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The Determinants and Outcomes of Internet Banking Adoption

Lorin M. Hitt, Mei Xue, and Pei-yu Chen

This study of 30,000 customers from a large U.S. bank suggests that banks can increase online banking adoption by working with customers to increase their use of self-service options and by developing channels for word-of-mouth product diffusion.

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Report Summary

Despite the potential benefits that online banking offers consumers, adoption has been limited. What factors drive consumers to adopt Internet banking? How does adoption affect product and service demand and profitability?

To address these questions, authors Hitt, Xue, and Chen use panel data for 30,000 customers from a large U.S. bank to study three facets of online banking adoption: consumers' choice to adopt online banking, effect of adoption on customer channel usage, and resulting impact on customer profitability, product usage, and loyalty. They formulate a random utility model that relates online banking adoption to customer demand for banking services, the availability of alternative channels, customers' efficiency in service co-production (i.e., ability to participate in the self-service process), and network effects.

Their results suggest that customer demand, customer efficiency, and network effects play a significant role in online banking adoption, whereas physical channel accessibility is less important. Upon adoption of online banking, customers significantly increase their transaction demand and their adoption of banking products by opening more accounts. As a result, they also increase their use of other bank channels, such as ATMs, customer support representatives (CSRs), and branch services. These behavioral changes are associated with lower short-run customer profitability, perhaps due to the initial costs involved in adopting more accounts. This drop in customer profitability is only temporary, as average profitability reverts to the pre-adoption levels within six months. In addition, customers show greater loyalty (i.e., increased customer retention) after online banking adoption.

Altogether, these results suggest that banks can potentially increase their online banking adoption by working with customers to increase their service co-production efficiency and by developing channels for word-of-mouth product diffusion. The managerial implications are applicable to other service industries that deploy multi-channel systems (including the Internet) to interact with and serve customers (e.g., retail and transportation.) ■

Introduction

Most modern banks have deployed Internet banking capabilities in an attempt to reduce cost while improving customer service levels. Despite the potential benefits that online banking offers consumers, adoption of online banking has been limited and, in many cases has fallen short of expectations (Bielski 2003; Wade 2003). According to the Gartner Group, all of the top 50 largest banks in the United States offered Internet banking by 2002, but only 17% of consumers adopted online banking at the time. This figure is not expected to exceed 30% by 2007 (Babej 2003).

Banks are concerned about managing and optimizing the adoption of online banking for several reasons. First, studies have suggested that online banking has direct cost benefits, with an online banking transaction being considerably less expensive than a similar transaction performed by a teller or call center representative (Booz Allen & Hamilton 1997). Second, customer adoption of online banking can reallocate service demand across multiple service channels, affecting capacity planning and service design in other channels, such as branches or automated teller machines (ATMs). Third, customers using online channels may show profitability-enhancing behaviors, such as increased loyalty or product utilization—although there is some debate as to whether this is due to behavioral changes or simply differences in customer populations (Hitt and Frei 2002).

Prior research on online banking adoption has principally used survey methods to examine social and technical aspects of the adoption decision (such as attitudes toward new technology, awareness, access and usability) as the causes of variation in Internet banking adoption decisions (Sathye 1999; Karjaluoto, Mattila, and Pento 2001; Wang et al. 2003; Gerrard and Cunningham 2003; Lee, Eastwood, and Lee 2004). Although these studies are able to consider a wide variety of potential drivers of Internet banking adoption, they have at least two significant limitations. First, they are typically limited to a single time period and thus cannot examine factors that evolve over time, such as learning or word-of-mouth product diffusion effects. Secondly, they rely on self-reported behavior rather than actual observation, which may introduce measurement error and which limits the study of outcomes to those that are perceptible to customers. For instance, these approaches cannot be used to investigate whether bank profitability increases following Internet banking adoption.

In this study we utilize panel data for approximately 30,000 randomly-selected customers from a large U.S. bank to study three facets of adoption of online banking: the consumers' choice to adopt online banking; the effect of online banking adoption on customer channel usage; and the resulting impact on customer profitability, product usage, and loyalty. Our model focuses on four sets of adoption correlates: the customers' demand for banking services; the availability of alternative banking channels; the efficiency of the customer in service co-production; and network effects. Our results suggest that customer demand, customer efficiency, and network effects play a significant role in online banking adoption, whereas physical channel accessibility is less important. Moreover, upon adoption of online banking, customers significantly increase their transaction demand, increase their adoption of banking products by opening more accounts, and as a result also increase their use of other bank channels, such as ATMs, customer support representatives (CSRs), and branch services. These behavioral changes, however, are associated with lower short-run customer profitability, perhaps due to the initial costs involved in adopting more accounts. Such a drop in customer profitability is only temporary, as average profitability reverts to the pre-adoption levels within six months. In addition, customers show greater loyalty (i.e., increased customer retention) after online banking adoption.

Overall, this study makes several unique contributions. First, it uses panel data consisting of real customer transaction data over an extended time period, which enables the use of objective and potentially more accurate measures of the factors that impact the timing of Internet banking adoption. Moreover, the time series data also allow us to understand the longer-term impact of Internet banking adoption on customer demand and transaction behaviors, which has not been well studied in the literature. Second, we present a model based on random utility theory to model consumers' choices of channel use, and provide a connection between random utility theory and survival analysis—two separate approaches commonly used for adoption analysis. In addition, to understand the impact of online banking adoption on behavioral change, we adopt a difference-in-difference matching estimator approach proposed by Abadie and Imbens (2006) to control for systematic behavioral changes over time and to identify potential causal effects on Internet banking choice. Third, our model integrates several factors from the operations literature, including customer efficiency, customer co-production costs, and channel accessibility with network and product diffusion effects (more commonly considered in the marketing, economics, and information systems literature). Although the empirical evidences are from the retail banking industry, the managerial applications of the findings should be generally applicable to other service industries that also use the multichannel systems (including the Internet) to interact with and serve customers (e.g., retail and transportation).

Internet Banking Adoption

Literature review

The most relevant literature to our analysis are studies that examine consumer adoption of technology (e.g., Bass 1969; Davis 1989; Davis, Bagozzi, and Warsha 1989; Forman and Goldfarb 2005), especially research related to the adoption of self-service technology (Curran, Meuter, and Surprenant 2003).

The well-known Bass (1969) model relates aggregate product adoption to perceived characteristics of the product, as well as to the number of previous adopters. Later research has extended the same ideas in the Bass model to individual adoption decisions rather than aggregate adoption (Chatterjee and Eliashberg 1990) and has incorporated modeling of both timing and probability of adoption (Sinha and Chandrashakaran 1992). The key observation that comes from these models is that product adoption follows a diffusion path depending on market-wide factors (total adoption), individual characteristics, and product characteristics. The literature on network externalities has also considered the importance of both individual customer characteristics as well as overall market adoption (driven possibly by word-of-mouth diffusion). For instance, Goolsbee and Klenow (2002) demonstrated that adoption of personal computers is strongly related to demographic characteristics, as well as to the number of other adopters in the same geographic region.

The relationship between individual characteristics and technology diffusion has been examined in the literature on the technology acceptance model (TAM) (Davis 1989; Davis, Bagozzi, and Warshaw 1989; Venkatesh et al. 2003), which considers how individual intentions and beliefs can shape the choice of technology adoption. Prior studies utilizing TAM found that adoption of Internet banking is associated with computer capability and perceptions about usefulness, credibility, and ease of use of the service (Wang et al. 2003) which, in turn, is influenced by service design (Chau and Lai 2003). The TAM approach has also been employed to explain the adoption of self-service technology (Curran, Meuter, and Surprenant 2003), as well as other types of end-user technology, and has found that product perceptions of usefulness and ease of use play a substantial role in technology adoption

(Davis 1989; Mahajan, Muller, and Bass 1990; Dabholkar 1996; Swaminathan, Lepkowska-White, and Rao 1999; Karjaluoto, Mattila, and Pento 2001; Gerrard and Cunningham 2003). In some cases these perceptions are measured directly, while in others they arise endogenously as information about a product arrives over time (see Chatterjee and Eliashberg 1990).

A more recent approach, in the service operations literature, considers factors such as perceived ease of use or usefulness to arise due to customers' capabilities in engaging in service co-production. In these models, customers differ in their ability to participate in the self-service process (termed customer efficiency), leading them to perceive the relative cost of self-service over full-service alternatives differently and thus make different service choices (Xue and Harker 2002; Xue, Hitt, and Harker 2007).

We extend and integrate these two literature streams. Specifically, our panel data allow us to model the diffusion of Internet banking as it is driven by aggregate effects (product diffusion, network effects, and availability of alternatives) as well as by individual customer characteristics (service demand, demographics, and customer co-production capabilities). Moreover, our study relies on highly accurate, objective customer data so we are not subject to the self-reporting biases that are potentially present in survey-based research. In addition, we can also examine outcomes related to the adoption of online banking by utilizing matching estimators that enable inferences about the effects of a "treatment variable" (i.e., the adoption of online banking) on relevant outcome conditions such as customer loyalty, service utilization, and profitability.

Our work is also closely related to the existing literature on online banking that has considered the impact of online banking adoption on performance (Hitt and Frei 2002; Campbell and Frei 2004). These studies collectively suggest that online banking adopters are significantly different from the general customer population, and that they tend to be more profitable both before and after their adoption of online banking. However, it is less clear that customer profitability increases as a result of this adoption (Hitt and Frei 2002), or that these profit differences persist in the long term (Campbell and Frei 2004). We extend this literature by considering a broader set of determinants of online adoption, and we provide a set of complementary results using modern econometric methods (matching estimators) on customer outcomes following the adoption of online banking.

Background: Retail banking

Retail banks are consumer depository lending institutions that offer deposit accounts (interest and non–interest-bearing transactional accounts, certificates of deposit); loan accounts (personal loans, secured loans, credit cards, and mortgages); and sometimes other financial services (trust, asset management, and insurance). Service costs related to transactional deposit accounts are one of the largest cost components of a retail bank. Due to the relatively high cost and high customer visibility of these activities, retail banks have been one of the leading adopters of technology for improving service operations. A typical retail bank offers customers numerous ways to perform banking transactions: ATMs; automated telephone banking using voice-response units (VRUs); telephone-based CSRs; in-branch representatives, such as tellers and "platform" employees; direct deposit and automated withdrawals through Automatic Clearing House (ACH) systems; and Internet-based banking. Tellers in branches often perform routine and standard transactions, such as deposits, withdrawals, transfers, and inquiries, while in-branch sales representatives manage the more complex interactions and platform transactions, such as taking loan applications, opening accounts, and selling certificates of deposit (CDs). Similarly, in the technologically-mediated service channels, some transactions are typically routine (VRUs, ATMs, and ACH transactions), while telephone-based CSR transactions are often tailored to the customer and are more complex (error correction, new account questions).

Although consumers have had the ability to perform transactions at home using a personal computer for more than two decades in the form of "PC banking" (home computer-based banking using proprietary software and a dial-up network),[1] significant adoption of these services did not occur until they were made available over the Internet (what we will refer to as Internet banking) in the late 1990s. Internet banking provides the convenience of banking at home (24-hour access, no physical travel time), with minimal adoption costs for the majority of consumers who have Internet access, and modest but not insignificant requirements for customer skill. From the bank's perspective, the Internet channel has significantly lower operations costs than do human-staffed channels. Moreover, online banking converts a largely variable cost (i.e., labor per transaction) into a mostly fixed cost technology infrastructure, therefore, profitability increases in number of adoptions and usage. Recognizing that the Internet also represents an important customer contact point, banks have developed sales and promotional strategies to attract new customers through the Internet and to encourage existing customers to broaden their relationship with the bank.

Collectively, the combination of branches, ATMs, VRUs, telephone-based CSRs, and Internet banking reasonably represent the service options available to bank customers. Our analysis focuses on what drives the consumer's channel choice toward the adoption of Internet banking, how this adoption affects the use of other channel alternatives, and what impact these choices have on customer retention and profitability.

Theoretical Framework and Hypotheses

A framework of Internet banking adoption

We use a random utility framework to model customer channel preferences that affect Internet banking adoption. The basic random utility framework represents the utility of a product as a function of: the observable characteristics of the customer, the characteristics of the product, and an idiosyncratic customer component (usually modeled as a draw from a random distribution). When faced with product alternatives, customers choose the alternative that offers the highest utility. Since its introduction in the literature by McFadden (1974), the random utility framework has become a standard way of modeling consumer behavior and has been extensively utilized in marketing, economics, and information systems research. Based upon the random utility framework, we hypothesize that a customer's adoption decision of the Internet banking channel is determined by the relative value and cost that this customer faces in using Internet banking, both in perception and reality. This cost-benefit tradeoff is determined by four key factors: the demand for banking services, the customer's capability for self-service co-production, the availability of channel alternatives, and product diffusion and network effects. The first three factors encompass the costs and benefits directly experienced by the customer, while the fourth item, product diffusion and network effects, may influence the customer's perception of usefulness, ease of use, and reliability, and therefore influence customer purchase decisions.

Formally, consider a customer (i) at time t, with an exogenous demand for banking services (D^i), who is making a decision on how to allocate his or her demand among all available channels to obtain a service interaction that maximizes utility.[2] If, at time t, the optimal allocation includes a self-service channel for the *first* time, then this customer is a potential adopter of self-service technology at time t.

We represent the initial adoption of online banking by the indicator variable Y_{it}: i.e., $Y_{it} = 1$ if the customer adopts e-banking at time t and by $Y_{it} = 0$ if the customer does not adopt.

For model exposition, we normalize the customer utility of using the full-service teller channel to zero and consider deviations from this allocation of activity. In the following discussion, capital letters (*C, E, D, M, Z*) will represent observable and measurable individual and market factors, and Greek letters (α, β, χ, δ, ϕ, γ) will represent the estimated weight or importance of the respective observable and measurable factors. We model the utility of each service alternative as the sum of seven terms as follows: (1) the customer-specific cost of accessing each channel (C^{it}) and the estimated importance of channel access (α); (2) the overall service demand (D^{it}) and the direct effect of service demand (ϕ); (3) customer efficiency level (E^{it}) and its importance (γ); (4) the customer service co-production cost (which depends on the customer efficiency level, E^{it}, and the total service demand, D^{it}) weighted by the importance, χ; (5) the spillover effects due to network effects or learning resulting from online banking adoption (the product of the number of existing adopters, M^{t-1}, and the strength of network effects, β); (6) observable customer characteristics, Z^{it} and their importance, δ; and (7) a random component, ε^{it}, reflecting unobserved customer characteristics. For each channel allocation alternative, this yields an equation of the form:

$$u^{it} = C^{it}\alpha + D^{it}\phi + E^{it}\gamma + D^{it}E^{it}\chi + M^{t-1}\beta + Z^{it}\delta + \varepsilon^{it} \tag{1}$$

A customer will adopt Internet banking at time t if his or her optimal channel allocation includes the Internet channel. Formally, we can write the utility that customer i can obtain with the availability of the Internet banking channel (labeled with the subscript "I") and without Internet banking (labeled as "O") at time t as:

$$\begin{aligned} u_I^{it} &= C_I^{it}\alpha_I + D^{it}\phi_I + E_I^{it}\gamma_I + D^{it}E_I^{it}\chi_I + M_I^{t-1}\beta + Z^{it}\delta_I + \varepsilon_I^{it} \qquad (2)\\ u_O^{it} &= C_O^{it}\alpha_O + D^{it}\phi_O + E_O^{it}\gamma_O + D^{it}E_O^{it}\chi_O + Z^{it}\delta_O + \varepsilon_O^{it} \end{aligned}$$

Note that we do not require customers to shift all transactions to Internet banking when adopting it; rather, u_I^{it} is the utility consumers can get when the Internet channel becomes available, even though they may continue using other channels for some or even most services. Thus, u_O^{it} is the utility the consumers can get when none of their services can be carried out by Internet channel, and it represents the utility a customer receives prior to Internet banking adoption.

Following the standard approach for random utility models, the customer adopts Internet banking ($Y_{it} = 1$) if adopting Internet banking will lead to increased utility ($u^{it} = u_I^{it} - u_O^{it} > 0$). Because customers have an idiosyncratic utility component (ε), customers with identical observable characteristics may not adopt online banking at the same time. Altogether, customer i's probability of adopting online banking at time (t) is given by:

$$\begin{aligned} &\text{Prob}(Y_{it} = 1) = \text{Prob}(u^{it} > 0)\\ &= (C_I^{it}\alpha_I - C_O^{it}\alpha_O) + D^{it}(\phi_I - \phi_O) + E_I^{it}\gamma_I - E_O^{it}\gamma_O + D^{it}(E_I^{it} - E_O^{it})\chi + M^{t-1}\beta + Z^{it}(\delta_I - \delta_O) + \varepsilon_I^{it} - \varepsilon_O^{it})\\ &= C^{it}\alpha + D^{it}\phi + E^{it}\gamma + D^{it}E^{it}\chi + M^{t-1}\beta + Z^{it}\delta + \varepsilon^{it} \qquad (3) \end{aligned}$$

In our model, the event ($Y_{it} = 1$) occurs only after the customer has not adopted in all prior time periods. The construct $\text{Prob}(Y_{it} = 1)$ measures the hazard rate of Internet banking adoption at time t, i.e., $h(t)$. Specifically, we can write:

$$\text{Prob}(Y_{it} = 1) = h(t) = \frac{f(t)}{1 - F(t-1)} \tag{4}$$

$$= C^{it}\alpha + D^{it}\phi + E^{it}\gamma + D^{it}E^{it}\chi + M^{t-1}\beta + Z^{it}\delta + \varepsilon^{it}$$

where $f(t)$ is the unconditional probability that a customer will adopt e-banking at time t, while $F(t-1) = \int_0^{t-1} f(x)$ is the cumulative probability that a customer has not adopted e-banking before time t. Equation 4 forms the primary idea for the empirical model of this research, which is also the main concept behind survival analysis methods.[3]

Hypotheses: Internet banking adoption

The model presented above presents a framework that summarizes how the relative value and cost of using Internet banking are affected by four major factors that have been considered in the literature on technology adoption/product diffusion: consumers' service demand, relative cost of access to substitute channels, customer efficiency, and network effects. We discuss each of these issues and related hypotheses in turn.

Service Demand. Different consumers will have differing demand for banking services, which affects the total value they would receive from efficiencies by using the online banking channel. Customers who perform many transactions that are amenable to Internet banking are more likely to seek efficiency gains from Internet banking when it becomes available. However, this relationship is moderated by customer efficiency in using self-service technology, which will be discussed in more detail below. Given the same level of customer efficiency, we expect that a customer with a higher demand for banking services has more to gain from adopting Internet banking.

H1: Higher transaction volume is associated with faster Internet banking adoption.

Channel Access. Depending on their geographic location, different customers may have different access to branches and ATMs. Customers for whom it is more costly to use traditional channels (i.e., there is a lower density of branches in the region near their homes) will receive greater value from the online banking channel and thus are more likely to adopt Internet banking. Because channel access costs vary across consumers, principally due to travel time and the attendant opportunity costs, we will model these costs as being proportional to the density of branches and ATMs in their home zip code. This would imply the following hypothesis:

H2a: Greater availability of offline channels is associated with slower Internet banking adoption.

Opportunity Cost of Time. If we consider the fact that each consumer may experience a different disutility of travel time, we should also consider the interaction between opportunity cost and channel accessibility. Following Becker (1992), we assume that household income is a reasonable proxy for the opportunity cost of time. Therefore, we also consider the following:

H2b: Lower opportunity cost of offline channel access (proxied by income and channel availability x income) is associated with slower Internet banking adoption.

Customer Efficiency. Customers who are more able to participate in the self-service process will potentially receive greater value from adopting Internet banking. Although customer efficiency is difficult to measure directly, it is potentially observable in two ways. First, customer efficiency may be correlated with certain customer demographic characteristics. Xue, Hitt, and Harker (2007) found that customers who are more educated and younger tend to adopt self-service channels more readily, which the authors attribute to customer efficiency. This provides a potential indicator of the sign of our demographic variables. However, a more direct test of the customer efficiency hypothesis is to utilize the measure of customer efficiency proposed by

Xue, Hitt, and Harker (2007) which suggests that customer efficiency can be inferred by revealed channel choice (that is, customers who perform more self-service transactions, ceteris paribus, are more efficient). Adoption of online banking may be either affected by the cost of adoption of online banking directly (proportional to efficiency) or due to greater total benefits of online banking resulting from efficiency gains (i.e., lower customer service co-production costs) for future transactions (proportional to the product of efficiency and transaction demand). Thus, we posit that:

H3a: Higher customer efficiency is associated with faster Internet banking adoption.

H3b: Lower customer service co-production costs (proxied by efficiency x channel demand) are associated with faster Internet banking adoption.

Network Effects. The Bass diffusion model (1969) and subsequent research (e.g., Katz and Shapiro 1986; Bikhchandani, et al. 1998) suggests that the demand for a product is related to the number of prior adopters of the product. In some cases, this is due to direct interaction effects, such as the possibility that customers adopt a product because they receive direct benefits of interaction with other customers who adopt the same product (e.g., adopting Microsoft Word and sharing compatible files). Although customers do not directly interact with each other in the Internet banking context, there are at least two other reasons why network effects may play a role. First, online banking may be subject to similar word-of-mouth diffusion or learning effects as has been argued for personal computers (Goolsbee and Klenow 2002). Second, there may be indirect network effects, such as complementary investments by billers or other service providers who interact with online banking, or service improvements made by the bank that become economic as a result of simple economies of scale.

Either of these explanations would indicate that adoption rate is increasing in the number of prior adopters. However, it may be interesting and useful to distinguish between market-wide effects (which are related to all customers and are commonly considered in the product-diffusion literature) versus local network effects (or local spillovers) such as word-of-mouth, which are likely to exist over smaller geographic regions after controlling for local characteristics. We also try to distinguish either of these explanations from simple changes in the adoption rate over time.[4] We will not state the time effect as an explicit hypothesis but will control for time as part of the analysis. Thus we have:

H4a: Internet banking adoption rates are increasing in the number of total adopters.

H4b: Internet banking adoption rates are increasing in the number of adopters in a local geographic region.

Figure 1 gives an overview of our model on Internet banking adoption.

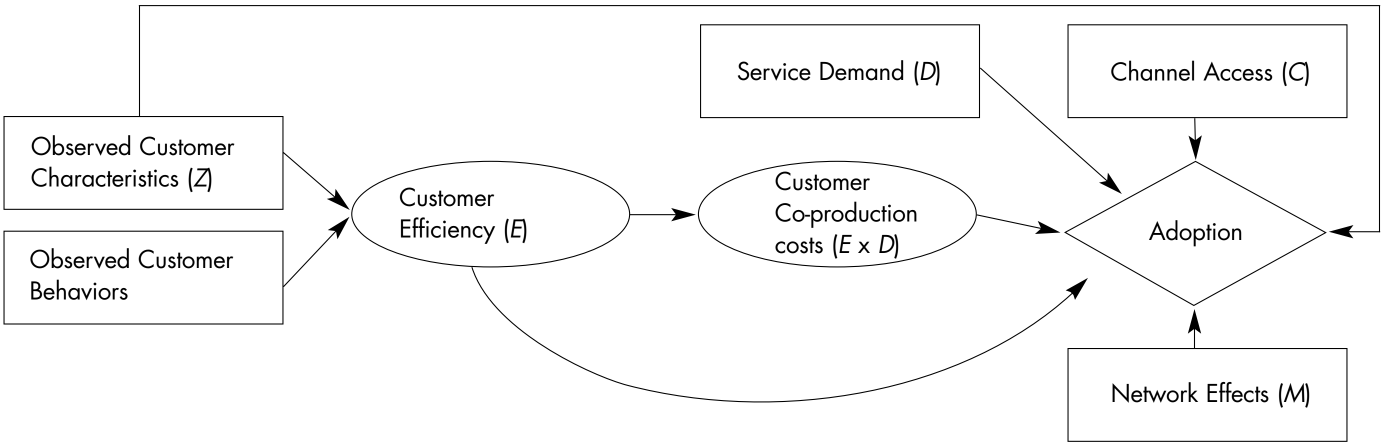
Hypotheses: Behavior change after adopting Internet banking

The value proposition of Internet banking, especially from the bank perspective, is heavily dependent on whether consumers change their banking behavior after adopting online banking. Prior research on online banking behavior suggests that customers who adopt online banking are more profitable (see e.g., Hitt and Frei 2002), but it is unclear whether or not this is due to unobserved heterogeneity (high-profit customers choose online banking) or behavioral change (customers become more profitable upon adoption of online banking). Our time series data on adoption provide an opportunity to investigate how profit and profit-related behaviors change following online banking adoption.

Upon adopting online banking, there are four possible behavioral changes that might be relevant.

Figure 1

The Conceptual Model of Internet Banking Adoption



First, customers might change the proportion of transactions they conduct in different channels, specifically directing some transactions to the online channel that might have been performed in another (higher cost) channel. Second, customers may choose to increase their product utilization due to the increased convenience of the online channel, either opening new accounts or consolidating balances from other banks. Third, greater access to services might encourage customers to increase the overall number of transactions they perform. The subsequent effect on the bank depends on relative changes in the number of transactions and the cost of performing these transactions given the amount of business (e.g., number of accounts, total balances) that the customer does with the bank. If the customer does no additional business but only subdivides his or her existing level of business across more transactions, then this could lead to increased cost but not increased revenue for banks—especially if the customer persists in utilizing high cost service channels (such as tellers) in addition to alternative channels. On the other hand, if self-service channels can replace other higher cost channels, there may be significant cost reductions even if the total number of transactions increases. Moreover, if the increase in transactions arises from new business then it could lead to higher profits for the bank if the increased revenues outweigh the costs to serve the increased demand.

Examining the effect of adoption on customer transaction volume may also give some insight into the extent to which our prior assumption of transactions as a proxy for service demand is reasonable. Overall, the above discussions also suggest that customer profitability (from the bank's point of view) might change post Internet adoption. Customer profitability may increase if customers shift their transactions from high-cost channels to low-cost ones and/or if they adopt more banking products from the bank due to the convenience and higher efficiency level of the Internet channels. On the other hand, customer profitability may decrease if customers do not adopt new products but merely utilize more resources to fulfill the same banking needs. Finally, customers may experience a change in the degree of "lock-in" (which could be either positive or negative) when provided with access to online banking. Specifically, consumers may experience greater lock-in because customers may react to the increased ease of access to banking services by concentrating their accounts at a single institution. There may also be lock-in from learning effects as customers become experienced with a particular bank's online services. However, consumers may also become less loyal because it is also relatively easy to access other banks' services and the learning benefits gained from experience with online banking may be transferable across institutions (Chen and Hitt 2002).

Using detailed transactional data, it is possible to investigate whether any of these possible changes have occurred by examining changes in transaction use, product use, and profitability following online banking adoption. This leads to the following five hypotheses (for convenience, stated in the form that supporting the hypothesis is "good" from the bank perspective):

H5a: After adopting Internet banking a customer's total transaction demand increases.

H5b: After adopting Internet banking, a customer reduces his or her use of other channels.

H5c: After adopting Internet banking, customers acquire more bank products.

H5d: After adopting Internet banking, a customer's profitability increases.

H5e: After adopting Internet banking, the customer is less likely to depart the bank (i.e., more loyal).

Data and Methodology

Data

From a large retail bank's customer population, we took a random sample of 28,945 customers. Among them, since the inception of Internet banking at the bank (January 1999), 9,359 adopted Internet banking from the bank during a 56-month period: February 1999 to September 2003.[5] The data contain each customer's monthly transaction record from July 2002 through June 2003 in addition to the initial account opening date, the date (if any) that Internet banking was initiated, and categorical demographic information, including home zip code.[6] The transaction and account data are drawn from the bank's operational systems and are believed to be highly accurate and complete. The demographic information was developed via a combination of the bank's own data collection supplemented by third-party market research data. The transactional and accounting data are essentially complete, although the demographic data have some missing values.[7] For the demographic variables that have missing values, we include an additional category labeled "missing" when the value is not present on the dataset. We also match the data to additional information on the number of bank branches (from the FDIC) and ATMs (a proprietary data source) by the zip code of the customer's primary residence. A detailed description of the variables in our analysis is presented in Table 1.

Methodology

The analysis tools we used include survival analyses for Internet banking adoption, a difference-in-difference matching estimator analysis for post adoption changes, and survival analysis for the impact of Internet banking adoption on customer retention. A detailed analysis can be found at http://www.msi.org/techapp/07-122.

Results

Internet banking adoption

Table 2 summarizes our regression coefficient estimates for the model of the adoption process under the log-logistic (AFT) formulation. Column 1 reports the regression coefficients in a log-time format where a negative coefficient implies a faster percentage rate of failure (earlier adoption), while Column 2 reports the same analysis in time ratio format, which is the ratio of fail time to normal time. A TR coefficient less than one implies faster adoption. We corroborated these results with a Gompertz proportional hazard (PH) model

Table 1

Variable Definition and Summary Statistics

Variable	Definition	Obs	Mean	Std. Dev.	Min	Max
Dependent variable:						
_t(adp)	time span (in days) since a customer is onset of risk of adopting the Internet channel till the current month	1,097,322	797.60	492.46	1	1,733
_t(atr)	time span (in days) since a customer is onset of risk of leaving the bank till the current month	22,037	1968.47	2424.38	1	17,588
Time trends						
Month	number of months since the beginning of the time window	1,675,686	29	16.45196	1	57
month2	square of the number of months since the beginning of the time window	1,675,686	1111.67	984.42	1	3,249
Network effects measures (M):						
adp_zipk	the total count (in 1k) of bank Internet channel adopters within a customer's primary residence zip code area by the end of the month	1,675,686	.84	1.25	0	9.22
adp_other_zipk	the total count (in 1k) of bank's customers in the U.S. but outside the customer's primary residence zip code area by the end of the month	1,675,686	349.59	204.25	0	689.70
Customer Efficiency Measure (E)						
std_ce_at	monthly customer efficiency measure	236,239	0	1.00	–5.648	3.96
Service Demand (D)						
ct_tot	monthly transaction total	236,239	–2.36	94.14	–11092.930	974.14
ceXtot	interaction term of customer efficiency and monthly transaction total	236,239				
Channel access (C)						
atm_tot	count of bank's own ATMs in the zip code area	352,776	1.54	1.81	0	14
Num_br	count of bank's own branches in the zip code area	1,675,686	1.22	1.66	0	9
Observable customer characteristic (Z)						
Income	0-missing (34.75%), 1-low income (< = $40k, 24.61%), 2- medium ($40~75k, 19.88), 3-high income (> = $75k, 2.76%) annual household income	1,675,686				
incXbr	interaction term of income and bank branch count in the zip code area	1,675,686				
incXatm	interaction term of income and bank's ATM count in the zip code area	1,675,686				
Intcomp	0- data missing (39.021%) 1- having no interest (47.688%) 2-having interest (3.58%) interest in using computer	1,675,686				

Table 1 continued

Table 1 continued

Variable	Definition	Obs	Mean	Std. Dev.	Min	Max
age	current age (in years) of the primary account holder	1,675,686	46.07	17.43	.003	100
age2	the square term of "age"	1,675,686	2425.94	1792.79	0	10,000
education	0-missing (89.45%) 1-high school/vocation/tech (3.74%), 2-college (4.08%), 3-graduate school (2.61%) highest education degree	1,675,686				
gender	1- male (51.49%) 2- female (48.51%) gender of primary account holder	1,675,686				
children	0- no children (84.29%), 2- having children (15.71%) having children living at home	1,675,686				
zip	zip code of household residence	1,675,686				
state	residence state	1,675,686				
marital	0 - missing (46.09%), 1- married (26.86%), 2 – single (27.06%) marital status	1,675,686				
Observed customer behaviors and derived profitability						
mon_onaf_ebadp	1 if the customer has already adopted Internet channel by the beginning of the current month and zero otherwise	1,542,390	.181	.39	0	1
nact	number of bank deposit accounts owned by a customer in the current month	200,404	1.85	1.26	1	26
nast	number of bank assets accounts owned by a customer in the current month	76,192	1.63	.97	1	16
ninv	number of investment accounts owned by a customer in the current month	16,195	1.27	.62	1	5
ct_tl	monthly count of teller transactions for a customer	236,239	2.65	5.47	0	285
ct_plt	monthly count of branch platform transactions for a customer	236,239	2.28	8.27	0	327
ct_csr	monthly count of call center CSR transactions for a customer	236,239	2.13	11.41	0	581
ct_vruinq	monthly count of VRU transactions for a customer	236,239	5.35	17.44	0	875
ct_atm	monthly count of ATM transactions for a customer	236,239	3.48	6.94	0	150
ct_ach	monthly count of ACH transactions for a customer	236,239	1.77	4.30	0	286
profit	customer profitability (in $, updated bi-monthly)	109,621	11.20	122.82	–3452.83	14062.06
lntl	logarithm transformation of monthly teller transaction count	236,239	.84	.89	0	5.66
lnatm	logarithm transformation of monthly ATM transaction count	236,239	.80	1.07	0	5.02
lnxfr	logarithm transformation of monthly transfer transaction count	236,239	.06	.27	0	3.14

Table 1 continued

Table 1 continued

Variable	Definition	Obs	Mean	Std. Dev.	Min	Max
lninq	logarithm transformation of monthly inquiry transaction count	236,239	1.12	1.40	0	6.82
lnwd	logarithm transformation of monthly withdrawal transaction count	236,239	1.79	1.46	0	7.43
lndep	logarithm transformation of monthly deposit transaction count	236,239	.83	.80	0	5.66

(see Appendix) and found very consistent results in direction, effect size, and significance (note that the signs of the Gompertz model have the opposite interpretation to those of the AFT model).

Service Demand. In terms of our specific hypotheses, our results show that a customer with higher service demand *D* (in terms of total monthly transactions, "ct_tot") adopts Internet banking faster ($\phi = -.013$, $p < .01$), thus supporting H1. In particular, for each added monthly transaction, a customer's time to adopt Internet banking is reduced by about 1.3% ($p < .01$).

Channel Access. The findings in regard to the relationship between channel access and individual choices to adopt online banking (H2a) are mixed. Branch density (C) is shown to have a strong relationship with Internet banking adoption but the direction is in contrast with H2a ($C = -.099$, $p < .01$). That is, with the addition of one more branch in the zip code area of a customer's primary residence, the customer will adopt Internet banking in 10% less time. The finding that branch access actually accelerates customer Internet banking adoption contradicts H2a. However, a closer examination of the data reveals that this may be due to facility location choices—banks often locate a greater number of branches in high-wealth areas, which are also areas where online banking is more likely. Simple correlations in our data suggest that this is true, but not in large numbers (correlations between income and the number of branches is 10% or less). Meanwhile, there is no statistically significant association between access to bank ATMs and individual choices to adopt online banking. The finding that ATM access does not have a strong relationship to customers' choice of Internet banking adoption may also suggest that customers do not view Internet banking and ATMs as direct or close substitutes due to their different functionality. For example, as a physical channel, ATMs are a preferred means for cash withdrawal and deposit, a function which the virtual Internet channel cannot provide. Thus, H2a is not supported and partially rejected.

Opportunity Cost of Time. As noted in our H2b, we expect that a customer's decision to adopt Internet banking would depend on the customer's total opportunity cost of branch access (or co-production cost). We posit that, given the same channel availability, higher income customers (who can potentially save more by shifting their transactions to online channels) are likely to adopt Internet banking sooner. This is indeed what we find. Our results show that income is positively associated with online banking adoption: A customer in the "low" income segment in our data takes about 40% more time ($p < .01$) to adopt online banking than does a customer with "medium" income, while it takes a customer in the "high" income segment 37% less amount of time to do so compared to a customer in the medium-

Table 2
Internet Banking Adoption Analysis

	Model with time trend terms Loglogistic		Model without time trend terms Loglogistic	
	_t(adp) Reg. Coeff.	_t(adp) TR. Coeff.	_t(adp) Reg. Coeff.	_t(adp) TR. Coeff.
Time trend effects				
Month	–.16065 (.00840)**	.85159 (.00715)**		
month2	.00193 (.00017)**	1.00194 (.00017)**		
Importance of network effects (M) on adoption decision (β)				
adp_zipk	–.21272 (.03815)**	.80838 (.03084)**	–.24301 (.03871)**	.78426 (.03036)**
adp_other_zipk	–.00018 (.00029)	.99982 (.00029)	–.00471 (.00023)**	.99531 (.00023)**
Importance of customer efficiency (E) on adoption decision (χ)				
std_ce_at	–.67872 (.13875)**	.50727 (.07038)**	–.73913 (.14799)**	.47753 (.07067)**
Effects of service demand (D) on adoption decision (ϕ)				
ct_tot	–.01303 (.00229)**	.98706 (.00226)**	–.01460 (.00252)**	.98551 (.00249)**
Effects of the interaction of customer efficiency and service demand				
ceXtot	.00472 (.00197)*	1.00473 (.00198)*	.00532 (.00235)*	1.00533 (.00236)*
Importance of channel access (C) on adoption decision (α)				
atm_tot	.07775 (.04557)	1.08085 (.04926)	.08434 (.04641)	1.08800 (.05049)
num_br	–.09920 (.02974)**	.90556 (.02693)**	–.08083 (.02877)**	.92235 (.02654)**
Impact of customer characteristics (Z) on adoption decision(δ)				
intcomp	–.20626 (.17905)	.81362 (.14568)	–.01483 (.01202)	.98528 (.01184)
low income	.33814 (.09207)**	1.40234 (.12911)**	.33704 (.08868)**	1.40080 (.12423)**
high income	–.46854 (.10159)**	.62591 (.06359)**	–.41516 (.09685)**	.66023 (.06394)**
incXbr	.03133 (.01559)*	1.03182 (.01609)*	.03187 (.01483)*	1.03239 (.01531)*
incXatm	–.01774 (.01257)	.98242 (.01235)	–.01483 (.01202)	.98528 (.01184)

Table 2 continued

Table 2 continued

	Model with time trend terms Loglogistic		Model without time trend terms Loglogistic	
	_t(adp) Reg. Coeff.	_t(adp) TR. Coeff.	_t(adp) Reg. Coeff.	_t(adp) TR. Coeff.
Age	–.00498	.99503	.00101	1.00101
	(.01246)	(.01240)	(.01196)	(.01198)
age2	.00132	1.00132	.00124	1.00124
	(.00015)**	(.00015)**	(.00014)**	(.00014)**
College Degree	–.51020	.60038	–.48113	.61808
	(.23324)*	(.14003)*	(.22265)*	(.13762)*
Graduate Degree	–.60383	.54671	–.56032	.57103
	(.26285)*	(.14370)*	(.25079)*	(.14321)*
Female	.33510	1.39809	.28555	1.33049
	(.07477)**	(.10454)**	(.07172)**	(.09543)**
With Children	–.24572	.78214	–.24454	.78306
	(.09514)**	(.07441)**	(.09091)**	(.07119)**
Single	.38718	1.47283	.41156	1.50917
	(.10125)**	(.14913)**	(.09664)**	(.14585)**
Constant	8.01655		7.23563	
	(.36598)**		(.35291)**	
Observations	1,097,322	1,097,322	1,097,322	1,097,322

Note: Robust standard errors in parentheses; * significant at 5%; ** significant at 1%. Residence state is also used as a control and the results are omitted due to space limitations. "Reg. Coeff." regular regression coefficient; "TR Coeff." time ratio coefficient; and "HR Coeff." hazard ratio coefficient.

income segment (p < .01). In addition, since for each transaction a higher income customer can potentially gain more by banking online than by using a physical channel, his or her decision to adopt Internet banking will be less sensitive to physical channel availability than a lower income customer's. That is, physical channel access is apparently a better substitute for Internet banking for low income people than for high income people.

Table 2, column 1 shows that the interaction term of income and branch access, which act as proxies for the total opportunity cost of branch access, is statistically significant. This suggests that the impact of one more branch added on for a high income customer is –.068 (–.099 + .031) while the impact of one more branch added on for a low income customer is –.099, confirming that high income customers are less sensitive to increases in branch accessibility. On the other hand, the interaction term of income and ATM access is statistically insignificant; this once again confirms that the ATM channel is not a good substitute for online banking, regardless of customer opportunity cost.

Customer Efficiency. Our results suggest a strong correlation between Internet banking adoption and customer efficiency. A customer whose efficiency (E) is one standard deviation above the average requires 49% less amount of time to adopt Internet banking from the bank (γ = –.679, TR_γ = .507, p < .01), which is consistent with H3a. While the positive interaction effect between efficiency (E) and transaction demand (D) suggests that high efficiency and high demand together do not accelerate Internet adoption even more, the results do support that customers with high efficiency and high demand adopt Internet banking the fastest. Specifically, given a unit increase in banking demand, its impact on the adoption decision of a customer with an average efficiency level is −.013, while its impact on those customers whose efficiency is one standard deviation above the average is −.687(−.679 − .013 + .005). Control variables that have been associated with customer efficiency, such as education (e.g., Xue, Hitt, and Harker 2007) are also associated with more rapid adoption—a customer with a graduate degree adopts online banking 46% faster than a customer with a high school diploma ($p < .01$) and a customer with a college degree does it 40% faster than a customer with a high school diploma.[8]

Network Effects. We try to distinguish and examine the impact of local and market-wide network effects on customers' Internet banking adoption, in addition to adding to our analysis some time trends that capture product diffusion over time. After controlling for time trends, our results suggest the presence of local network effects (M) but not overall network effects: The coefficient estimate for area effects within zip code is ($\beta = -.213$, $TR_\beta = .808$, $p < .05$), while the coefficient estimate for overall adoption is statistically insignificant. However, if we exclude the time trends (see columns 3 and 4 of Table 2), both measures are significant ($TR_\beta = .784$ for local network effects and $TR_\beta = .995$ for market-wide network effects). This finding is interesting, as it suggests that the linear and squared time trends basically capture the market-wide network effects. In previous product diffusion literature (e.g., Bass 1969), time trends are usually not added in the analysis; instead, the number of prior adopters in time $t - 1$ is used to predict number of adopters in time t. Our coefficients of linear and quadratic time trends appear to replicate the shape of the adoption hazard curve. Our results further imply that local customers have a higher influence on adoption than adopters in general.

There are two implications from our findings. First, they suggest that in a product diffusion analysis without reliable measures on total adopters, one may substitute a quadratic function of time as a way to capture the market-wide network effects. Second, while market-wide network effects (or number of total adopters) have a strong predictive power on product adoption, the significance and higher magnitudes of our local network effects findings further suggest that by disaggregating network effects (or the separation of different adopters), the predictive power of incorporating prior adoption can increase. Overall, H4a and H4b are supported.

Post-Adoption Analysis

Customer behavioral changes following Internet banking adoption

The results of post-adoption analysis, using matching estimators, are shown in Table 3, and figures 2, 3, and 4. Table 3 shows one-month, three-month, and five-month moving averages analyses, after matching observations on beginning-of-period service demand, efficiency, income, age, and zip code (three-month moving average values used for time varying variables in matching). Using three-month moving average values as an example, we find that a customer's monthly total transaction demand increases by 14.026 transactions after adopting the Internet channel ($p < .01$), which lends support to H5a. This increase in transaction demand appears to be spread across all channels: A customer's monthly teller transactions increase by 1.191 ($p < .01$), platform transactions increase by 2.24 ($p < .01$), CSR transactions increase by 1.941 ($p < .01$), ATM transactions increase by 1.692 ($p < .01$), and ACH transactions increase by .472 ($p < .01$). The impact of

Table 3
Average Treatment Effect of Internet Adoption

	One-month moving average		Three-month moving average		Five-month moving average	
Dependent variable	Coefficient (Std. Err.)	No. of Observations	Coefficient (Std. Err.)	No. of Observations	Coefficient (Std. Err.)	No. of Observations
Dif_tot	12.306 (1.169)**	3,928	14.026 (1.464)**	2,326	16.450 (2.894)**	771
Dif_tl	1.165 (.120)**	3,928	1.191 (.145)**	2,326	.937 (.278)**	771
Dif_plt	2.590 (.324)**	3,928	2.240 (.323)**	2,326	2.183 (.504)**	771
Dif_csr	2.011 (.417)**	3,928	1.941 (.441)**	2,326	3.341 (.778)**	771
Dif_vru	–.007 (.512)	3,928	.526 (.464)	2,326	1.744 (.865)*	771
Dif_atm	1.495 (.167)**	3,928	1.692 (.207)**	2,326	1.611 (.384)**	771
Dif_ach	.360 (.077)**	3,928	.472 (.128)**	2,326	.336 (.317)	771
Dif_pro	–31.118 (4.374)**	3,113	–13.599 (8.312)	1,697	–1.637 (13.324)	558
Dif_nact	.209 (.020)**	2,957	.254 (.028)**	1,555	.234 (.052)**	499
Dif_nast	.053 (.036)	1,319	.105 (.042)*	692	.119 (.081)	229
Dif_ninv	–.002 (.011)	245	.039 (.018)*	131	.017 (.013)	35

Internet adoption on VRU transactions is not statistically significant. These results are robust when using one-month and five-month moving average values (Table 3, Figure 2).

Thus, although it is not surprising that when a customer obtains access to a lower-cost channel, he or she performs more transactions, it is less intuitive that he or she performs more transactions in all channels. This may be due to the fact that customers increase their overall banking activity following Internet adoption. Using three-month moving average values, Internet banking adoption is linked to an additional acquisition of .254 more deposit accounts ($p < .01$), .105 more asset (loan) accounts ($p = .011$) and .039 ($p < .05$) investment accounts by a customer from the bank, which supports H5c (Table 3, Figure 3).

Interestingly, we find that, with one-month moving average values, there is an immediate profit drop of $31.12 ($p < .01$) around the time of Internet banking adoption (H5d is not supported). However, this negative profit change becomes statistically insignificant and decreases in magnitude as longer moving averages are considered (Table 3, Figure 4). Overall, the findings seem to suggest that there is a temporary profit drop after a customer adopts Internet banking, which could be attributed to a combination of greater transaction usage and

Figure 2

Difference-in-Difference Estimate of Post-Adoption Service Demand Change

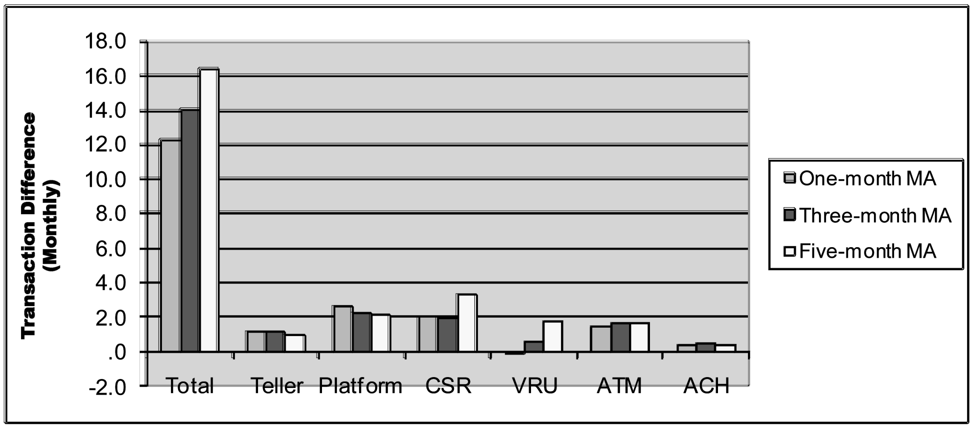
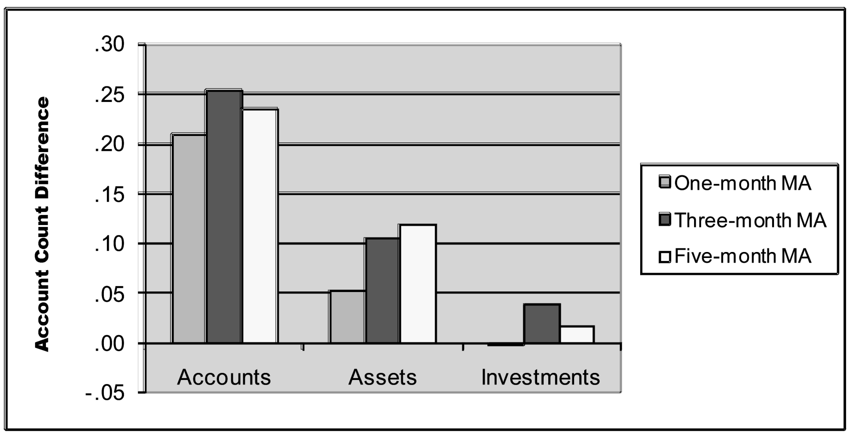


Figure 3

Difference-in-Difference Estimate of Post-Adoption Product Adoption Change

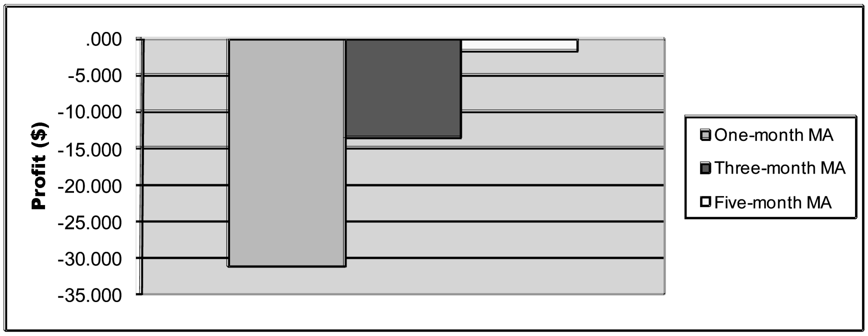


initial costs involved in utilizing new services. However, this drop in profitability is not persistent as some initial costs do not recur, and additional transaction activity is offset by greater product use. Consequently, our analysis suggests a potentially negative short-run profit impact that dissipates over time.

In Table 4 we present the results of our customer retention analysis. Our model results suggest that a customer's chance to leave the bank is reduced by 30% (p < .05, Gompertz model, Table 4), or it takes a customer 45% more time to leave the bank (on average) upon Internet banking adoption (p < .05, Exponential model, Table 4). The results from both models support H5e.

Collectively, these results suggest that adoption of online banking is associated with changes in consumer behavior that are beneficial to the bank, but are offset by the direct cost of online banking adoption as well as increased demand for transaction services. Thus, adoption of online banking is unlikely to show short-run profitability benefits, but increased product utilization and greater relationship length alone or in combination are likely to increase the lifetime value of Internet banking customers.

Figure 4
Difference-in-Difference Estimate of Post-Adoption Profit Change



Discussion and Conclusion

The Internet provides an attractive channel for banks to broaden their service capabilities by increasing the amount of customer self-service through low-cost automated channels. While it is clear that offering online banking has become a "competitive necessity," it is useful to understand which customers are likely to adopt these channels, how those customers will change their banking behavior post-adoption, and what measurable changes this will create in banks' internal performance metrics.

Our results suggest that customers who perform more transactions and are more efficient in service co-production are faster to adopt online banking. In addition, customers appear to be influenced by network effects both locally and overall, with local network effects having a stronger impact. This suggests that word-of-mouth effects and complementarities with other services potentially affect online banking adoption. Given that the rate of online banking adoption has been declining, it suggests that banks may have an opportunity to increase penetration of online banking services by offering training or other customer programs to increase service co-production efficiency, especially to customers with high transaction utilization who may already be inclined to seek alternative service methods.

Our results also suggest that online banking adoption is largely unaffected by the number of ATMs near the customer, although some customers are found to be more likely to adopt Internet banking in areas where more bank branches are available. This may be due to banks optimizing their branch locations based on other customer characteristics (e.g., income). On the other hand, we also find that a low income customer is more sensitive to branch accessibility in adopting online banking than is a high income customer, suggesting that branch access is a better substitute for low income customers than for high income ones. This has interesting implications to bank managers, as it suggests that adding a branch in a low income area may encourage customers to rely more on branches and inhibit online banking adoption, while the size of the physical service network (branches and ATMs) neither enhances nor inhibits diffusion of Internet banking in more wealthy areas.

Our results also represent one of the first analyses that can make a reasonable causal argument between change in service and product utilization and the adoption of online banking. Customers who adopt online banking do increase their use of bank services. However, any profit impact of these changes in the short run is offset by increased transaction demand in non-online channels and the likely costs

Table 4
Survival Analysis of Attrition

	Exponential _t(atr)		Gompertz _t(atr)	
	Reg. Coeff.	**TR. Coeff.**	**Reg. Coeff.**	**HR. Coeff.**
Effects of Internet adoption on retention/attrition				
mon_onaf_ebadp	.37400	1.45354	–.35633	.70024
	(.14699)*	(.21365)*	(.15027)*	(.10522)*
Time trends				
Month	–.01947	.98072	.01935	1.01953
	(.07784)	(.07634)	(.07779)	(.07931)
month2	.00434	1.00435	–.00436	.99565
	(.00607)	(.00610)	(.00606)	(.00604)
Effects of customer efficiency (E) on retention/attrition				
std_ce_at	–.10619	.89925	.10596	1.11178
	(.09511)	(.08552)	(.09499)	(.10561)
Effects of service demand (D) on retention/attrition				
ct_tot	–.00726	.99277	.00725	1.00728
	(.00067)**	(.00066)**	(.00067)**	(.00067)**
Effects of the interaction of customer efficiency and service demand				
ceXtot	–.00029	.99972	.00030	1.00030
	(.00051)	(.00051)	(.00051)	(.00051)
Effects of channel access (C) on retention/attrition				
atm_tot	.07855	1.08172	–.07554	.92724
	(.12721)	(.13761)	(.12727)	(.11801)
num_br	.05674	1.05838	–.05738	.94424
	(.04538)	(.04803)	(.04555)	(.04301)
Impact of customer characteristics (Z) on retention/attrition				
Intcomp	–.01950	.98068	.00187	1.00187
	(.43161)	(.42327)	(.43241)	(.43322)
Age	.01469	1.01480	–.01567	.98445
	(.02549)	(.02586)	(.02542)	(.02502)
age2	–.00017	.99983	.00017	1.00017
	(.00031)	(.00031)	(.00031)	(.00031)
College	–.01510	.98501	–.00438	.99563
	(.70626)	(.69567)	(.70916)	(.70607)
Graduate	–.46719	.62676	.44924	1.56711
	(.80412)	(.50399)	(.80588)	(1.26291)
Low Income	.10843	1.11452	–.11061	.89529
	(.33754)	(.37620)	(.33758)	(.30223)
High Income	–.02387	.97641	.02333	1.02361
	(.27169)	(.26528)	(.27138)	(.27778)

Table 4 continued

involved in setting up new accounts or services after Internet banking adoption. Thus, banks may see little or even a negative impact in overall profitability from the diffusion of Internet technology in the short run. However, our analysis suggests that such negative impact on customer profitability is temporary and such a profitability gap eventually closes up in the long run, perhaps due to the benefits of increased product use that we measure. In addition, given that online customers appear to be more loyal, this can have a direct benefit in increasing the lifetime value of the customer, and also an indirect benefit that increased loyalty may enable banks to compete less aggressively (reducing expenditures on customer acquisition) and earn greater profits (Chen and Hitt 2006). Thus, although we have evidence of a significant payoff for online banking, this payoff may take a longer period of time before it becomes visible in banks' financial statements.

While our focus is on Internet banking, the different issues studied and the methodologies used in the paper are relevant and can be in fact applied to any multi-channel service industry, such as retailing, industrial wholesale, and other types of financial services. Specifically, the factors considered in our adoption framework: Customer demand (in terms of frequency and breadth), channel/technology accessibility, relative customer efficiency in using the different channels, and local and global network effects, are all factors that could affect service channel choices generally. In addition, consumer behavior changes, such as transaction frequency, overall product demand (including existing and new demand), channel usage, profitability and loyalty level, are also likely to change after the adoption of a new technology or a new channel. To assess the effectiveness and efficiency of a new technology or new channel, one needs to not only evaluate the costs of implementing the new technology/channel, but most importantly, to understand what drives consumers' adoption decision and consumer behavior changes—which are often ignored or not well

Table 4 continued

	Exponential _t(atr)		Gompertz _t(atr)	
	Reg. Coeff.	TR. Coeff.	Reg. Coeff.	HR. Coeff.
incXbr	.01507	1.01519	–.01505	.98506
	(.04009)	(.04070)	(.04034)	(.03974)
incXatm	–.04636	.95470	.04514	1.04618
	(.05640)	(.05384)	(.05643)	(.05903)
Female	–.09506	.90932	.09547	1.10017
	(.14061)	(.12786)	(.14083)	(.15493)
With Children	.25130	1.28570	–.25091	.77809
at Home	(.24821)	(.31913)	(.24876)	(.19356)
Single	.36760	1.44427	–.38021	.68372
	(.31217)	(.45086)	(.31321)	(.21415)
Constant	8.81627		–8.81840	
	(.79967)**		(.79725)**	
Observations	21,290	21,290	21,290	21,290

Note: Robust standard errors in parentheses; * significant at 5%; ** significant at 1%; and Residence state is also used as control and the results are omitted due to space limitations. "Reg. Coeff." regular regression coefficient; "TR Coeff." time ratio coefficient; and "HR Coeff." hazard ratio coefficient. Note that Gompertz signs are interpreted in such a way that negative is increased retention and the exponential model has positive as increased retention.

understood—in the cost/benefit analysis of investing in a new technology/channel.

Our empirical findings also have important managerial implications to other non-banking settings. For instance, we find that, while in general, more access to physical branches can promote Internet adoption, the effect is conditional on local income: In a high income area, the promotion effect is significant but adverse effect may be found in low income area. Whether this relationship is unique to financial services or more broadly relevant to all types of transactional services is unclear since income is both a measure of opportunity cost as well as related to potential retail banking profitability. However, this finding does highlight the fact that different segments of the customer population may have a different propensity to substitute among service channels, a finding that is likely to extend beyond banking. Moreover, this result highlights the importance of channel accessibility and customer efficiency in managing multi-channel businesses—by changing/boosting customer efficiency in using lower cost channels and by proper allocations of resources to different channels in a way that promotes use of more efficient channels, one can optimally use multiple channels to manage consumer relationships. In addition, our results also suggest that creating and promoting local network effects beyond the market-wide network effect can help manage the adoption of new technology/channels more efficiently and effectively. This finding is consistent with the finding of Goolsbee and Klenow (2002) in the adoption of personal computers.

What is perhaps uniquely interesting in our study is that we find network effects to be substantial even when customers need not interact directly. Thus, the network effects we observe are likely due to indirect interactions such as word of mouth, which are much more broadly relevant than the direct network effects exhibited by, for example, pure communications technologies. Finally, our results on post-adoption analysis suggest that it is important to recognize the cost-value tradeoff inherent in expanding channel access, especially in industries where channel access is not priced. On the one hand, the efficiency and low transaction cost nature that are often associated with new technology/channels can increase consumers' transaction frequency given existing demand, potentially raising service costs, but at the same time they can reallocate transactions to lower cost channels, and more importantly change the overall demand for revenue-producing services. Firms making these investments in alternative service channels should pay particular attention to product design, to ensure that the firm offers products that are especially attractive to customers who do increase their service demand through the interaction with virtual channels.

While this analysis includes innovations both in the modeling of online banking adoption and in utilizing matching estimators to identify potential causal effects on online banking choice, our approach has several significant limitations. First, our data are limited to a single bank, so we cannot observe either the totality of a customer's banking behavior (which may span institutions) or examine how variations in service design affect adoption rates and behavior changes. This presents an opportunity for future work both to improve the precision of these results as well as to consider competitive effects that may influence profitability and retention. Second, although our matching estimators have a direct causal interpretation, it is still possible that the adoption decision is correlated with behavior changes in ways we cannot observe. Finally, while we find strong evidence for network effects, even when controlling for the time path of adoption, we do not have direct evidence of the mechanism by which these network effects arise, thus creating the possibility of confounding network effects with some other time-varying changes in the banking environment, despite our use of time controls.

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Notes

1. Dial-up home banking dates to at least 1983. See: http://fic.wharton.upenn.edu/fic/papers/97/9748.pdf.

2. Note that, given our setting, each alternative is an allocation decision across different channels. In addition, by assuming that demand is exogenous, we can utilize transaction counts to infer service demand. This is clearly an approximation, because customers may also alter their demand for service given different channel options, but these effects are small compared to the variation in transaction demand across customers. On the other hand, as noted earlier, we allow consumer demand to change post Internet adoption in later analysis.

3. Interestingly, this derivation shows an underlying linkage between random utility approaches, which attempt to explain choices in a cross-sectional analysis, and survival analysis, which attempts to explain changes over time. In our setting, it is the interaction of these two effects that gives rise to the adoption decisions we observe in our data.

4. One should note that with proper selection of time trends, time trends can mimic any overall product diffusion trend over time. If adoption rates are driven by local externalities, this will cause diffusion rates in a narrow geographic region to differ from the overall rate.

5. The empirical analysis requires one month prior data for the model covariates.

6. Due a limit imposed by our data source, we were only able to obtain one-year detailed monthly transaction and account information data from July 2002 to June 2003. Our primary adoption analyses use the full 57-month time period. We code variables that are missing for part of the time period to zero, and include a dummy variable for missing value for each variable coded in this way. Results using a sample restricted to one year show similar results.

7. We restrict our sample to the customers who have no missing values for key demographics: age, income and zip code of primary residence area.

8. As a robustness check, we performed the adoption analysis with the 12-month time window (July 2002–June 2003) for which the monthly transaction record and thus CE measure are not missing. The corresponding sample, which is a subset of the larger 57-month time window sample, includes 19,220 customers who had not adopted Internet banking by July 2002. Among them 1,978 customers adopted Internet banking during the period from August 2002 to June 2003. The results (including the effects of CE and its interaction term with total service demand on adoption) are largely consistent with those from the 57-month time window analysis shown in Table 2. We also ran the analysis using the full 57-month dataset, but replacing missing transaction variables with their average value in the last year—results are directionally similar, but some transaction variables are no longer significant (perhaps due to measurement error introduced by filling missing values over a long time period).

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