.113)	-0.909*** (0.039)
log(*Last Statement Min Payment*)							1.536*** (0.039)
Last Statement Balance/Credit Line						14.525*** (0.820)	3.161*** (0.288)
Tenure					0.048*** (0.012)	0.219 (0.153)	0.058 (0.075)
Low Income					-0.098*** (0.032)	0.182 (0.259)	0.035 (0.155)
log(*Average # of Transactions*)					-0.007*** (0.001)		
log(*Average Balance*)					0.045*** (0.000)		
Overdraft Protection					0.120*** (0.024)		
Average Statement Balance/Credit Line						1.753*** (0.237)	-0.192 (0.278)
# Cards						-0.748*** (0.239)	-0.836*** (0.131)
Apr	-0.087*** (0.004)	-0.065*** (0.004)	-0.091*** (0.004)	-0.208*** (0.013)	-0.132*** (0.021)	0.061 (0.222)	-0.100 (0.122)
May	-0.274*** (0.004)	-0.266*** (0.004)	-0.286*** (0.004)	-0.331*** (0.013)	0.220*** (0.021)	-0.060 (0.225)	-0.045 (0.121)
Number of Observations	140,138	140,138	140,138	140,138	140,138	35,535	35,535

Note: each column represents a separate regression, and the column header is the dependent variable. The dependent variables for regressions (1)-(5) are the count of customer monthly transactions, and the dependent variables for regressions (6) and (7) are binary indicators for incurrence of a credit card penalty fee in a month. Robust standard errors are in parentheses. Significance level: * p<0.1; ** p<0.05; *** p<0.01. I marked the estimates of zero-inflation variables with cells that have a gray background. *Last Statement Balance/Credit Line* and *Average Statement Balance/Credit Line* are percentage values. The unit of analysis is at the customer-month level.

4.6.1 Service Demand and Channel Complementarity and Substitution

The results validate the augmentation effect of the mobile channel on customer service demand. Compared to PC-only users, mobile phone and tablet users had higher service consumption through all the digital channels combined (β_1 = 0.279 in Column 1 of Table 4.2a and β_2 = 0.182 in Column 1 of Table 4.2b for mobile phone and tablet; $p < 0.01$ for both). In particular, the use of a mobile phone increased digital banking transactions by 27.9%, and by 21.8% when a tablet was also used. The use of a tablet increased transactions by 18.2% or 10.3% whether a mobile phone was used for mobile banking. Thus, the results supported the Augmentation Effect of the Mobile Channel Hypothesis (H1). The augmentation effect of the mobile channel was consistent with the results of PC banking adoption in Campbell and Frei (2010) and Xue et al. (2011).

I found the evidence that the lower ATM density and higher branch density were associated with higher service consumption through all of the digital channels (β_4 = -0.003 and β_5 = 0.014 in Column 1 of Table 4.2a, β_4 = -0.002 and β_5 = 0.015 in Column 1 of Table 4.2b; $p < 0.01$). The existence of more bank branches near the customer were associated with a higher usage level of the digital channels due to greater customer awareness and engagement from the physical full-service channel (Bell et al. 2015, Xue et al. 2007). However, the availability of an ATM self-service channel inversely affects customer service demand through the digital channels: customers substituted transactions from traditional physical channels to digital channels through multiple devices when there were fewer ATMs around them. The results supported the Influence of Physical Channel Density Hypothesis (H2A). Prior research has not formally tested the effect of physical channel density on digital channel usage in the post-adoption stage.

I also found that the use of the mobile phone channel increased the number of transactions through the PC channel, while the use of the tablet channel negatively affected service demand through the PC channel. In particular, the use of a mobile phone increased transactions through the PC channel by 7.4% ($\beta_1 = 0.074$ in Column 3 of Table 4.2a, $p < 0.01$), and the use of a tablet decreased transactions through the PC channel by 6.9% ($\beta_2 = -0.069$ in Column 3 of Table 4.2b, $p < 0.01$). The results provide support for the Channel Complementarity and Substitution Hypothesis (H2B) that the mobile phone channel serves as a complement to the PC channel, while the tablet channel served as a substitute for the PC channel. Furthermore, the mobile phone and tablet channels acted as complements for each other (See Column 4 in Table 4.2a and Table 4.2b).

4.6.2 Customer Inquiry and Banking Behavior

Column 2 in Table 4.2a and Table 4.2b shows the results of the Customer Inquiry Hypothesis (H3). My panel analysis suggests that customers acquired more information by performing inquiries through digital channels ($\beta_1 = 0.308$, $p < 0.01$ for the effect of the mobile phone channel only; $\beta_2 = 0.228$, $p < 0.01$ for the effect of the tablet channel only). When a PC, a mobile phone, and a tablet were all used, the use of the mobile phone and tablet channels increased by 22.7% ($\beta_1 + \beta_3 = 0.227$ in Column 2 of Table 4.2a, $p < 0.01$) and by 14.9% ($\beta_2 + \beta_3 = 0.149$ in Column 2 of Table 4.2b, $p < 0.01$) of inquiries through the digital channels. Thus, the empirical evidence supports H3, suggesting that the use of the mobile channel increased a customer's inquiries about their accounts.

My zero-inflated count-data analysis for the Mobile Channel and Overdraft Frequency Hypothesis (H4) indicates that the use of a tablet had a significant impact on reducing a customer's overdraft frequency (i.e., β_2 = -0.045, $p < 0.1$), as shown in Column 5 of Table 4.2b. However, the use of a mobile phone had a significant and positive association with a customer's overdraft frequency: β_1 = 0.385, $p < 0.01$ (see Column 5 of Table 4.2a). The results partially support H4 that the use of the mobile channel reduced a customer's overdraft frequency. As expected, the binary zero-inflated variable, *Overdraft Protection*, for linking a customers' checking account to their demand deposit account and enabling automatic value transfer among different accounts was instrumental in decreasing the possibility of overdrawing the checking account.

In addition, the use of the mobile phone channel was promising for reducing customer credit card over-limit charges, partially supporting the Mobile Channel and Over-Limit Charge Hypothesis (H5A). Customers who used the mobile phone channel were less likely to incur over-limit charges, β_1 = -0.230, $p < 0.1$, while there was no significant impact of the use of a tablet on over-limit charges (see Column 6 of Table 4.2a and Table 4.2b). On the other hand, the results do not support the Mobile Channel and Late Payment Charge Hypothesis (H5B) that the use of a mobile device can curb credit card late payment changes. The use of a mobile phone had a significant positive association with incurrence of late payment charges (see Column 7 of Table 4.2a).

4.7 Robustness Checks and Additional Analysis

I carried out a series of robustness checks and additional analysis for further validation of my results.

4.7.1 Robustness Checks

Given that the regressions for the number of transactions through different channels were conducted on the same sample of customer observations, it is unrealistic to expect that the separate regression errors are uncorrelated. The errors ought to be correlated across equations for a given customer, but uncorrelated across customers. In this case, to investigate the robustness of my main results, I applied a *seemingly unrelated regression* (SUR) to take the information structure of the error terms into account. A SUR system that contains a number of linear equations uses the correlations between the errors in different equations to improve the efficiency of estimation (Fiebig 2001).

I created a cross-sectional sample for matched mobile phone users, and took the average value for non-binary independent and dependent variables, and maximum value for binary independent variables. In Table 4.3, the coefficients for the variables of interest remain qualitatively the same in terms of the sign and statistical significance, with the use of the logarithm value of the transaction number for each channel as dependent variables. Although the underlying assumptions and interpretation of the results differ for negative binominal regression models and ordinary least-square regression models, I present the results for SUR to mitigate the concern that the cross-equation correlations might have significantly affected my results.

Table 4.3. Results for Seemingly Unrelated Regression

	ALL DIGITAL CHANNELS log(# *Transactions*)	TABLET CHANNEL log(# *Tablet*)	PC CHANNEL log(# *PC*)
Mobile	0.254*** (0.008)	0.081*** (0.008)	0.033*** (0.008)
Tablet	0.108*** (0.012)		-0.042*** (0.013)
Mobile×Tablet	-0.101*** (0.017)		-0.009 (0.018)
ATM Density	-0.001*** (0.000)	-0.000 (0.001)	-0.001* (0.000)
Branch Density	0.015*** (0.005)	0.012** (0.006)	0.011** (0.005)
External Transfer	0.402*** (0.008)	0.146*** (0.009)	0.436*** (0.008)
Service	0.787*** (0.008)	0.142*** (0.009)	0.871*** (0.008)
Maintenance	0.207*** (0.015)	0.049*** (0.019)	0.216*** (0.016)
Tenure	0.072*** (0.004)	0.038*** (0.005)	0.080*** (0.005)
Low Income	0.024** (0.009)	-0.088*** (0.011)	0.014 (0.010)
log(*Current Balance*)	0.020*** (0.002)	0.051*** (0.002)	0.029*** (0.002)
Number of Observations	81,440	81,440	81,440

Note: each column represents a separate regression, and the column header is the dependent variable. Robust standard errors are in parentheses. Significance level: * $p<0.1$; ** $p<0.05$; *** $p<0.01$. The dependent variables are the natural log of the average number of customer monthly transactions. The regressions are on the cross-sectional sample of users matched by mobile phone treatment. The unit of analysis is at the customer level.

For a second robustness check, I examined whether the results were affected by the usage intensity of the mobile channel. I re-ran the regressions on two subsamples of treated customers who had low and high levels of transaction intensity through the mobile phone channel. In particular, I selected the customers at the lower and upper quartiles, who were considered *inactive* and *active* mobile phone users. Columns 1 and 2 in Table 4.4 show that the active mobile users had much more total and inquiry transactions than the inactive ones, which consolidates the augmentation effect of the mobile channel. In addition, the complementary effects of the mobile phone channel on the PC and tablet channels were also much stronger for active users, and the inactive users did not have a statistically significant estimate for the effect on PC channel.

For further validation, I examined the robustness of the results using weekly aggregated transaction records instead of monthly observations. The use of the mobile phone channel still had positive and significant effects for the total and inquiry transactions through all three channels combined, as shown in Columns 1 and 2 of Table 4.5. Nevertheless, the mobile phone channel acted as a substitute for rather than a complement to the PC and tablet channels. I observed that customers were used to banking through a single device, and different devices exhibited a substitution pattern. A distinctive characteristic of financial services is repeated service encounters and the long-term contractual relationship between customers and financial institutions (Hatzakis et al. 2010). So to analyze transaction-making more effectively, it is appropriate to do so at the monthly level and over a longer period to understand the relationship between different channels.

Table 4.4. Robustness Check for Usage Intensity of Mobile Channel

	(1) # TRANSACTIONS		(2) # INQUIRIES		(3) # PC		(4) # TABLET	
	Inactive	**Active**	**Inactive**	**Active**	**Inactive**	**Active**	**Inactive**	**Active**
Mobile	0.084*** (0.008)	0.457*** (0.006)	0.096*** (0.009)	0.464*** (0.006)	0.007 (0.009)	0.103*** (0.006)	0.118*** (0.032)	0.281*** (0.028)
Tablet	0.243*** (0.010)	0.183*** (0.013)	0.268*** (0.011)	0.233*** (0.013)	-0.007 (0.011)	-0.059*** (0.014)		
Mobile×Tablet	-0.017 (0.021)	-0.057*** (0.017)	0.029 (0.022)	-0.047*** (0.018)	0.050*** (0.023)	0.120*** (0.019)		
ATM Density	-0.002*** (0.000)	-0.000 (0.000)	-0.002*** (0.000)	-0.001 (0.000)	-0.001*** (0.000)	0.000 (0.000)	-0.003* (0.002)	0.003* (0.002)
Branch Density	0.014*** (0.004)	0.004 (0.004)	0.025*** (0.005)	0.004 (0.004)	0.013*** (0.004)	0.002 (0.004)	0.022 (0.018)	0.021 (0.019)
External Transfer	0.443*** (0.007)	0.322*** (0.006)			0.455*** (0.007)	0.334*** (0.006)	0.297*** (0.027)	0.302*** (0.029)
Service	0.689*** (0.007)	0.552*** (0.006)			0.715*** (0.007)	0.640*** (0.006)	0.336*** (0.027)	0.439*** (0.028)
Maintenance	0.228*** (0.021)	0.133*** (0.018)			0.231*** (0.021)	0.137*** (0.019)	0.101 (0.091)	0.038 (0.092)
# External Transfers			0.028*** (0.000)	0.020*** (0.000)				
# Services			0.008*** (0.000)	0.008*** (0.000)				
# Maintenance			0.164*** (0.011)	0.123*** (0.013)				
log(*Current Balance*)	0.020*** (0.001)	0.021*** (0.001)	0.049*** (0.000)	0.037*** (0.001)	0.022*** (0.001)	0.030*** (0.001)	0.130*** (0.007)	0.115*** (0.007)
Apr	-0.089*** (0.006)	-0.077*** (0.006)	-0.083*** (0.007)	-0.066*** (0.006)	-0.090*** (0.007)	-0.073*** (0.006)	-0.078*** (0.028)	-0.116*** (0.029)
May	-0.247*** (0.007)	-0.301*** (0.006)	-0.248*** (0.007)	-0.291*** (0.006)	-0.251*** (0.007)	-0.308*** (0.006)	-0.171*** (0.029)	-0.209*** (0.030)
Number of Observations	60,070	67,054	60,070	67,054	60,070	67,054	60,070	67,054

Note: each column represents a separate regression, and the column header is the dependent variable. Robust standard errors are in parentheses. Significance level: * p<0.1; ** p<0.05; *** p<0.01. The lower quartile of usage intensity of mobile phone is considered to be inactive users, and the upper quartile of usage intensity of mobile phone is considered to be active users. The dependent variables are the number of customer transactions each month. The unit of analysis is at the customer-month level.

Table 4.5. Robustness Check for Weekly Observations

	(1) # TRANSACTIONS	(2) # INQUIRIES	(3) # PC	(4) # TABLET
Mobile	0.152^{***} (0.002)	0.143^{***} (0.002)	-1.002^{***} (0.003)	-0.230^{***} (0.011)
Tablet	0.125^{***} (0.003)	0.138^{***} (0.003)	-1.183^{***} (0.006)	
Mobile×Tablet	0.161^{***} (0.006)	0.166^{***} (0.006)	0.911^{***} (0.013)	
ATM Density	-0.001^{***} (0.000)	-0.000^{***} (0.000)	-0.000 (0.000)	-0.002^{***} (0.001)
Branch Density	0.006^{***} (0.001)	0.003^{**} (0.001)	0.007^{***} (0.002)	0.042^{***} (0.007)
External Transfer	0.573^{***} (0.002)		0.610^{***} (0.002)	0.370^{***} (0.009)
Service	0.820^{***} (0.004)		0.878^{***} (0.005)	-0.102^{***} (0.027)
# External Transfers		0.130^{***} (0.000)		
# Services		0.038^{***} (0.000)		
log(*Current Balance*)	0.019^{***} (0.000)	0.025^{***} (0.000)	0.027^{***} (0.001)	0.077^{***} (0.000)
Number of Obs.	819,182	819,182	819,182	819,182

Note: each column represents a separate regression, and the column header is the dependent variable. Robust standard errors are in parentheses. Significance level: * p<0.1; ** p<0.05; *** p<0.01. The dependent variables are the number of customer transactions each week. The control variables for the maintenance transaction are excluded due to the sparseness of observations. The estimates for the week dummies are not reported due to lack of space. The unit of analysis is at the customer-week level.

4.7.2 Additional Analysis

To examine the impact of the use of the mobile channel across different types of transactions through digital channels, I used the number of external transfer transactions (# *External Transfers*), service transactions (# *Services*), and maintenance transactions (# *Maintenance*) in place of the number of inquiry transactions (# *Inquiries*) as the dependent variables (see Table 4.6). The results indicate that the use of the mobile phone channel increased the number of external transfer transactions and decreased the number of service transactions through all of the channels, but the effect on the number of maintenance transactions was not visible. A plausible explanation is that mobile banking apps provide a simple and clear input interface to perform basic inquiries and money transfers. But service transactions, such as activating online statements and ordering checks and supplies, require more complex or multi-step operations, which are more difficult on small-sized mobile phone screens. Maintenance actions, such as changing a password or updating personal particulars, are rare, so they are not likely to be affected by the use of the mobile channel.

Table 4.6. Impact of the Mobile Channel on Different Types of Transactions

	# External Transfers	# Services	# Maintenance
Mobile	0.126*** (0.007)	-0.192*** (0.008)	0.002 (0.020)
Tablet	0.186*** (0.010)	0.145*** (0.011)	0.006 (0.033)
Mobile×Tablet	0.041*** (0.016)	0.161*** (0.018)	-0.004 (0.057)
ATM Density	0.000 (0.000)	-0.003*** (0.000)	-0.001 (0.001)
Branch Density	0.012*** (0.005)	0.017*** (0.005)	-0.002 (0.012)
# Inquiries	0.002*** (0.000)	0.002*** (0.000)	-0.005*** (0.000)
# External Transfers		0.014*** (0.000)	0.000 (0.002)
# Services	-0.007*** (0.000)		-0.001 (0.001)
# Maintenance	0.126*** (0.012)	0.124*** (0.015)	
log(*Current Balance*)	0.125*** (0.002)	0.134*** (0.002)	-0.002 (0.004)
Apr	-0.189*** (0.005)	-0.107*** (0.006)	-0.023 (0.020)
May	-0.347*** (0.006)	-0.296*** (0.007)	-0.025 (0.020)
Number of Observations	244,118	244,118	244,118

Note: each column represents a separate regression, and the column header is the dependent variable. The dependent variables are the number of customer transactions each month. Robust standard errors are in parentheses. Significance level: * p<0.1; ** p<0.05; *** p<0.01. The unit of analysis is at the customer-month level.

4.8 Discussion and Implications

4.8.1 Omni-Channel Banking Services

Digitalization has been transforming every aspect of the traditional retail banking business model, and most banks tend to incorporate digital channels to gain a competitive edge over traditional incumbents (Olanrewaju 2014). The customer mobile experience is a crucial aspect of digital banking strategy. First, my results show that the use of the mobile channel had a substantial effect on increasing customer service demand. In addition, high-balance customers tended to conduct more activities through the digital channels. As major retail banks have been pursuing growth in interaction and revenues from their own customer segmentation (Corbat and Kirkland 2015), to engage high-income customers who are active through mobile channels and meet their growing financial needs is vital for banks to succeed. In addition to making basic financial transactions, the digital customers are also provided with cross-channel, targeted, just-in-time product or service information in an effective and seamless way through the mobile channels (van Bommel and Edelman 2015).

The rapid shift toward digitalization might suggest that banks should be able to shrink their branch network to reduce costs. Nevertheless, my findings suggest that more branches located closed to where customers live augment digital service consumption, and indicate that the lower access cost of a physical full-service channel results in higher and more diverse digital transactions. In the digital age, customers are utilizing omni-channel banking services, rather than turning solely to digital or branch services.

Yet bank branches still play an important role in taking customers from physical to digital banking. Compliance with regulations, demand for personal advice, and concerns about digital banking security continue to drive the need for branch services (Barquin and Vinayak 2015). Nonetheless, there has been a reduction in physical branches in the banking industry and a transition toward automated banking branches (Egan 2015). When both short- and long-term interest rates are extremely low and it is difficult for banks to turn a profit on the difference between what they pay out for deposits and the amount earned on loans, they have little incentive to attract customers into branches to deposit their money, and operating the branches is costly.

In contrast, customers who live in an area with a lower ATM density have greater digital transaction demand. This indicates that the higher access cost of physical ATM locations enhances the usage of digital channels. The mobile apps for check deposits and peer-to-peer money transfers also substitute transaction demand away from the ATM channel. There are significant costs associated with maintaining

ATMs, and revenues from the surcharges for non-customer usage have become increasingly limited. In the near future, ATM will be another area where banks can cut costs, and banks have turned ATMs into a marketing vehicle for advertising, customization, cross-selling opportunities, customer data collection, and brand reinforcement.

Recent research has found that among the digital channel the tablet channel serves as a substitute for the PC channel, and as a complement to the mobile phone channel for the purpose of online shopping. In banking services, I found that the mobile phone channel complemented the PC channel, the tablet channel substituted for the PC channel, and the mobile phone channel and tablet channel were complementary. My results show similar relationships in the omni-channel context of banking services. The similarity between tablets and PCs in terms of screen size and functionality can explain the substitutive relationship. Tablets are not as portable as smartphones and mostly not equipped with 3G capabilities. PCs are bulkier and restricted to certain locations, so customers tend to use tablets at home. Mobile phones have ubiquitous wireless network connections and are used while customers are on the move, indicating a complementary effect to the PC channel.

4.8.2 Customer Banking Behavior

A customer's sense of well-being is closely intertwined with services (Hatzakis et al. 2010). How banks can leverage mobile technology to work differently for a better customer experience and operational efficiency is more important than simply adding a new service channel. My findings show that customers who connected with their banks via smartphones, tablets and PCs performed inquiries more often than PC-only customers. The increased inquiry activities indicated that the mobile channel enhanced a customer's *connectivity* with their bank and information about its products and services. Recent research has examined how the increased availability of online, social, and mobile information drives different individual choices and behavior (Ghose et al. 2015, Goh and Bockstedt 2013, Li and Kauffman 2012).

An industry report showed that 68% of consumers would rather have a transaction declined than forfeit an overdraft fee (Vasel 2015). Customers' *limited attention* and high *information acquisition cost* for obtaining all available information account for a large proportion of overdraft transactions. My findings indicate that the mobile channel significantly reduced customer transaction costs and increased information availability, and informed customers can avoid spending more than what is available in their checking account and maintain the balance above zero. Financial institutions can generate additional revenue by offering liquidity-management services for overdraft protection to inattentive customers.

When cardholders attempt to make purchases that will put them over their limit, card issuers used to routinely decline the transaction. However, now issuers have automatically enrolled customers in programs that allow the transaction, and then charge over-limit fees. The Credit Card Account Responsibility and Disclosure Act of 2009 requires that card issuers give account holders the option to opt in to over-limit fees (CFPB 2013). For consumers who consent to the over-limit transactions, their inattention in monitoring credit card accounts is one of the reasons for unnecessary financial charges. The reduction in over-limit fees through the use of the mobile channel suggests that implementation of mobile alerts and redesign of fee structures will effectively improve customer experience and satisfaction. The federal regulation also prohibits a range of practices where the issuers artificially increase the frequency of late payment fees (CFPB 2013). Under the rules for reasonable and proportional penalty fees, the cause of a late payment fee is more endogenous, and customers' opting in to late payments might affect my results when they know the billing cycle and due date exactly. As late payments may affect a customer's good credit history, the implementation of mobile alerts will reduce complaints from the customer.

5 Conclusion, Limitations and Future Research

Operations in financial services are characterized by extensive use of IT, which acts as an important driver of product, service and business innovations in the industry. My dissertation was inspired by the business problems related to IT in the financial services sector, especially *mobile financial services*. I focused on senior manager decision-making and firm strategy related to IT-enabled financial innovations. I examined the impact of mobile payments and mobile banking innovations on firm's technology investment decision-making and customer behavior in omni-channel banking services.

Essay 1 extended the *technology ecosystem paths of influence model* to understand how competition, cooperation, and regulation influence financial IS and technology innovation and evolution. The application to m-payments technology innovation is among the first instances of research that looks at the development of m-payments services from an evolutionary point of view. More importantly, I raised the point that competition, cooperation, and regulation jointly shape the development paths of financial IS and technology innovations in markets. My theoretical enrichment of the original framework identified various patterns of innovation and technology evolution in the m-payments ecosystem, and supports this competition-and-regulation argument. It demonstrated how the evolution of technology ecosystems plays out, based on the analysis of paths of influence and the role of key events in an industry sector's technology innovation timeline.

The limitations of this study are worth mentioning though. One of the important characteristics of Adomavicius et al.'s (2008a) technology ecosystem evolution model is that it only focuses on the internal influence paths of the ecosystem. The mutual effects of the m-payments ecosystem and the external environment are simplified as external facilitators or inhibitors. In addition, my extended approach is mainly for retrospective explanation and interpretation of how m-payments have evolved, but it may not be accurate for forecasting future technology evolution. I demonstrated a test case and the possibility for further investigation though.

The future direction of my research on financial IS and technology ecosystems will focus on validating the proposed new constructs on the demand-side, in addition to the supply-side dynamics. Both have influenced the evolution of technology-based financial innovations. I will adopt a historical data collection approach from prior research on technology evolution in the IS and Marketing disciplines. I plan to create an advanced forecasting capability for the evolutionary patterns of industry-centered innovations and cross-level effects among different clusters of technologies: components, services and business infrastructures.

In Essay 2, my contributions are threefold. First, I proposed a new modeling perspective that considers the mean reversion property for the stochastic drift of investment cost and benefit flows, to enrich managerial knowledge on how real option theory can be used to support decision-making under uncertainty for IT investments. Second, I applied my modeling approach to a real-world m-payments technology investment case to illustrate its applicability and offer insights to decision-makers so they understand the value of deferral and establish an effective strategy for investment timing. Third, I demonstrated that the simulation-based option valuation, known as the Longstaff-Schwartz method, is useful when the market experiences shocks that affect firm-level and market-level perceptions associated with technology investments, such as the investment in mobile payments technology.

A number of limitations in Essay 2 deserve comment. The advantage of being a first-mover is not considered in the current model, nor did I consider the entry of any competing firm. Also, I assumed that the system will become available immediately once the investment decision is made. This made it possible for benefits to flow without uncertainty about a lag in the accrual of business value.

The reality is different, of course: a firm will need some additional period of time to develop the necessary infrastructure. So the business value from investment will be obtained only some time later. In the investment process, the time at which the benefit flows start to be received is also a random variable, and the benefit flows that will be obtained during the development process will be relatively small. If I assume an appropriate amount of time for the installation of the infrastructure and the start-up of the benefit flows, my model can be adapted for application in a variety of settings. My assumptions, such as a risk-neutral firm, and uncorrelated cost and benefit flow changes, also simplified the analysis. Excluding these factors may result in a loss of contextual richness. By limiting the number of factors that I considered, I traded off complexity to gain some intuition about the results. Finally, it will be beneficial to validate my results by examining other settings involving successful IT investments and implementations that can be studied in greater depth.

Most firms have been cautious investors in large-scale IT infrastructures, leaving the door open for a leader to emerge and gain significant strategic advantage. An interesting direction for future research is to address the issue of investment timing in a competitive setting. This will only be valuable if we can discover aspects of the IT investment process that are truly unique in certain industry settings, since so much research has already been done on investment timing with competition. For example, for new technologies, I often see firms that are able to leapfrog the competition and adopt previously unavailable systems, which will invalidate the assumptions of most standard game-theoretic approaches. In addition, blended models involving wait-and-see interactions between competitors, along with information updates that occur over time to motivate evaluation, contextualized in a well-defined multi-stakeholder technology services marketplace, are worthwhile to explore for building additional theory.

A key observation about technology-based innovations over the years is that *co-opetition* (Brandenberger and Nalebuff 1996), rather than direct firm-to-firm competition, offers the best description of how firms actually have interacted in the industry. Market leaders become most successful when they create value by supporting the participation of other potential competitors (Teece 1992). Such firms act as *value-makers* in the larger market – for themselves, customers and competitors; and they also may be able to become successful *value-takers* as a result (Kauffman and Walden 2001). This will require them to find ways to appropriate value from their innovations though (Teece 1986).

In Essay 3, I examined the impact of the mobile channel on customer service demand and banking behavior in omni-channel banking services. As customer behavior patterns move away from physical channels and towards more digital transactions, it becomes a competitive necessity for banks to launch the mobile channel to improve customer service and experience. First, this study contributes to the research on mobile banking by examining the complementary and substitutive patterns among the digital channels using a large-scale dataset of customer-level transactions, enabling banks to better understand customer channel usage patterns, and target more active and profitable customer segments. Second, I assessed how the use of the mobile channel influenced customer's financial decision-making. My results indicate that customers acquire more information for financial decision-making following the use of the mobile channel. This study has implications for banks' managers related to the design and management of service delivery channels.

There are a number of limitations in Essay 3. First, my sample consisted of three months of observations of customer banking transactions through all of the digital channels, and I could not identify when the customers had adopted the mobile channel. This restricted my study to examining the long-term and lagged effect of the mobile channel. Second, I did not incorporate the effect of consumer learning from previous overdraft and credit card penalty fees on the incurrence of subsequent fees. Third, I did not consider the specific amounts of credit card over-limit and late payment fees in my analyses. Finally, the propensity score method to control for the selection bias might not be sufficient to solve the endogeneity issue of customers' mobile adoption. In the future, I will implement a set of falsification tests for further validating the effects of the mobile channel.

My future empirical research on mobile banking will include a firm-level analysis of the real-world timing of mobile banking adoption. I have crawled mobile banking app data from the Apple iTunes store and obtained bank financial and structural information from the U.S. Federal Deposit Insurance Corporation (FDIC). In addition, I will study digital banking problems that span payment and card services, and examine the performance of banking digital channels for consumer purchases and payments by working with large banks. I plan to apply data analytics to examine the effectiveness of banks' sponsored search marketing activities and explore the consumer's entire search journey in the digital channels for credit card usage also.

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Appendix A. The Evolution of M-Payments Technology

Since the 1950s and 1960s, banks have grappled with significant problems created by fast economic growth that drove an increase of financial intermediation-related activities. This has generated high demand for processing payments and handling other financial instruments. In the 1960s and 1970s, the automation of banking products and processes by computers and networks was just beginning, and since then, electronic payments made through payment card networks and ACH systems have become central to the industry's operations. The automated processing of payments has driven several waves of innovations in the banking and payments sector, leading to improvements in the efficiency and effectiveness of payments systems. The emergency of m-payments has been stimulated by the integration of advances in contactless payments, online and mobile banking, mobile and smart phones, mobile phone-based applications, and the digital convergence of e-commerce and m-commerce (Montgomery 2012).

Since the first mobile commerce and banking initiative using SMS was launched in Finland in the late 1990s, new possibilities that allow banking customers to use their mobile phones to perform many new financial functions have been proposed. (See Figure A1 and Table A1.) Also around that time, entrepreneurs connected with Stanford University-founded Fieldlink, which supported the digital encryption of information on hand-held computing devices and the creation of Confinity (Fried 2002, Plotkin 1999). These start-up technology innovation firms sought to support money transfers on devices such as Palm Pilots, which led to the rise of PayPal and digital wallets (Lillington 1999, Reuters 2002). The acquisition of PayPal in 2002 further enabled eBay to perfect its online auction platform by supporting the digital exchange of electronic payments (Kane 2002), inclusive of online merchants that were demonstrating increasing interests to participate in eBay's e-marketplace. Meanwhile, Alipay's growth in China skyrocketed during these years, supporting consumers via Internet banking and e-commerce (Heggestuen 2014).

The developments in electronic money and the first generation of Cybercash (e.g., electronic checks by Clifford Neuman's NetCheque, smart cards by Gemplus and Mondex in Europe, digital coins by David Chaum's DigiCash, and e-wallets by CyberCash in U.S.) set the stage for contactless payments that are now widely used in public transportation fare collection systems (Neuman and Medvinsky 1995, Humbert et al. 1997, Levy 1994). The successful applications include the Octopus card system in Hong Kong, the EZ-Link card in Singapore, the Oyster electronic ticketing in London, and other innovations in the rapidly-changing payment ecosystem in the Netherlands (BIS 2001). Most of them utilize the FeliCa contactless smart card from Sony in Japan, which set up the earliest de facto standard for electronic money and mobile payments. Later, MasterCard's PayPass and Visa's PayWave global innovations further standardized contactless payments in point-of-sale (POS) networks (BusinessWire 2007, Stevens 2014). These well-accepted contactless payments platforms have provided compatible infrastructures for mobile payments solutions using smartphones that have embedded RFID chips. The resulting convenience and benefits perceived by customers have increased the potential for user acceptance of m-payments.

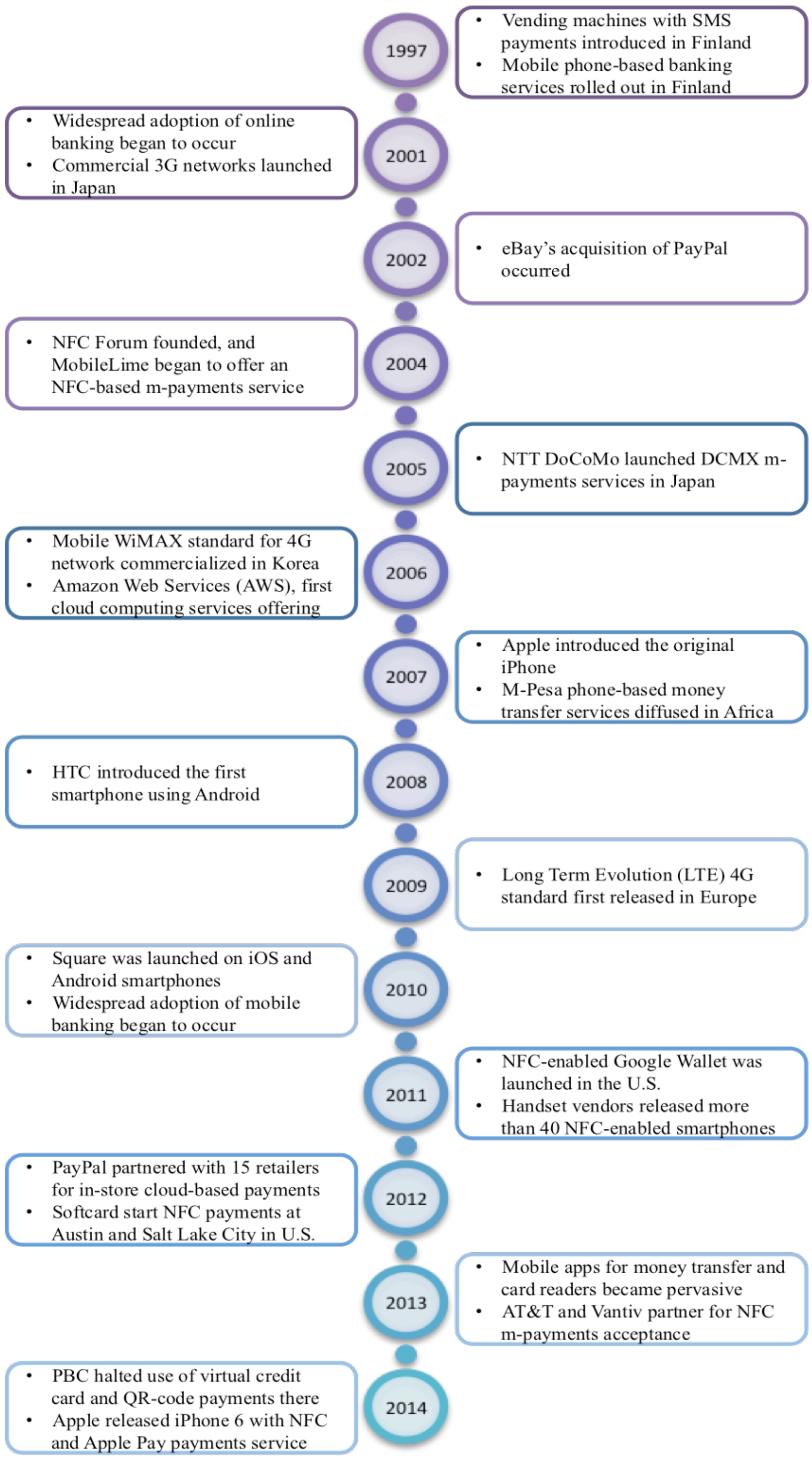
Nevertheless, most of the mobile financial services offerings of the early 2000s failed to meet consumer and market expectations due to their limited capability for handling data via mobile networks (Montgomery 2012). Their adoption rate was lower than the prediction by many industry observers. By 2006 though, mobile phone manufacturers introduced smartphones, which offered enhanced Web browsing and data transfer capabilities. Smartphones differed from traditional featured phones in their better usability, improved information security, and also their connected developer and mobile app ecosystems. Their capabilities were further supplemented by the arrival of third-generation (3G) and fourth-generation (4G) telecom network technologies and the transaction-making capabilities of Internet banking. All these have been driving the market demand for more advanced m-payments services.

In 2007, the M-Pesa phone-based money transfer service started rolling out in Kenya and African countries (Graebner 2014). After 2011, a number of new technology solutions for m-payments emerged. At present, the infrastructure for safe and efficient m-payment systems is largely based on the NFC contactless technology (Eldrige 2014). This is now included in smartphones and merchant terminals, and has become available from the Softcard, Google Wallet, and Apple Pay initiatives (Kharif 2011, Warren 2011, Turner 2014). Cloud-based m-payments represent another technology solution, with payment credentials stored on a secure cloud server. Solutions such as PayPal App and Alipay Mobile App are good at reducing customer security concerns, and taking advantage of the existing online payment platform to achieve network effects and interoperability (Jesdanun 2014). There are other innovative schemes that use third-party applications on various smart-phone platforms or quick response (QR)-codes to make the role that banks play in card payments more central (Lunden 2013). They enable small merchants who would otherwise be “unbanked” in payments to process card payments. For example, Square, a payments application that supports merchant and consumer transactions, serves as a wallet filled with virtual credit cards for authorized merchants, offering payment connectivity for cards via mobile phones (Wilhelm 2014).

Table A1. Events and Reference Sources for M-Payments Developments

YEAR	EVENT	SOURCE
1997	Vending machines with SMS payments introduced in Finland	Montgomery 2012
	Mobile phone-based banking services also rolled out in Finland	
2001	Widespread adoption of online banking began to occur	Xue et al. 2011
	Commercial 3G networks launched in Japan	Yamada 2001
2002	eBay's acquisition of PayPal occurred	Kane 2002
2004	NFC Forum founded, and MobileLime began to offer an NFC-based m-payments service	Buckley 2006
2005	NTT DoCoMo launched DCMX m-payments services in Japan	Nita 2009
2006	Mobile WiMAX standard for 4G network commercialized in Korea	Whitney 2010
	First commercial cloud computing service offered by Amazon Web Services (AWS)	Raghupathi 2011
2007	Apple introduced the original iPhone	Honan 2007
	M-Pesa phone-based money transfer service spread out in Africa	Graebner 2014
2008	HTC introduced the first smartphone using Android	German 2011
2009	Long Term Evolution (LTE) 4G standard first released in Europe	Klasson 2010
2010	Square application to read credit cards launched on iOS and Android smartphones	Wilhelm 2014
	Widespread adoption of mobile banking began to occur	Kahn 2010
2011	Google Wallet, an NFC-enabled m-payments solution, launched in the U.S.	Warren 2011
	Handset vendors released more than 40 NFC-enabled smartphones	Balaban 2011
2012	PayPal partnered with 15 retailers for in-store cloud-based payments	Perez 2013a
	Apple awarded a patent for its iWallet technology innovation	Webster 2013
	Softcard brought NFC mobile payments to Austin and Salt Lake City in the U.S.	Perez 2014
2013	Mobile apps enabling money transfer, NFC m-payments and card readers became pervasive	Romann 2014
	AT&T, Vantiv partner for m-payments acceptance, and NFC platforms began rolling out	Eddy 2014
2014	The People's Bank called back virtual credit card and QR-code payments in China	Zhao and Xie 2014
	Apple released iPhone 6 that supports NFC, and use Apple Pay for payments service	Garside and Hern 2014
	Apple Pay's compliance with MasterCard, Visa and American Express NFC POS terminals	Townsend 2014

Figure A1. A Visual Timeline of M-Payment Technology Evolution and the Related Technology Innovations



Appendix B. Simulation Parameters and Procedure

The firm knows the current investment cost I_0 = \$10 million, the expected long-run cost $\bar{I}$ = \$5 million to which I tends to revert, and the speed of cost reversion α_I = 0.1. In addition, the cost volatility is σ_I = 50%. The investment decision must be made prior to the end of the investment time horizon T. Assume that L = 3 years and T = 5 years, which is a reasonable length of time for the technology to be available. Once the investment decision is made at time t, the benefit flows will be received up to time T. This benchmark case uses the same assumption as the data mart consolidation project for the change in mean benefit flows (Kauffman et al. 2015b). The maximal expected benefit flow is \$1,982,759. The estimated benefit growth rate g is 1.5, and its decay rate d is 1.37. The mean benefits flow reverting speed is α_B = 1.5, and the volatility σ_B of this benefit flow is 50%. In addition, I assume that the discount rate is 7%.

I used Matlab to code the simulations and run the numerical analysis. Based on the parameters I selected, I first simulated 100,000 sample paths for the state variables I and B. I used a large number of sample paths to make sure that the distributions of timing and payoffs were close enough to the expected technology investment outcome. Future profit at time t can be calculated by adding the discounted cash flows from t to T, and the value of m-payment investment project is the present value of future profits minus the current investment cost at time t. The goal is to compare the discounted present value of the payoff at each time and then determine the optimal investment time based on the simulated values associated with all of the paths that occur.

Table B1. Simulation Parameters Used in the Base Case

Parameter	Description	Value	Parameter	Description	Value
I_0	Initial investment cost	\$10 million	B_{max}	Maximal log value of benefit	\$1,983,000
$\bar{I}$	Long-run investment cost	\$5 million	T	Maximal deferral time	5 years
α_I	Speed of cost reversion	0.1	L	Technology lifecycle	3 years
α_B	Speed of benefit reversion	1.50	$\overline{B_L}$	Mean benefit flow at time L	\$1,699,000
σ_I	Investment cost volatility	50%	r_f	Annual risk-free discount rate	7%
σ_B	Benefit flow volatility	50%	N	Number of simulated paths	100,000
g	Mean benefit growth rate	1.50	d	Mean benefit decay rate	1.37

Appendix C. Sensitivity Analysis Results for Key Input Parameters

Table C1. Sensitivity Analysis Results for Key Input Parameters

Parameter	Max Payoff	Min Payoff	Mean Payoff	Average Timing (Year)
Base case	\$24,222,000	-\$1,872,000	\$5,483,000	0.68
T = 4 years	\$18,985,000	-\$4,087,000	\$1,464,000	0.44
T = 6 years	\$28,827,000	-\$490,000	\$8,933,000	0.90
σ_B = 25%	\$14,857,000	-\$910,000	\$5,051,000	0.70
σ_B = 75%	\$51,501,000	-\$2,789,000	\$6,233,000	0.68
α_B = 1.2	\$20,808,000	-\$3,404,000	\$2,416,000	0.71
α_B = 1.8	\$25,484,000	-\$1,044,000	\$7,770,000	0.68
L = 2.5 years	\$25,711,000	-\$1,608,000	\$6,229,000	0.60
L = 3.5 years	\$23,578,000	-\$1,896,000	\$5,847,000	0.76
r_f = 5%	\$24,445,000	-\$1,907,000	\$6,325,000	0.68
r_f = 9%	\$24,848,000	-\$2,267,000	\$4,724,000	0.70
$\bar{I}$=10 million	\$25,420,000	-\$2,471,000	\$5,292,000	0.65
$\bar{I}$=15 million	\$23,192,000	-\$2,280,000	\$5,167,000	0.62
g = 1.2	\$13,424,000	-\$4,151,000	\$1,312,000	0.80
g = 1.8	\$34,940,000	-\$890,000	\$8,958,000	0.63
α_I = 0.05	\$23,803,000	-\$2,042,000	\$5,361,000	0.66
α_I = 0.15	\$22,521,000	-\$1,882,000	\$5,569,000	0.71

Appendix D. Numerical Solution Procedure

An important problem in option pricing theory is the valuation and optimal exercise of derivatives with American-style exercise features. In the management of IT investment risk, these types of real options also can be found. When more than one factor affects the value of the option, valuation and optimal exercise of an American option is an especially challenging problem. The Longstaff-Schwartz (2001) provides a simple, yet powerful simulation approach to approximating the value of American options. The method is readily applied when the option value depends on multiple factors. Simulation also allows state variables to follow general stochastic processes, such as a jump diffusion process (Merton 1976).

At the final exercise date, the optimal exercise strategy for an American-style option is to exercise it if it is in the money. Prior to the final date, however, the optimal strategy is to compare the immediate exercise value with the expected cash flows from continuing, and then exercise if immediate exercise is more valuable. Thus, the key to optimally exercising an American option is identifying the *conditional expected value of continuation*. A central part of the Longstaff-Schwartz method is the approximation of a set of conditional expectation functions, so it is appropriate to use the cross-sectional information in the simulated paths to identify the conditional expectation functions.

I solved the model by applying a variant of the Longstaff-Schwartz method to approximate the value of all future benefit flows at each date, given the current value of the two governing state variables, I and B. This involved first simulating 100,000 sample paths for the two state variables. I regressed the subsequent project benefits flows from continuation on a set of functions of the values of the relevant state variables. The fitted values of this regression are efficient unbiased estimates of the conditional expectation function. The regression coefficients are used to approximate the expected value of continuation. I also used another procedure to compare the exercise value and continuation value at each date to determine the optimal stopping rule. The optimal stopping rule estimated by the conditional expectation regressions from one set of paths should lead to out-of-sample values that closely approximate the in-sample values for the investment option (Stentoft 2004).

Then I compared the value of the technology investment project for the case where there is no possibility of a jump, $\lambda = 0$, and when a jump may occur with the probability of $\lambda = 0.05$. When λ increases, the conditional variance of the future benefit flow increases. I adjusted the parameter values of the means and variances for the two cases to give a more meaningful comparison. Because of the martingale restriction implied by the risk-neutral framework, the means for the two cases will be the same.

Appendix E. Propensity Score Matching Process and Results

I used the SAS software to perform multivariate logistic regression to calculate propensity scores for the time-invariant explanatory variables (*Tenure*, *Low Income*, *Mobile*, *Tablet*, *Average # of Transactions*, *Average Balance*, *ATM Density*, *Branch Density,* etc.). I accounted for both customers' demographics and banking status in the calculation of the propensity score. I applied a stepwise selection procedure to remove the effects that did not meet the 5% significance level for entry into the model.

See Table E1 for the logistic estimation results. I estimated each customer's propensity to adopt a mobile phone and a tablet, respectively, and matched the customers with similar propensity scores in both treatment and control groups while maintaining the global distributions over two groups. I applied a *OneToManyMTCH* macro to perform the one-to-one static propensity score matching, and selected an untreated customer that was paired with the treated one within the same state of the U.S. (Parsons et al. 2004). After matching, I constructed an unbalanced panel data for the mobile phone treatment that contained over 200,000 observations for more than 80,000 customers during a period of three months, and another unbalanced panel data for the tablet treatment that contained over 140,000 observations for more than 40,000 customers. See Table E2 for a comparison of characteristics between the treatment and control groups.

Table E1. Logistic Estimation of Propensity Score

MOBILE TREATMENT		TABLET TREATMENT	
INDEPENDENT VARIABLE	ESTIMATE (STANDARD ERROR)	INDEPENDENT VARIABLE	ESTIMATE (STANDARD ERROR)
Low Income	0.168^{***} (0.017)	*Low Income*	-0.228^{***} (0.022)
Tablet	0.804^{***} (0.016)	*Mobile*	0.756^{***} (0.016)
Tenure	0.018^{**} (0.008)	*Tenure*	-0.048^{***} (0.009)
log(*Average Transaction Number*)	0.490^{***} (0.008)	log(*Average Transaction Number*)	0.340^{***} (0.009)
log(*Average Balance*)	-0.195^{***} (0.004)	log(*Average Balance*)	0.089^{***} (0.004)
ATM Density	-0.004^{***} (0.001)	*Branch Density*	0.034^{***} (0.006)
Number of Observations	194, 493	Number of Observations	194, 493
Note: Robust standard errors are in parentheses. Significance level: * p<0.1; ** p<0.05; *** p<0.01.			

Table E2. Comparison of Treatment and Control Groups

VARIABLE	TREATMENT: MOBILE = 1 (N=40,720)		CONTROL: MOBILE = 0 (N=40,720)	
	MEAN	STD. DEV.	MEAN	STD. DEV.
Tenure	4.48	0.86	4.47	0.90
ATM density	10.53	12.52	10.64	12.52
Branch density	1.23	1.12	1.24	1.13
log(*Average Balance*)	8.90	2.68	8.77	2.95
log(*Average Transaction Number*)	4.13	0.99	4.16	1.11
	N	%	N	%
Tablet	7908	19.42	7469	18.34
Low income	6570	16.13	6420	15.77
VARIABLE	TREATMENT: TABLET = 1 (N=23,374)		CONTROL: TABLET = 0 (N=23,374)	
	MEAN	STD. DEV.	MEAN	STD. DEV.
Tenure	4.58	1.07	4.57	1.02
ATM density	11.11	12.48	11.09	12.92
Branch density	1.30	1.13	1.29	1.14
log(*Average Balance*)	7.70	2.51	7.76	2.34
log(*Average Transaction Number*)	3.86	0.81	3.87	0.83
	N	%	N	%
Mobile	8572	36.67	8539	36.53
Low income	2631	11.26	2695	11.53