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Determinants and Outcomes of Internet Banking Adoption

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This paper examines the drivers of adoption of Internet banking and the linkages among adoption drivers and outcomes (product acquisition, service activity, profitability, loyalty). We relate Internet banking adoption to customer demand for banking services, the availability of alternative channels, customers' efficiency in service coproduction ("customer efficiency"), and local Internet banking penetration. We find that customers who have greater transaction demand and higher efficiency, and reside in areas with a greater density of online banking adopters, are faster to adopt online banking after controlling for time, regional, and individual characteristics. Consistent with prior work, we find that customers significantly increase their banking activity, acquire more products, and perform more transactions. These changes in behavior are not associated with short-run increases in customer profitability, but customers who adopt online banking have a lower propensity to leave the bank. Building on these observations we also find that the adoption drivers are linked to the postadoption changes in behavior or profitability. Customers who live in areas with a high branch density or high Internet banking penetration increase their product acquisition and transaction activity more than Internet banking adopters in other regions. Efficient customers and those with high service demand show greater postadoption profitability.

Key words: Internet banking adoption, customer efficiency, network effects
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1. Introduction

Most modern banks have deployed Internet banking capabilities in an attempt to reduce costs while improving customer service. Despite the potential benefits that online banking offers consumers, the adoption of online banking has been limited and, in many cases, has fallen short of expectations (Bielski 2003, Wade 2003). Although all of the top 50 largest banks in the United States offered Internet banking by 2002 and approximately 91% of U.S. households had a bank account (Kolodinsky 2004), only 17% of consumers adopted online banking. At the time, analysts estimated that this online banking penetration would not exceed 30% of all bank households by 2007 (Babej 2003). This prediction appears to have been realized—an American Bankers Association survey in the summer of 2007 found that only 23% of U.S. consumers use online banking as their primary banking method (Fisher 2007).

Banks are concerned about managing and optimizing the adoption of online banking for several reasons. First, it has been suggested that online banking reduces service costs. For example, according to Chang (2002), the cost to process an account transfer is about $1.07 through a branch and $0.27 by an automated teller machine (ATM), but is only $0.01 through the Internet. Second, customer adoption of online banking can reallocate service demand across multiple service channels, affecting optimal capacity and service design decisions in other channels, such as branches or ATMs. Finally, customers using online channels may show profitability-enhancing behaviors such as increased loyalty or product utilization, although there is some question as to whether this is because of behavioral change or simply differences between online and offline customer populations (Hitt and Frei 2002).

Prior research on online banking adoption has principally used survey methods to attribute social and technical dimensions—such as attitudes toward new technology, awareness, access, and usability—to the variation in Internet banking adoption and usage (Karjaluoto et al. 2001; Gerrard and Cunningham 2003; Lee et al. 2003, 2004; Lichtenstein and

Williamson 2006; Tan and Teo 2000). 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. Second, 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 the consumers' choice to adopt online banking and the interrelationship between the factors that affect online banking adoption and customer behavior (transaction activity) and performance (customer profitability, product acquisition, and loyalty). In addition, we replicate some prior results on the relationships among online banking adoption and outcomes (Campbell and Frei 2010). Our model focuses on four sets of adoption drivers or correlates: customer demand for banking services, the availability of alternative banking channels such as branches and ATMs, the efficiency of the customer in service coproduction ("customer efficiency"), and the number of other Internet banking users in the same geographic region ("local penetration"). Our results suggest that customer demand, customer efficiency, and local penetration play significant roles in online banking adoption, whereas physical channel accessibility is less important. Consistent with prior work, customers significantly increase their transaction demand and open more accounts. Perhaps as a result, customers also increase their use of almost all bank service delivery channels including electronic and branch services. These behavioral changes are associated with lower short-run customer profitability, but the drop in customer profitability is only temporary, with average profitability reverting to the preadoption levels within six months. In addition, customers show greater loyalty (i.e., increased customer retention) after online banking adoption. Some of the adoption drivers are also linked to postadoption changes. In particular, although branch density does not appear to affect Internet banking adoption rates, customers who live in areas with high branch density increase their product adoption after Internet banking adoption more than other customers who live in areas with lower branch density. This relationship also holds for local Internet banking penetration. Both of these observations are consistent with branch access and local penetration effects enhancing the marketing benefits of online banking. In addition, efficient customers and those with high service demand have a greater tendency to substitute electronic for physical channels after adopting online banking than other Internet banking adopters, which softens the short-run negative profitability effects of Internet banking adoption.

This paper makes several research contributions. First, we improve upon existing research on Internet banking technology adoption by examining actual customer behavior over time in a panel data set and examining a broader set of adoption correlates than prior studies. We also have customer location data, enabling the use of geospatial data analysis methods to better identify local penetration effects and the role of physical infrastructure. Second, we apply a number of new methodological approaches to studying Internet banking including utilizing a measure of customer service coproduction capability (Xue et al. 2007), applying a survival analysis framework specifically adapted to study online service adoption, and employing difference-in-difference (DID) matching estimators (Abadie and Imbens 2006) to better control for customer heterogeneity when measuring outcomes. These methods potentially reduce bias due to customer self-selection and reverse causality. Finally, we are able to examine the interrelationships between drivers of technology adoption and the resulting outcomes, which have rarely been considered together.

2. Internet Banking Adoption

2.1. Literature Review

Our analysis is directly related to the literature on the diffusion of technology and innovation (Bass 1969, Davis 1989, Davis et al. 1989, Rogers 1995, Zhu et al. 2003, Zhu and Kraemer 2005), and more specifically to research related to the adoption of self-service technology (Meuter et al. 2000, Curran et al. 2003) and especially the adoption of online banking (Chang 2002, Tan and Teo 2000, Lee and Lee 2001, Lee et al. 2003, Lichtenstein and Williamson 2006).

Much of the research on innovation diffusion is based on concepts introduced in the well-known Bass (1969) model, which relates aggregate product adoption to product characteristics and the number of previous adopters. Later research has extended the ideas in the Bass (1969) 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 Chandrashekaran 1992). The key observation of these models is that product adoption follows a diffusion path depending on marketwide factors (total adoption), individual characteristics, and product characteristics.

The relationship between existing users and future adoption is also emphasized in the literature on network externalities. For instance, Goolsbee and Klenow (2002) demonstrate that the adoption of personal computers is strongly related to user demographic characteristics as well as to the number of current 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 et al. 1989), which considers how individual intentions and beliefs can shape the choice of technology adoption.

A substantial body of literature has utilized product diffusion, network effects and TAMs to study online banking. Most of these studies are based on survey data and focus on modeling the relationship between customer demographics and online banking diffusion (Kolodinsky et al. 2000, Karjaluoto et al. 2002, Perumal and Shanmugam 2004). Other factors that have been considered in the prior research include technological expertise, such as customers' prior computer experience or experience with other similar technologies (Karjaluoto et al. 2002; Kim et al. 2005, 2006; Lee and Lee 2001); convenience (Chung and Paynter 2002, Ramsay and Smith 1999, Thornton and White 2001, Lichtenstein and Williamson 2006); desire to use innovative products (Tan and Teo 2000, Chung and Paynter 2002); and security, privacy, and trust (Chung and Paynter 2002, Ramsay and Smith 1999, Suh and Han 2002).

A related literature in service operations further suggests that adoption of a technology-enabled service is closely related to customers' capabilities in engaging in service coproduction (Chase 1978, 1981). In these models, customers differ in their ability to participate in the self-service process (termed *customer efficiency*), which leads them to perceive the relative cost of self-service over full-service alternatives differently, and thus to make different service choices (Xue and Harker 2002, Xue et al. 2007). This literature also provides a framework for measuring customer efficiency (Xue et al. 2007).

Our paper extends these literature streams. Specifically, our panel data allow us to model the adoption of Internet banking as it is driven by aggregate effects (product diffusion, local penetration effects, and availability of alternatives) as well as by individual customer characteristics (service demand, demographics, and customer efficiency). By using objective customer data we are also less subject to self-reporting biases that are potentially present in survey-based research, and our use of a large set of geographic control variables enable us to better distinguish local penetration effects from other unobserved factors that drive adoption over time. Another advantage of our data is that we can examine actual customer-level outcomes to a technology adoption event, which is uncommon in the existing literature (see Zhu and Kraemer 2005 for an exception). Understanding of how consumers may change their behaviors after adoption is necessary for understanding the value of the online channel for banks.

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). Recent work using a similar data set to ours suggests that after controlling for customer characteristics, online banking adopters increase their transaction activity and customer retention, while showing lower profitability (Campbell and Frei 2010). They also find that banks with greater adoption of online customers increase their market share. We extend this literature by considering a broader set of determinants of online adoption, and by considering the interactions among adoption drivers and outcomes.

2.2. Background: Retail Banking

Retail banks are consumer depository and lending institutions that offer deposit accounts (interest- and noninterest-bearing transactional accounts, and 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. Because of 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 customer support representatives (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.[1]

[1] 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

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 already have Internet access, and modest but not insignificant requirements for customer skill. From the bank's perspective, the Internet channel is attractive because it may reduce service costs directly or may convert the variable cost of human-staffed service channels to the largely fixed cost technology infrastructure, thereby increasing economies of scale.

3. Hypotheses

The random utility framework (McFadden 1974) provides a basis for understanding why some customers adopt Internet banking adoption whereas others do not. Random utility theory posits that customers choose the product that offers them the highest utility given the relative costs and benefits of the product, and idiosyncratic customer tastes. In our analysis, these costs and benefits are captured by four key factors: the *demand* for banking services, a *customer's capabilities* in using self-service technology, the *availability* of channel alternatives, and *local penetration effects*. The first three factors encompass the costs and benefits directly experienced by the customer, whereas the fourth item, *local penetration effects*, may influence the customer's perception of usefulness, ease of use, and reliability, thereby indirectly influencing customer adoption decisions.

3.1. Hypotheses: Internet Banking Adoption

Service Demand. Different consumers will have differing demand for banking services, which yields variations in the overall value obtained from using online banking. Customers who have a high demand for service interactions can expect greater total benefits from any service innovation and are therefore more likely to adopt Internet banking to reduce their service effort (Lee and Lee 2001). All else equal, we expect that a customer with higher demand for banking services has more to gain from adopting Internet banking.

Hypothesis 1 (H1). *Higher transaction volume is associated with faster Internet banking adoption.*

Channel Access. A number of studies have identified convenience as an important adoption factor for electronic banking or other services (Ramsay and Smith 1999, Thornton and White 2001, Lichtenstein and Williamson 2006). A related argument is that new technology adoption can be affected by the relative inconvenience of using existing channel alternatives (Ramsay and Smith 1999). Because the primary "cost" of a customer using a physical service channel is the cost to travel to the physical facility, and both customers and service locations are dispersed geographically, different customers will face different costs of using physical channels. Recent work by Forman et al. (2009) confirms that density of physical locations affects the online versus offline purchase decision. Similarly, we expect that customers for whom there are fewer nearby branches or ATMs are more likely to use online banking. This would imply the following hypothesis:

Hypothesis 2A (H2A). *A lower density of offline channels (branches and ATMs) near the customer is associated with faster Internet banking adoption.*

Different consumers likely face different opportunity costs of the same amount of travel. This suggests that online banking adoption is also affected by the interaction between opportunity cost and channel accessibility. Following prior literature (Becker 1993, Kim et al. 2006), we will use *household income* as a proxy for the opportunity cost of time. Thus,

Hypothesis 2B (H2B). *The effect of offline channel density on Internet banking adoption is larger (in absolute value) for customers with higher income.*

Customer Efficiency. Customers who are more able to participate in service coproduction will potentially experience a lower cost in adopting and using Internet banking. In prior work, *customer efficiency* has either been proxied by customer demographic characteristics or investigated by direct measurement (Xue et al. 2007). Here, we use the latter approach although will note that the "efficiency as demographics" interpretation may help sign some of the demographic control variables in our model. Because the benefits of greater efficiency yield a larger total effort savings when a customer performs more transactions in total, we allow for customer efficiency to moderate the effect of *transaction volume*. Thus, we expect the following:

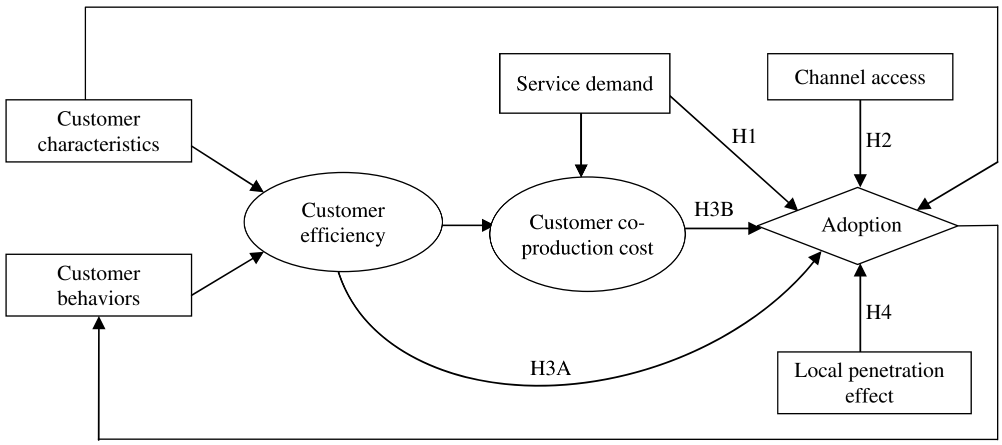
Hypothesis 3A (H3A). *Higher customer efficiency is associated with faster Internet banking adoption.*

Hypothesis 3A (H3B). *The rate that Internet banking adoption increases with service demand is increasing in customer efficiency.*

Local Penetration Effects. The product diffusion literature (e.g., Bass 1969) and the network effects literature (e.g., Katz and Shapiro 1985) suggest that the

proprietary software and a dial-up network), 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.

Figure 1 Conceptual Model of Internet Banking Adoption



demand for a product can be related to the number of adopters of compatible products. This is certainly true in products where value is created by direct customer interaction (e.g., file sharing in software, telecommunications). Although customers do not directly benefit from interacting with each other in the Internet banking context, there are at least two reasons why the level of product penetration of Internet banking may play a role in influencing a customer's online banking adoption decision. First, online banking may be subject to similar local word-of-mouth or imitation effects as has been found for many products, such as personal computers, books, and online groceries (Goolsbee and Klenow 2002, Stavins 2002, Forman et al. 2008, Choi et al. 2011). Second, there may be other indirect effects that could influence a customer's adoption decision such as complementary investments by billers or other service providers who interact with online banking or simple service improvements made by the bank that become economic as a result of economies of scale. Either of these explanations would indicate that adoption rate is increasing in the number of prior adopters, with adopters who are geographically close being especially important.

An empirical challenge in measuring the role of local penetration effects is distinguishing these effects from geographically driven customer heterogeneity. In particular, we are concerned that areas with high adoption may have customers with a greater propensity to adopt, regardless of any network or "word-of-mouth" effect (this is described as the "reflection problem"; see Manski 1993). Absent information about specific mechanisms that drive local penetration effects, we cannot be certain to eliminate this problem. However, we can adopt an aggressive approach for controlling for geographic heterogeneity (as in Goolsbee and Klenow 2002) by including additional control variables. Thus, we measure our *local penetration effect* as the number of adopters within a zip code area over time, conditional on the characteristics of the zip code area, the number of adopters in the market as a whole, and additional time-series controls. These controls make it less likely our adoption results are driven by differences across regions unrelated to online banking.

Hypothesis 4 (H4). *Higher local penetration is associated with faster adoption of Internet banking (after suitably controlling for geographic and time-series heterogeneity).*

A conceptual model of our key arguments appears in Figure 1.

3.2. Hypotheses: Behavior Change After Adopting Internet Banking

The value proposition of Internet banking, especially from the bank perspective, is heavily dependent on whether and how 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) and suggested, but could not confirm, that this was because of customer heterogeneity. Recent research shows that indeed this profit difference is largely driven by customer heterogeneity and that the short-run profit impact of online banking adoption is negative (Campbell and Frei 2010). Using our data, we are able to replicate some of these results in our setting,[2] and then explore a novel set of hypotheses about the connection between factors

[2] Campbell and Frei (2010) use similar data from a different bank but have a longer time series (30 months). They also focus their analysis on active and inactive online banking adopters which is more appropriate in their bank given the way online banking was extensively marketed in their target institution. Our approach is similar, except our reference population is nonadopters rather than inactive adopters and we utilize a slightly different approach for matching customers.

that influence adoption and the resulting changes in postadoption behavior and outcomes. For clarity, we present the main arguments for postadoption changes below; similar arguments are used in Campbell and Frei (2010).

3.2.1. Changes After Internet Banking Adoption. *Product Acquisition.* Customers utilizing online banking may be able to identify additional products from the same institution more easily because of lower search costs for product information, or face lower costs of adopting incremental products because of the efficiency of online interaction (Strothkamp 2005). From the bank perspective, technology-enabled service delivery may also create new opportunities for technology-enabled cross-selling, opening up a new sales channel and providing an opportunity for data-driven customer targeting. The net effect is that online banking adoption provides a bank with enhanced marketing capabilities, which is potentially associated with additional product adoption:

Hypothesis 5 (H5). *Internet banking adoption is associated with increasing product acquisition from the bank.*

Transaction Activities. Facing lower costs of performing transactions in the online channel, customers may increase the number of transactions they perform. If they also adopt more products, as the prior discussion would suggest, that should further increase transaction activity. Therefore,

Hypothesis 6A (H6A). *Internet banking adoption is associated with increased total transaction activity.*

However, some of their online transaction activities are likely to substitute for transactions that can be performed elsewhere. Given that we expect more total transactions, it is unclear whether the net effect of online banking adoption on the number of transactions in a specific channel is positive or negative. Given that this is an empirical question, we will state our hypothesis in the form where supporting the hypothesis is "good" from the bank perspective (a convention we will follow for the remaining hypotheses):

Hypothesis 6B (H6B). *Internet banking adoption is associated with decreased usage of other channels.*

Customer Profitability. On the one hand, greater product use is likely associated with greater customer profitability because of higher revenues generated from greater product use, which may be due to increased use of existing products or adoption of new products (as per H5). On the other hand, greater product use is likely associated with higher transaction activities, which in turn lead to higher costs for banks (as per H6A), although this may be moderated by shifts of transactions from high cost to lower cost channels (H6B). Because the relationship between online banking is ultimately an empirical question, we test:

Hypothesis 7 (H7). *Internet banking adoption is associated with an increase in a customer's profitability.*

Customer Loyalty. Customers may experience a change in the degree of "lock-in" (that could be either positive or negative) when provided access to online banking. This may arise because increased ease of access to banking services encourages them to consolidate accounts, or because there is lock-in from the effort required to learn to use a bank's online services. Furthermore, increased product acquisition (H5) may also lead to higher customer loyalty. However, the opposite could also be true—customers could become less loyal if online banking facilitates using multiple banks or if learning is transferable across institutions (Chen and Hitt 2002). Therefore,

Hypothesis 8 (H8). *Internet banking adoption is associated with lower likelihood of customer departure from the bank.*

3.2.2. Linking Adoption Correlates and Postadoption Changes. We may expect that the factors that lead to Internet banking adoption may also lead to changes in customer behavior after adoption. From our prior discussion, we observe two forces that contribute to both Internet banking adoption and postadoption changes. First, improved marketing capabilities associated with Internet banking adoption may also lead to more product acquisition. Second, incentives for channel substitution that encourage Internet banking adoption may also encourage transactions to migrate to the Internet channel. Below we discuss how the four drivers of adoption could interact with these two effects and lead to differences in customer product use (acquisition, transactions), the allocation of transactions across channels, and profitability after Internet banking adoption.

Customers who have greater exposure to the bank, either because of a high availability of offline channels, a high local penetration of online banking users, or because they routinely interact with the bank for service activities (high service demand), have greater contact with the bank's marketing channels. This greater marketing contact could encourage more product acquisition from the bank. Other online customers may play a disproportionate role (compared to all customers) in driving new product use through word of mouth and other potential peer influences. Thus, we might expect customers who adopt online banking in areas with a high density of branches or strong online penetration, and those customers that perform frequent transactions, to acquire more products from the bank. Customers who adopt more products may also further increase their transaction activity. These observations can be formally stated as follows:

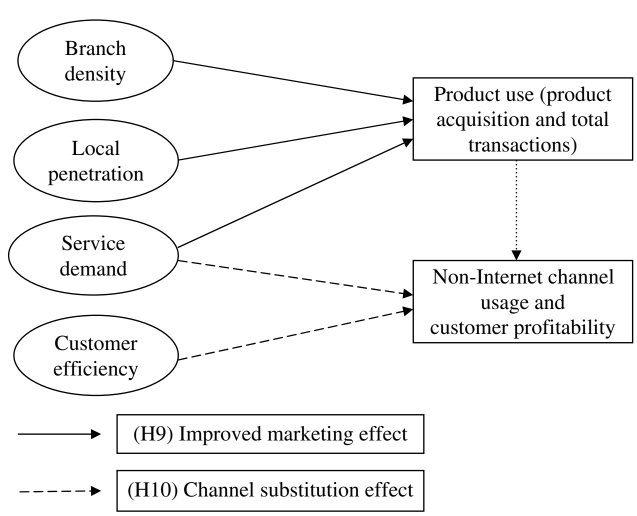
Hypothesis 9 (H9). *Adoption correlates that are likely to affect cross-sell potential (local penetration, branch density, and service demand) are associated with greater product use after online banking adoption.*

Customers who perform large numbers of transactions and those who are efficient at using self-service have the incentive and ability to shift transactions from full-service to self-service channels. Consequently, we expect customers with high service demand and high efficiency to show the greatest degree of channel substitution. Given that we expect these same factors to increase total transactions as a result of new product adoption (per H6A), we do not necessarily expect a decrease in transaction activity in offline channels (H6B), but a lower increase relative to other customers. Regardless of whether customers use more or less offline channels, we expect that service demand and customer efficiency play important roles in understanding how customer behavior may differ between the Internet channel and offline channels. Because the allocation of transaction activities across channels has a significant influence on service costs, we would expect the channel substitution to be associated with greater customer profitability. Thus, we have the following:

Hypothesis 10 (H10). *Adoption correlates that increase channel substitution (service demand and customer efficiency) are associated with less usage of non-Internet channels and greater profits after online banking adoption.*

Figure 2 summarizes how the four adoption drivers may be associated with postadoption behavioral changes via improved marketing and channel substitution effects (H9 and H10).

Figure 2 Theoretical Predictions for Effect of Adoption Correlates on Postadoption Outcomes



4. Data and Methodology

4.1. Data

From a large retail bank's customer population, we take a random sample of 28,945 customers. Among this sample, 9359 customers adopted the bank's Internet banking during our 57-month study period starting from January 1999, the time when the institution we study first offered Internet banking, to September 2003. These data include cross-sectional data on the date the customer opened her first account with the bank, the date Internet banking was initiated (if any), and categorical demographic information including home zip code.[3] For the period July 2002 through June 2003, we also have data on transactions by channel, as well as month-end account balances for all deposit products. The transaction and account data are drawn from the bank's operational systems and are complete and highly accurate. The demographic information was developed by a combination of the bank's own data collection and third-party market research data. Because of this process, some of the demographic data have missing values, which we code as an additional category of "missing" for these variables.

We use two types of geographically based data. First, we include additional demographic information for each zip code area obtained from census and internal bank sources, including the number of business establishments and the number of automated teller machines. We also count the total number of bank customers who adopt online banking in each zip code area (not just the number in our selected sample) in each month. It should be noted that our focal bank primarily serves regions of the country with high population density, so the majority (99%) of the zip codes we analyze include metropolitan areas (with 50,000 or greater population). Using data on customer locations as well as street addresses for branch locations for all bank branches in the United States tabulated annually by the Federal Deposit Insurance Corporation, we can construct a measure of the number of branches within two miles of each customer for both the focal bank and all banks. The two-mile radius was chosen based on the industry observation that most customers bank within two miles of where they live or work. A detailed description of the variables in our analysis is presented in Table 1.

4.2. Methodology

4.2.1. Internet Banking Adoption. We test our hypotheses about online banking adoption (H1–H4)

[3] Because of a limit imposed by our data source, we were only able to obtain detailed monthly transaction and account information data from July 2002 to June 2003. However, our primary adoption analyses use the full 57-month time period. Results using a sample restricted to one year show similar results.

Table 1 Variable Definition and Summary Statistics

Variable	Definition	Mean	Std. dev.
local penetration	Count of adopters in customer primary zip code (end of month) (in thousands)	0.83	1.23
market adoption	Count of adopters outside primary zip code (end of month) (in thousands)	343.6	200.95
customer efficiency	Customer efficiency measure (per month)	0	1
service demand	Transaction total (per month)	28.27	44.1
own ATM count	Number of ATMs in customer zip code	1.54	1.81
own branch count	Number of own branches within two miles of customer	9.89	15.34
rival branch count	Number of other bank branches within two miles of customer	46.89	59.13
age	Age of primary account holder	46.03	17.43
population	Population of zip code (in millions)	0.04	0.03
household income	Household income of zip code (in thousands)	50.82	24.89
household zip	Households in zip code (in thousands)	17.38	12.22
age—zip	Median age for zip code	34.25	7.51
establishments	Total business establishments in zip code	1,170	1,246
adoption indictor	1 if customer adopted Internet banking, 0 otherwise (end of month)	0.32	0.47
deposit count	Number of deposit accounts held by customer (end of month)	1.91	1.24
asset count	Number of asset accounts held by customer (end of month)	1.68	1.01
investment count	Number of investment accounts held by customer (end of month)	1.3	0.65
teller	Teller transactions (per month)	2.75	5.24
platform	Branch platform transactions (per month)	2.43	9.52
CSR	Call center CSR transactions (per month)	2.45	12.72
VRU	VRU transactions (per month)	5.69	17.93
ATM	ATM transactions (per month)	4	7.16
ACH	ACH transactions (per month)	2.08	4.28
balance	Total deposit balances ($)	22,073	87,700
profit	Customer profitability (bimonthly)	10.23	116.64
income	Household annual income	0—missing (34.72%), 1—low income (≦ $40 K, 24.62%), 2—medium ($40 ~ 75 K, 19.89), 3—high income(≧ $75 K, 20.77%)	

using survival analysis methods. This approach relates the explanatory variables (including individual and time-varying measures) to the time the customer adopts Internet banking. For this survival analysis, a subject exits the panel at either the adoption event or by leaving the bank.

A variety of approaches can be utilized for survival analysis, including whether outcome is measured by an event time (accelerated failure time (AFT) models) or a hazard rate (proportional hazard (PH) models). In addition, within each general approach, different functional form assumptions can be made to relate the adoption event to its correlates. Because we are interested in the influence of the covariates as they evolve over the time interval, we use a parametric model because parametric models are known to be more statistically efficient in these settings than nonparametric or semiparametric survival analysis models (Hosmer and Lemeshow 1999, Tellis et al. 2003, Cleves et al. 2004). Following the product and innovation diffusion literature (Tellis et al. 2003), we fit the adoption model to a log-logistic distribution AFT model. The usual functional form for a parametric AFT model relates the event time for observation t_j to a set of covariates (x_j) and an error term (ε_j), and then estimates a set of parameter weights on the covariates (β_x):

$$\ln(t_j) = x_j\beta_x + \varepsilon_j. \tag{1}$$

For the model, we include covariates identified in §3.1. To measure *service demand*, we include the previous month's total counts of a customer's transactions for all her deposit accounts with the bank. For *channel access*, we include the counts of bank branches within two miles of the customer's primary residence and the number of ATMs within the same zip code as the customer's primary residence. These variables appear directly (H2A) and interacted with customer *income* to reflect opportunity cost of travel (H2B). We also include the count of other banks' branches within two miles of the customer's primary residence as a measure of the customer's access to alternative channels from the competitors to control for the effects of competition and other forms of local heterogeneity that drive the availability of banking services. For *customer efficiency*, we construct our measure following Xue et al. (2007). We capture local penetration effects with the total number of bank customers residing in the same zip code who have adopted Internet banking from the bank by the end of previous month. In addition, to address the Manski (1993) reflection problem, we include (1) linear and quadratic time trend variables; (2) the number of the bank's customers residing outside of a customer's own zip code area who have adopted Internet banking from the bank by the end of previous month; (3) customer demographic controls (*marital status*, *education*, *age*, *expressed interest in computers*, *presence of children in the household*, and *gender*);[4] and (4) a set of regional (zip code level) controls for *population*, *number of households*, *median income per household*, *median age* and its square, and the *number of business units*. Further details on the definitions of our variables and sample statistics appear in Table 1.

4.2.2. Postadoption Analysis: DID Estimation. To examine postadoption changes in customer behavior, we apply the DID matching estimator that compares the changes in behavior of online banking adopters against those of a matched sample of nonadopters to estimate an average effect of online banking adoption based on Abadie and Imbens (2006). The DID estimation approach has the advantage that it provides a control for both self-selection (e.g., higher-profit customers may be more likely to adopt online banking) as well as time-series heterogeneity (e.g., common shocks may affect demand for banking service over time in a manner common across customers) (see, for example, Forman et al. 2009). Matching estimators compare each customer who adopts Internet banking to a number of customers who do not adopt Internet banking with similar values in the matching variables prior to the adoption event. The estimator then calculates the difference in outcomes of these two matched populations before and after the event of interest. A similar approach was utilized for related analyses in Campbell and Frei (2010).

We focus on online banking adoption as the "event" and include in our matching parameters factors influential on customer banking behavior, specifically demographics (age, income, and zip code), access to alternative channels (bank branches and ATMs), and customer efficiency (measured in the month prior to adoption). Because we match customers based on zip code, we do not need further geographic controls. The matching parameters also include the ex ante value of the variables of interest: total service demand; service demands for different channels (teller, platform, CSR, VRU, ATM, and ACH), a profit measure generated by the bank;[5] and the counts of deposit, assets, and investment accounts for each customer, to control for any additional unobserved heterogeneity in product usage and transaction behavior. Because transactions have some random monthly variation and there may not be an exact correspondence between the month of online banking adoption and the resulting behavioral changes, we measure the before-and-after difference for each unit using one-, three-, and five-month moving averages, although for brevity we focus on the three-month moving average for the discussion and result presentation. For analyses that consider how adoption correlates affect postadoption changes, we perform the analysis by breaking the sample into quartiles for each adoption correlate we study and conduct separate DID analyses for the top and bottom quartiles.

We use the matching estimator based on the algorithm presented in Abadie and Imbens (2006), which computes a distance score between a treated unit and all possible untreated neighbors based on the matching parameters, and then matches each treated unit with the closest untreated units, with replacement. The exact procedure is implemented in the NNMATCH module for STATA, which also includes additional provisions for bias correction for finite samples and reports heteroscedasticity-consistent standard errors. This estimate is run using all Internet banking adopters who adopted Internet banking from the bank from July 2002 to June 2003, the time period for which we observe monthly transaction data—a sample of 2,413 customers. The matching algorithm then matches these customers to the three nearest neighbors from a random sample of 2,500 nonadopters drawn from our original data set.

4.2.3. Customer Retention Analysis. To measure customer retention, we use a survival analysis approach in which we relate the act of departing the bank, or the time of departure, to the covariates used in our prior models. To this model we add a measure of online banking adoption (*adoption indicator*),

[4] Because all demographic variables except age are categorical, we must omit a category for identification: the omitted categories in our model describe a male customer who has a high school diploma as the highest education obtained and a medium-level income, who is single with no children living at home, and who shows no interest in using computers.

[5] The profit measure is a bimonthly calculation done by the bank and used internally. The calculation is based on interest revenue and fees, less service costs, expected loan losses, and taxes.

Table 2 Survival Analyses for Internet Banking Adoption and Postadoption Attrition

	Adoption		Retention	
	Log-logistic		Exponential	
	Adoption	Adoption	Attrition	Attrition
Variable	Regular	TR	Regular	TR
adoption indicator			0.358 (0.151)*	1.430 (0.216)*
service demand	−0.007 (0.002)**	0.993 (0.002)**	−0.007 (0.001)**	0.993 (0.001)**
own ATM count	−0.012 (0.065)	0.989 (0.065)	0.081 (0.125)	1.085 (0.136)
own branch count	0.031 (0.019)	1.032 (0.019)	−0.000 (0.012)	1.000 (0.012)
rival branch count	0.002 (0.003)	1.002 (0.003)	−0.000 (0.003)	1.000 (0.003)
customer efficiency	−0.550 (0.130)**	0.577 (0.075)**	−0.119 (0.097)	0.888 (0.086)
efficiency × demand	0.004 (0.002)*	1.004 (0.002)*	−0.000 (0.001)	1.000 (0.001)
local penetration	−0.483 (0.121)**	0.617 (0.075)**		
market adoption	0.001 (0.001)	1.001 (0.001)		
month	−2.284 (0.736)**	0.102 (0.075)**	−0.058 (0.081)	0.944 (0.076)
month^2	0.023 (0.008)**	1.024 (0.008)**	0.008 (0.006)	1.008 (0.006)
low vs. medium income	(0.232) −0.148	(0.260) 0.863	0.069 (0.283)	1.071 (0.304)
high vs. medium income	(0.295) 0.004	(0.254) 1.004	0.782 (0.348)*	2.186 (0.762)*
income × branch	(0.005) −0.049	(0.005) 0.952	0.027 (0.040)	1.028 (0.042)
income × ATM	(0.042) (0.232)	(0.040) (0.260)	−0.050 (0.056)	0.951 (0.053)
age	−0.027 (0.029)	0.973 (0.029)	0.023 (0.026)	1.023 (0.026)
age^2	0.002 (0.000)**	1.002 (0.000)**	−0.000 (0.000)	1.000 (0.000)
zip-code-level controls	*Population, age, age*^{2}*, income, establishments, households*	*Population, age, age*^{2}*,income, establishments, households*		
Observations	207,972	207,972	20,843	20,843

Notes. Robust standard errors are in parentheses. Residence state, marital status, presence of children, education, gender, and computer interest are included as controls (only state is significant). Regular is the regular coefficient; TR is the time ratio coefficient.
*Significant at 5%; **significant at 1%.

which takes the value 0 prior to adoption and 1 thereafter. The coefficient of this variable provides a measure of the marginal effect of online banking adoption on retention. We use multiple distributional assumptions but report only the results from the exponential distribution because it provided the best fit. We excluded nonadopters to avoid sample self-selection bias problems because the lack of adoption may be correlated with factors that affect retention (for a further discussion of the motivation for this approach, see Maddala 1983, Wooldridge 2002).

5. Results

5.1. Internet Banking Adoption

The parameters are estimated by maximum likelihood with a robust variance estimator.[6] Table 2 shows the results with the log-logistic model (AFT). As a robustness check, we also fit the model in PH format and under different distribution assumptions with similar

[6] We used the STATA command STREG for the survival analysis estimates.

results (not shown). In Table 2, column 1 reports the regular regression coefficients ("Regular") in the log-time format, whereas column 2 reports the more easily interpreted time ratio coefficients (TR), which is the ratio of fail time to normal time. A negative regular coefficient or a time ratio coefficient less than one implies faster adoption.

Service Demand. Our results show that a customer with higher *service demand* adopts Internet banking faster ($\beta = -0.007$, $p < 0.01$), thus supporting H1. In particular, for each added monthly transaction, a customer's time to adopt Internet banking is reduced by about 0.7% ($p < 0.01$). This is consistent with the study by Lee and Lee (2001), which found that heavy users of banking services are more likely to adopt Internet banking.

Channel Access. We find little evidence that channel availability has any influence on online banking adoption (H2A not supported). Neither the focal bank's branch count nor the rival banks' branch count in the local area is shown to have any economically or statistically significant relationship with Internet banking adoption. The count of the number of ATMs is weakly associated with faster Internet banking adoption, although this is not significant statistically or economically. Although this finding seems surprising and is contrary to our hypothesis, it is consistent with a similar analysis by Khan (2004) using data from the Survey of Consumer Finances that showed that branch density does not affect online banking usage.

As noted in H2B, we expected that a customer's decision to adopt Internet banking would depend on the customer's total opportunity cost of branch access. However, neither income alone nor the interaction of income and branch density appears to affect online banking adoption rates.

Customer Efficiency. Our results suggest a strong correlation between Internet banking adoption and customer efficiency. A customer whose efficiency is one standard deviation above the average requires 43% less amount of time to adopt Internet banking from the bank ($\beta = -0.55$, $\text{TR} = 0.577$, $p < 0.01$), which is consistent with H3A. Moreover, we find that customer efficiency moderates the effect of service demand on Internet banking adoption, although the effect is small and not in the direction hypothesized (therefore, H3B not supported).

Local Penetration Effects. We find a strong effect of the local penetration variable ($\beta = -0.483$, $\text{TR} = 0.617$, $p < 0.01$), even after including extensive controls for time, individual and regional heterogeneity, and marketwide diffusion effects, thus supporting H4. Interestingly, the local penetration effect is much stronger than marketwide diffusion effect. In addition, estimates on the control variables suggest a larger local population is associated with slower Internet banking adoption, whereas the number of local businesses has a positive effect. Most of the demographic controls are insignificant, although we do find a curvilinear relationship between age and adoption, which is consistent with prior work suggesting that younger customers are generally more likely to adopt Internet banking (Kim et al. 2005, 2006; Perumal and Shanmugam 2004).

5.2. Postadoption Analysis

5.2.1. Changes Following Internet Banking Adoption. The major results of postadoption analysis, using DID matching estimators, are shown in Table 3, Figure 3 (accounts), and Figure 4 (profit). We focus our discussion on the three-month moving average results, but discuss differences with the other estimates where relevant.

Product Acquisition. In the three-month moving average estimates, Internet banking adoption is linked to the additional acquisition of 0.254 more deposit accounts ($p < 0.01$), 0.105 more asset (loan) accounts ($p = 0.05$), and 0.039 ($p < 0.05$) investment accounts by the customer from the bank, supporting H5 (Table 3 and Figure 3).

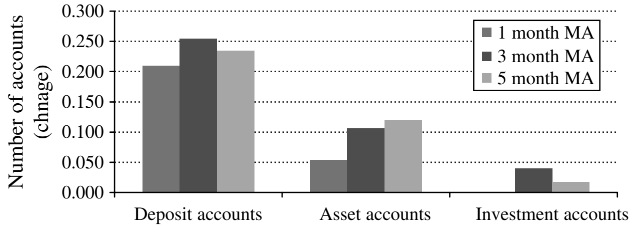
Transaction Activities. Not surprisingly, increased product adoption is also accompanied by increased transaction activities. Following adoption, a customer performs 14.026 more transactions per month

Table 3 Average Treatment Effect of Internet Adoption

Dependent variable	One-month moving average	Three-month moving average	Five-month moving average
total transaction change	12.306	14.026	16.450
	(1.169)**	(1.464)**	(2.894)**
teller transaction change	1.165	1.191	0.937
	(0.120)**	(0.145)**	(0.278)**
platform transaction change	2.590	2.240	2.183
	(0.324)**	(0.323)**	(0.504)**
CSR transaction change	2.011	1.941	3.341
	(0.417)**	(0.441)**	(0.778)**
VRU transaction change	−0.007	0.526	1.744
	(0.512)	(0.464)	(0.865)*
ATM transaction change	1.495	1.692	1.611
	(0.167)**	(0.207)**	(0.384)**
ACH transaction change	0.360	0.472	0.336
	(0.077)**	(0.128)**	(0.317)
profit change	−31.118	−13.599	−1.637
	(4.374)**	(8.312)	(13.324)
deposit account count change	0.209	0.254	0.234
	(0.020)**	(0.028)**	(0.052)**
assets account count change	0.053	0.105	0.119
	(0.036)	(0.042)*	(0.081)
investment account count change	−0.002	0.039	0.017
	(0.011)	(0.018)*	(0.013)

Note. Standard errors are in parentheses.
*Significant at 5%; **significant at 1%.

Figure 3 Difference-in-Difference Estimate of Postadoption Product Acquisition



Note. MA, moving average.

($p < 0.01$, supporting H6A), which is spread across all channels: a customer's monthly teller transactions increases by 1.191 ($p < 0.01$), platform transactions increase by 2.24 ($p < 0.01$), CSR transactions increase by 1.941 ($p < 0.01$), ATM transactions increase by 1.692 ($p < 0.01$), and ACH transactions increase by 0.472 ($p < 0.01$). The change in VRU transactions is not statistically significant. Results are similar when using one-month moving average and five-month moving average values. Thus, there are substantial changes of channel use across channels post adoption. Although it is not surprising that customers perform more transactions when channel access cost is lowered, it is somewhat surprising that this leads to increased demand for all channels (rejecting H6B). Note that because we use difference-in-difference estimators, it is unlikely that these results are due to self-selection between adopters and nonadopters of online banking.

Customer Profitability. Unlike the transaction and account usage analysis, our analyses of profitability show considerable variation when different time windows are considered. In the short run (one-month average), there is an immediate and substantial profit drop of \$31.12 ($p < 0.01$) around the time of Internet banking adoption. However, this negative profit change becomes statistically insignificant and decreases in magnitude over time, as evident when longer moving averages are considered (Table 3 and Figure 4). Thus, we do not find support for H7, especially in the short run.

Customer Loyalty. Finally, we examine the influence of Internet banking adoption on customer attrition (Table 2). Our results suggest that after Internet banking adoption, customers stay with the bank 43% longer on average ($p < 0.05$, exponential model; Table 2); therefore supporting H8. The results also suggest that high-income customers and those with higher service demand are less likely to leave the bank over our observation period.

Figure 4 Difference-in-Difference Estimate of Postadoption Profit Change

Note. MA, moving average.

5.2.2. Linking Adoption Correlates and Postadoption Changes. H9 and H10 argue that the four Internet banking adoption drivers are associated with postadoption changes through two possible effects: cross-sell potential and channel substitution incentives. We are most concerned about consumers' product use, use of non-Internet channels and profit change after Internet adoption. To understand consumers' product use, we consider both new product acquisition and total transactions performed, while studying consumers' use of non-Internet channels allow us to understand the drivers of any profit changes observed post adoption. Altogether, there are four types of postadoption changes that we consider: product acquisition, total transactions, transactions performed through non-Internet channels, and profitability. Tables 4 and 5 show the subsample DID analyses to test H9 and H10. Each analysis is based on a sample split into quartiles along the construct

Table 4 Summary of the Relationship Among Adoption Correlates and Outcomes (Products and Transaction)

	Product acquisition			
	Deposit	Assets	Investments	Total txns.
branch density				
High	0.243	0.141	0.127	17.250
	(0.032)*	(0.051)*	(0.030)*	(2.110)*
Low	0.239	−0.006	−0.008	1.096
	(0.054)*	(0.058)	(0.022)	(0.170)*
Difference	0.005	0.147	0.135	16.155
	(0.041)	(0.053)*	(0.027)*	(1.694)*
local penetration				
High	0.222	0.216	0.000	11.721
	(0.048)*	(0.068)*	(0.018)	(2.275)*
Low	0.208	−0.232	0.077	5.088
	(0.058)*	(0.082)*	(0.038)*	(5.462)
Difference	0.014	0.448	−0.077	6.633
	(0.052)	(0.071)*	(0.023)*	(3.665)*
service demand				
High	0.242	0.081	0.032	7.518
	(0.046)*	(0.063)	(0.066)	(3.945)
Low	0.001	0.318*	0.072	10.398
	(0.021)	(0.096)	(0.036)*	(2.384)*
Difference	0.241	−0.238	−0.041	−2.880
	(0.037)*	(0.076)*	(0.059)	(3.269)

Notes. Standard errors are in parentheses. All analyses are based on three-month moving averages. Txns., transactions.

*Significant at $p < 0.05$ (for coefficient, the test is against 0; for difference, the test is between groups).

Table 5 Summary of the Relationship Among Adoption Correlates and Outcomes (Transactions by Channel and Profit)

	Teller txns.	Branch txns.	CSR txns.	VRU txns.	ATM txns.	ACH txns.	One-month MA profit	Three-month MA profit	Five-month MA profit
service demand									
High	0.812	0.167	1.844	−1.214	1.192	0.428	−22.032	11.058	11.520
	(0.358)*	(1.151)	(1.592)	(1.291)	(0.433)*	(0.475)	(10.689)*	(15.908)	(22.901)
Low	0.685	1.967	1.021	0.115	0.917	0.426	−50.312	−31.157	−32.17
	(0.184)*	(0.469)*	(0.823)	(0.587)	(0.296)*	(0.136)*	(12.680)*	(11.926)*	(12.941)*
Difference	0.127	−1.799	0.822	−1.329	0.275	0.003	28.279	42.215	43.69
	(0.286)	(0.882)*	(1.271)	(1.006)	(0.372)	(0.351)	(11.647)*	(14.243)*	(19.167)*
customer efficiency									
High	0.671	0.619	0.150	−1.487	0.278	0.394	−18.688	−6.439	−2.158
	(0.174)*	(0.632)	(0.897)	(0.825)	(0.399)	(0.157)*	(5.679)*	(3.801)	(8.778)
Low	0.770	2.102	2.934	−0.390	0.828	0.345	−34.587	27.829	44.377
	(0.360)*	(0.748)*	(1.080)*	(0.939)	(0.342)*	(0.287)	(7.341)*	(44.580)	(82.207)
Difference	−0.100	−1.482	−2.783	−1.097	−0.551	0.049	15.899	−34.268	−46.535
	(0.282)	(0.692)*	(0.992)*	(0.883)	(0.372)	(0.231)	(6.552)*	(30.789)	(56.498)

Notes. Standard errors are in parentheses. All analyses are based on three-month moving averages except for profit. Txns., transactions; MA, moving average.
*Significant at $p < 0.05$ (for coefficient, the test is against 0; for difference, the test is between groups).

being analyzed (branch density, local penetration, service demand, customer efficiency) with separate DID analyses performed on the highest and lowest quartiles.[7] The results described below are based on three-month moving average values except for the profit analysis.

We begin with adoption correlates (branch density, local penetration, and service demand) that are likely to be associated with improved marketing effectiveness. To get a better understanding of product use (e.g., whether a particular product is more likely to be adopted), we look at each of the three product categories offered by the bank that we have previously considered: deposit, loan, and investment accounts. As noted earlier, we consider two dimensions of product use: new product acquisition and total transaction activities. Table 4 shows that customers who adopt online banking in areas with high branch density appear to adopt 0.147 ($p < 0.05$) more loan (asset) accounts and 0.135 ($p < 0.05$) more investment accounts than those from areas with low branch density, suggesting a potential complementary effect between branches and online banking, although the effect is neutral for deposit accounts. The results are mixed for local Internet banking penetration. Customers in areas with high local Internet banking penetration adopt 0.448 ($p < 0.05$) more loans from the bank compared to those in areas with low local Internet banking penetration. However, local penetration does not appear to generate significant differences in new deposit or asset accounts, and point estimates for asset accounts move in the "wrong" direction. Thus, we have mixed support for the effect of local penetration on product acquisition. Service demand is shown to be linked to a larger increase in deposit account acquisitions from the bank (0.241, $p < 0.05$) but not loan and investment account acquisitions. This is perhaps not surprising because it suggests that marketing benefits from increased contact in service interactions for transactional accounts are limited to increased penetration of transactional accounts. Altogether, we find some evidence that branch accessibility, local penetration, and service demand are associated with increased product acquisition.

We now consider the relationships among adoption drivers and total transaction activity. Branch density and local penetration are found to be linked to larger increases in total transaction activities. The difference in postadoption transaction changes between high- and low-branch-density groups is 16.155 transactions ($p < 0.05$), whereas the corresponding figure is 6.633 transactions between the high- and low-online-penetration groups ($p < 0.05$). There are no significant differences in transaction behavior after Internet banking adoption related to ex ante service demand. Thus, we find support for the positive effects of branch density and local penetration on transaction volume, but not for service demand. Thus, H9 is partially supported.

[7] For example, the "low local penetration" subsample includes the observations living in a zip code area where the customers using the focal bank Internet banking is no greater than 1.3% of the population (1.3% is the lower quartile value (i.e., bottom 25%) of the ratio of the count of customers using the focal bank Internet banking over the zip code area population, whereas the "high local penetration" subsample includes the observations living in a zip code area where the customers using the focal bank Internet banking is no less than 3.8% of the population (3.8% is the higher quartile value (i.e., upper 25%) of the ratio of the count of customers using the focal bank Internet banking over the zip code area population).

To examine channel substitution effects, we repeat the previous transaction analysis, but now consider each service channel individually, because customers' usage pattern across channels is likely to shed light on the sources of customer profitability changes. We are especially concerned about the use of teller, branch platform, and CSR channels, which are the most costly services to provide. In Table 3, we showed that Internet banking adoption is associated with increased total transactions and also with increased transactions in other offline channels. Given these observations, we expect that any differences in offline service demand due to efficiency or other adoption correlates manifest as lower increases rather than decreases. Consistent with our expectations (H10), both service demand and customer efficiency are associated with lower increases in branch platform transactions (the most complex full-service transaction type)—the effect size is −1.8 transactions for service demand, and −1.5 transactions for customer efficiency (both significant at $p < 0.05$). We also find a smaller increase in telephone CSR transactions for high-efficiency customers (−2.783, $p < 0.05$), but no significant difference in CSR transactions for the different service demand groups. It also appears that there is essentially no difference in branch teller transactions. These findings provide partial support that customers with high service demand and high customer efficiency use less full-service channels.

Finally, we consider the linkages between adoption drivers and changes in profitability. Because our earlier results suggested substantial differences depending on the time window (an issue not present for the other results), we perform the profitability results using one-, three-, and five-month moving average values. Although customer profitability generally drops after adoption, as found in §5.2.1, our analysis shows that customers with higher service demand exhibit significantly less profitability reduction after adoption, and the resulting profit gains are substantial: \$28.28 for one-month profit change, \$42.22 for three-month profit change, and \$43.69 for five-month profit change ($p < 0.05$ for all). Customers with high efficiency are also shown to have less profit reduction based on one-month moving average values with a net gain of \$15.90 ($p < 0.05$) whereas the impact of customer efficiency on profit change based on three- and five-month moving average values is not significant. These results provide some support for the argument that customers with high customer efficiency and high service demand show more favorable profit changes following Internet banking adoption. Therefore, the results offer partial support for H10. Collectively, these results suggest that the adoption drivers we consider are also associated with changes in postadoption outcomes, especially product acquisition and profitability.

6. 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. Although it is clear that offering online banking has become a "competitive necessity," it is useful to understand which customers are likely to adopt this new channel, how those customers will change their banking behavior after adoption, what measurable changes this will create in banks' internal performance metrics, and whether some factors that encourage online banking adoption are more closely linked to favorable after adoption outcomes.

Our results (Table 6 summarizes the results of our hypotheses testing) suggest that *service transaction demand*, *customer efficiency*, and *local penetration* are associated with increased online banking adoption, whereas *availability of offline* (*branch*) *channels* appears to be unrelated to online banking adoption. As has been found previously, demographics (notably age) are related to online banking adoption but tend to have a relatively small effect overall. We also find some behavioral changes associated with Internet

Table 6 Summary of Hypotheses Tests

Hypothesis	Result
The determinants of Internet banking adoption	
H1: Higher transaction volume is associated with faster Internet banking adoption	S
H2A: A lower density of offline channels is associated with slower Internet banking adoption	NS
H2B: The effect of offline channel density higher for high income customers	NS
H3A: Higher customer efficiency is associated with faster Internet banking adoption	S
H3B: The rate that Internet banking adoption increases with service demand is increasing in customer efficiency	NS
H4: Local penetration of online banking is associated with faster Internet banking adoption	S
The outcome of Internet banking adoption	
H5: Internet banking adoption is associated with increased product acquisition from the bank	S
H6A: Internet banking adoption is associated with increased total transaction activity	S
H6B: Internet banking adoption is associated with decreased usage of other channels	NS
H7: Internet banking adoption is associated with an increase in a customer's profitability	NS
H8: Internet banking adoption is associated with lower likelihood of customer departure from the bank	S
Linking adoption correlates and postadoption changes	
H9: Adoption correlates that affect cross-sell potential (local penetration, branch density, and service demand) are associated with greater product use after online banking adoption	PS
H10: Adoption correlates that affect channel substitution (service demand and customer efficiency) are associated with less usage of non-Internet channels and increased profits after online banking adoption	PS

Note. S, supported; NS, not supported; PS, partially supported.

banking adoption. Consistent with prior work, following the adoption of Internet banking, customers increase their consumption of services across channels, which can lead to increases in cost and is reflected by an immediate profit drop upon adoption. Even if there is some reallocation of activity across channels, the finding of the short-run profitability drop suggests that it is not sufficient to offset the costs of an overall increase in service transaction demand in the short run. However, online customers show greater product acquisition from the bank and a longer relationship length with the bank (less attrition), which collectively suggests that Internet banking adopters have a deeper and longer relationship with the bank that is likely to result in greater lifetime customer value. These results replicate prior analyses using data from a different bank (Campbell and Frei 2010) and slightly different measures, which strongly suggests the robustness of these and prior results, particularly on unanticipated outcomes such as the short-run profit reduction.

Our exploration of the linkages between adoption correlates and outcomes also suggests that the adoption correlates in our proposed theoretical framework are also associated with differences in post-adoption changes. Correlates that might presumably affect cross-sell potential (*local penetration*, *branch density*, and *service demand*) are associated with greater product use after online banking adoption. Interestingly, although more branches do not make customers more likely to adopt online banking, they do make it more likely for customers to adopt and use more banking products or services after online banking adoption. This analysis also suggests there is substantial value in moving high-demand and high-efficiency customers online. For these customers, we are able to identify a substitution effect between the Internet channel and the offline channels, and beneficial profit changes are especially pronounced for the high-service-demand segment. Unfortunately, without long-term profit data, we cannot know whether banks ultimately reap benefits from greater product sale, although it would appear likely.

Our results are potentially useful for practice because they identify potential mechanisms by which banks can increase their online banking penetration, as well as delineate how these efforts are likely to affect the bottom line. Banks routinely use customer demographics to segment their customer base and target product promotions. However, current practice and existing research provide little guidance beyond this strategy. First, our results validate the approach of targeting customers who have high service demand or high efficiency for online banking—they are not only more likely to adopt, but also increase their relative profitability following adoption. These results are interesting, as both service demand and customer efficiency are measurable in transaction data, yet it is unlikely banks have been considering this factor in designing their online promotion strategies. It also suggests that banks may benefit from interventions, such as online customer training or pricing strategies that encourage channel experimentation (e.g., discounts for ATM or Internet usage), that lead to increased coproduction efficiency. Second, our results also show that local penetration is correlated with online banking adoption, but the same is not true for the marketwide diffusion effect. To the extent that our controls address the reflection problem, this suggests a strategy of geographically tailored promotions, including those that promote customer-to-customer contact, and highlights potential benefits of focusing marketing resources sequentially on specific regions (building penetration in one area and then moving to others) rather than a broad-based marketwide approach. Promoting local penetration effects can be especially useful when some consumers may choose to wait for cost and demand uncertainty to be resolved before they commit themselves to a new technology (Chang 2002). Although we do not see a high profit impact of these strategies in the short run, we do find some evidence that they are associated with greater product sale. The fact that physical channel availability does not influence online banking adoption is somewhat puzzling. This may be due to customers optimizing their use of banking services to limit their use of physical channels even prior to the availability of online banking. The widespread availability of ATMs and the increasing number of nontraditional branches may have also nullified any marginal effect of physical infrastructure on customer behavior. However, our results do not suggest that branches are unimportant in an era of Internet banking. Indeed, consumption of branch services may increase for those customers who choose to utilize online banking, consistent with other studies suggesting that few customers use the online channel exclusively (e.g., Fisher 2007). We also find that banks are able to capture a larger share of incremental investment business and loans when they have a larger branch footprint. This also casts doubt on any approach that justifies online banking investments through reductions in physical infrastructure. These observations are consistent with a rise in the number of branches over the last decade.

Our methodology likely extends to any multichannel service industry such as retailing, industrial wholesale, and other types of financial services. Specifically, the factors considered in our adoption framework—customer demand, channel accessibility, customer efficiency, and local penetration effects—are relevant to service processes generally. The same may be true of our outcome measures, such as product utilization, profitability, and service utilization. Our results do suggest that an introduction of a new channel can affect customer behavior in diverse and sometimes unexpected ways.

Although we believe that our data—and the methods that our new data enable—represent innovations over the prior literature, there are a number of significant limitations of this analysis. 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 across institutions) or examine how variations in service design affect adoption rates and behavior changes. Second, although the customer base of our focal bank is representative of other large national banks, our sample is drawn predominantly from "urban" areas (as classified by the Office of Management and Budget in 2000). Thus, whereas our results likely apply to the majority of customers of U.S. banks, they may not extend to rural areas or other smaller institutions such as credit unions. However, the convergence of our results on behavioral change with prior work does suggest that at least some of these findings generalize at least to the population of large banks. Third, although our matching estimators have a causal interpretation, it is still possible that the adoption decision is correlated with behavior changes in ways we cannot observe. Fourth, although we find evidence for local penetration effects, we do not have direct evidence of the mechanism by which these network effects arise. Thus, this may be an opportunity for other behavioral or survey approaches to better understand how network effects influence behavior. Finally, a study of more recent or longer time periods may provide further insights into whether the determinants we found persist as Internet banking continues to diffuse and whether the behavior changes we observe are persistent as well.

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References

Abadie, A., G. Imbens. 2006. Large sample properties of matching estimators for average treatment effects. *Econometrica* **74**(1) 235–267.

Babej, M. E. 2003. Web's real value is as part of multichannel environment. *Amer. Banker* (August 7), http://www.americanbanker.com/issues/168_154/-203345-1.html.

Bass, F. M. 1969. A new product growth for model consumer durables. *Management Sci.* **15**(5) 215–227.

Becker, G. S. 1993. *Human Capital: A Theoretical and Empirical Analysis*. University of Chicago Press, Chicago.

Bielski, L. 2003. Striving to create a safe haven online. *Amer. Bankers Assoc. Banking J.* **95**(5) 53–59.

Campbell, D., F. Frei. 2004. The persistence of customer profitability: Empirical evidence and implications from a financial services firm. *J. Service Res.* **7**(2) 107–123.

Campbell, D., F. Frei. 2010. Cost structure, customer profitability, and retention implications of self-service distribution channels: Evidence from customer behavior in an online banking channel. *Management Sci.* **56**(1) 4–24.

Chang, Y. 2002. Dynamics of banking technology adoption: An application to Internet banking. Working paper, University of Warwick, Coventry, UK.

Chase, R. B. 1978. Where does the customer fit in a service operation? *Harvard Bus. Rev.* **56**(6) 137–142.

Chase, R. B. 1981. The customer contact approach to services: theoretical bases and practical extensions. *Oper. Res.* **29**(4) 698–706.

Chatterjee, R., J. Eliashberg. 1990. The innovation diffusion process in a heterogeneous population: A micromodeling approach. *Management Sci.* **36**(9) 1057–1079.

Chen, P.-Y., L. M. Hitt. 2002. Measuring switching costs and the determinants of customer retention in Internet-enabled businesses. *Inform. Systems Res.* **13**(3) 255–274.

Choi, J., S. Hui, D. Bell. 2011. Bayesian spatio-temporal analysis of imitation behavior across new buyers at an online grocery. *J. Marketing Res.* Forthcoming.

Chung, W., J. Paynter. 2002. An evaluation of Internet banking in New Zealand. *Proceedings of 35th Hawaii Conference in System Sciences* (*HICSS 2002*), IEEE Computer Society, Washington, DC.

Cleves, M.A., W. W. Gould, R. G. Gutierrez. 2004. *An introduction to survival analysis using Stata*. Stata Press, College Station, TX.

Curran, J. M., M. L. Meuter, C. F. Surprenant. 2003. Intensions to use self-service technologies: A confluence of multiple attitudes. *J. Service Res.* **5**(3) 209–224.

Davis, D. 1989. Perceived usefulness, perceived ease of use and user acceptance of information technology. *MIS Quart.* **13**(3) 318–339.

Davis, D., R. P. Bagozzi, P. R. Warshaw. 1989. User acceptance of computer technology: A comparison of two theoretical models. *Management Sci.* **35**(8) 982–1003.

Fisher, M. 2007. Why banks still grow branches. *Washington Post* (September 18) B3.

Forman, C., A. Ghose, B. Wiesenfeld. 2008. Examining the relationship between reviews and sales: The role of reviewer identity disclosure in electronic markets. *Inform. Systems Res.* **19**(3) 291–313.

Forman, C., A. Ghose, A. Goldfarb. 2009. Competition between local and electronic markets: How the benefit of buying online depends on where you live. *Management Sci.* **55**(1) 47–57.

Gerrard, P., J. B. Cunningham. 2003. The diffusion of Internet banking among Singapore consumers. *Internat. J. Bank Marketing* **21**(1) 16–28.

Goolsbee, A., P. J. Klenow. 2002. Evidence on learning and network externalities in the diffusion of home computers. *J. Law Econom.* **45**(2) 317–343.

Hitt, L. M., F. X. Frei. 2002. Do better customers utilize electronic distribution channels? The case of PC banking. *Management Sci.* **48**(6) 732–749.

Hosmer, D. W., Jr., S. Lemeshow. 1999. *Applied Survival Analysis: Regression Modeling of Time to Event Data*. John Wiley & Sons, New York.

Karjaluoto, H., M. Mattila, T. Pento. 2001. Electronic banking in Finland: consumer beliefs and reactions to a new delivery channel. *J. Financial Services Marketing* **6**(4) 346-361.

Karjaluoto, H., M. Mattila, T. Pento. 2002. Factors underlying attitude formation towards online banking in Finland. *Internat. J. Bank Marketing* **20**(6) 261–272.

Katz, M., C. Shapiro. 1985. Networks externalities, competition and compatibility. *Amer. Econom. Rev.* **75**(3) 424–440.

Khan, B. S. 2004. Consumer adoption of online banking: Does distance matter? Working Paper E04-338, Economics Department, University of California, Berkeley, Berkeley.

Kim, B.-M., R. Widdows, T. Yilmazer. 2005. The determinants of consumers' adoption of Internet banking. *Consumer Behavior and Payment Choice Proceedings*, Federal Reserve Bank of Boston, Boston.

Kim, B.-M., T. Yilmazer, R. Widdows. 2006. *Adoption of Internet Banking Consumers' Payment Choices*. Working paper, Purdue University, West Lafayette, IN.

Kolodinsky, J. M. 2004. The adoption of electronic banking technologies by U.S. consumers. *Internat. J. Bank Marketing* **22**(4) 238–259.

Kolodinsky, J., J. M. Hogarth, J. F. Shue. 2000. Bricks or clicks? Consumer adoption of electronic banking technologies. *Consumer Interests Annual* **46** 180–184.

Lee, E., J. Lee. 2001. Consumer adoption of Internet banking: Need-based and/or skill based? *Market Management J.* **11**(1) 101–103.

Lee, E., J. Lee, D. Eastwood. 2003. A two-step estimation of consumer adoption of technology-based service innovations. *J. Consumer Affairs* **37**(2) 256–882.

Lee, E., D. B. Eastwood, J. Lee. 2004. A sample selection model of consumer adoption of computer banking. *J. Financial Services Res.* **26**(3) 263–275.

Lichtenstein, S., K. Williamson. 2006. Understanding consumer adoption of Internet banking: An interpretive study in the Australian banking context. *J. Electronic Commerce Res.* **7**(2) 50–66.

Maddala, G. S. 1983. *Limited-Dependent and Qualitative Variables in Econometrics*. Econometric Society Monographs. Cambridge University Press, Cambridge, UK.

Manski, Charles F. (1993). Identification of endogenous social effects: The reflection problem, *Rev. Econom. Stud.* **60**(3) 531–542.

McFadden, L. D. 1974. Conditional logit analysis of qualitative choice behavior. P. Zarembka, ed. *Frontiers in Econometrics*. Academic Press, New York, 105–142.

Meuter, M. L., A. L. Ostrom, R. I. Roundtree, M. J. Bitner. 2000. Self-service technologies: Understanding customer satisfaction with technology-based service encounters. *J. Marketing* **64**(3) 50–64.

Perumal, V., B. Shanmugam. 2004. Internet banking: Boon or bane. *J. Internet Banking Commerce* **9**(3) 1–6.

Ramsay, J., M. Smith. 1999. Managing consumer channel usage in the Australian banking sector. *Managerial Auditing J.* **14**(7) 32–33.

Rogers, E. M. 1995. *Diffusion of Innovations*, 4th ed. Free Press, New York.

Sinha, R. K., M. Chandrashekaran. 1992. A split hazard model for analyzing the diffusion of innovations. *J. Marketing Res.* **29**(1) 116–127.

Stavins, J. 2002. Effect of consumer characteristics on the use of payment instruments. *New England Econom. Rev.* **2002**(Q3) 19–31.

Strothkamp, B. 2005. How did Wells Fargo boost online sales? *Forrester Res.* (September 28), http://www.forrester.com/rb/Research/how_did_wells_fargo_boost_online_sales/q/id/37711/t/2.

Suh, B., I. Han. 2002. Effect of trust on customer acceptance of Internet banking. *Electronic Commerce Res. Appl.* **1**(3–4) 247–263.

Tan, M., T. S. H. Teo. 2000. Factors influencing the adoption of Internet banking. *J. Assoc. Inform. Systems* **1**(5) 1–42.

Tellis, G. J., S. Stremersch, E. Yin. 2003. The international takeoff of new products, the role of economics, culture, and country innovativeness. *Marketing Sci.* **22**(2) 188–208.

Thornton, J., L. White. 2001. Customer orientations and usage of financial distribution channels, *J. Services Marketing* **15**(3) 168–185.

Wade, W. 2003. Bank share of Web bill pay seen staying small. *Amer. Banker* (August 25), http://www.americanbanker.com/issues/168_166/-204148-1.html.

Wooldridge, J. M. 2002. *Econometrics of Cross Section and Panel Data*. MIT Press, Cambridge, MA.

Xue, M., P. T. Harker. 2002. Customer efficiency: Concept and its impact on e-business management. *J. Service Res.* **4**(4) 253–267.

Xue, M., L. M. Hitt, P. T. Harker. 2007. Customer efficiency, channel use and firm performance in retail banking. *Manufacturing Service Oper. Management* **9**(4) 535–558.

Zhu, K., K. L. Kraemer. 2005. Post-adoption variations in usage and value of e-business by organizations: Cross-country evidence from the retail industry. *Inform. Systems Res.* **16**(1) 61–84.

Zhu, K., K. L. Kraemer, S. Xu. 2003. Electronic business adoption by European firms: A cross-country assessment of the facilitators and inhibitors. *Eur. J. Inform. Systems* **12**(4) 251–268.