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Cost Structure, Customer Profitability, and Retention Implications of Self-Service Distribution Channels: Evidence from Customer Behavior in an Online Banking Channel

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This paper uses the context of online banking to investigate the consequences of using self-service distribution channels to alter customer interactions with the firm. Using a sample of retail banking customers observed over a 30-month period at a large U.S. bank, we test whether changes in service consumption, cost to serve, and customer profitability are associated with the adoption of online banking. We find that customer adoption of online banking is associated with (1) *substitution*, primarily from incrementally more costly self-service delivery channels (automated teller machine and voice response unit); (2) *augmentation* of service consumption in more costly service delivery channels (branch and call center); (3) a substantial increase in total transaction volume; (4) an increase in estimated average cost to serve resulting from the combination of points (1)–(3); and (5) a reduction in short-term customer profitability. However, we find that use of the online banking channel is associated with higher customer retention rates over one-, two-, and three-year horizons. The documented relationship between the use of online banking and customer retention remains positive even after controlling for self-selection into the online channel. We also find evidence that future market shares for our sample firm are systematically higher in markets with high contemporaneous utilization rates for the online banking channel. This finding holds even after controlling for contemporaneous market share, suggesting it is not simply the result of increased market power leading to the acquisition of online banking customers.

Key words: service operations; self service; online banking; customer profitability; cost to serve
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1. Introduction

This paper investigates the consequences of using self-service distribution channels to alter customer interactions with the firm and considers the implications of these consequences for performance measurement and management in service firms. Firms are increasingly implementing self-service technologies with the goals of reducing cost and increasing service quality, revenue, and customer retention rates (Meuter et al. 2000, Hitt and Frei 2002). However, the success of strategies for deploying these technologies depends on how customers use them (Dabholkar 2000). For example, although technologies such as the Internet and automated call centers reduce the *marginal* cost of customer interaction from the firm's perspective, they may also reduce the cost of interaction from the customer's perspective. This could lead to a significant expansion in overall service consumption and an increase in *total* distribution costs. In this paper, we examine the impact of one self-service channel, online banking, on customer-level service demand, cost, profitability, and retention. We also investigate whether increased customer acceptance of the online banking channel is associated with broader market outcomes in the form of increased market share.

Our paper makes four specific contributions. First, prior research in the area of self-service technologies has largely focused on identifying attitudinal, behavioral, and demographic factors associated with the consumer self-service adoption decision as well as the consumer self-service experience evaluation process (e.g., Froehle and Roth 2004, Zeithaml et al. 2002, Iqbal et al. 2003, Tsikriktsis 2004, Parasuraman and Zinkhan 2002, Bitner et al. 2000, Meuter et al. 2000, Curran et al. 2003). There has been limited attention to how such technologies alter actual customer demand for service and/or the financial performance of individual customer relationships. In one of the few studies that link utilization of self-service channels to performance, Xue et al. (2007) document that "efficient" customers who make more extensive use of self-service channels are more profitable than customers who are less efficient in their use of these channels. In this paper, we build on this literature to investigate the behavioral change around the adoption of online banking and attempt to identify a causal link between self-service adoption and performance.

Second, existing research in the operations management literature has specifically examined the online banking channel and found that online customers tend to be more profitable than offline customers (Hitt and Frei 2002, Xue et al. 2007).[1] However, because this past research leaves the issue of postadoption behavioral change as an open empirical issue, it remains unclear whether these differences are the result of more profitable customers selecting into the technology rather than being caused by its adoption (Hitt and Frei 2002). This is an important distinction, because distribution strategies in many retail banks involve allocating resources to actively migrating customers to online banking under the assumption that cost, revenue, and retention benefits will follow. We build on this literature to examine the extent to which performance differences among online and offline customers result from postadoption individual *behavioral change* as opposed to *selection* of more profitable customers into the online channel.

Third, prior literature has documented that one-year customer retention rates are increasing in the utilization of self-service channels (Hitt and Frei 2002, Xue et al. 2007). There are two potential alternative explanations for the increases associated with the use of self-service channels: (1) the use of self-service channels such as online banking may increase retention rates through increased switching costs, enhanced service quality, or both (Dabholkar 1991, Bitner et al. 2000, Buell et al. 2010); or (2) increased retention rates may simply reflect a particularly loyal segment of customers self-selecting into the online channel. In this paper, we attempt to isolate the effect of online banking on customer retention through the use of instrumental variable techniques designed to control for the self-selection. We also contribute to the literature by examining the relationship between online banking and customer retention over a multiyear horizon. Extending our analysis beyond the one-year horizon common in previous studies allows us to identify potentially changing patterns in the strength of the self-service retention link further into the duration of the customer relationship.

Finally, prior studies have not examined the link between market outcomes and the use of self-service channels by the firm's customers. Broad acceptance of self-service channels among its customer base may help a firm maintain or increase market shares to the extent that such channels attract relatively more profitable customers or increase retention rates. We provide initial evidence on the extent to which market shares are associated with the utilization of the online banking channel among a firm's customer base.

Although self-service technologies vary significantly across service industries and individual service firms, banking represents an ideal setting to investigate the consequences of using self-service channels to alter customer-firm interactions for two reasons. First, in service firms such as retail banks, variation in the demand for organizational resources is tied directly to customer behavior (Chase 1978, 1981; Cooper and Kaplan 1999; Fitzsimmons and Fitzsimmons 2001). As a result, customer interaction is widely regarded as a key driver of cost and profitability in the banking industry. Second, banks have a relatively long history of introducing technologies aimed at lowering the costs of customer interaction (e.g., automated teller machines (ATMs), touch-tone banking, centralized telephone call centers, and online banking; Clemons et al. 2002, Frei and Harker 2000, Roth and van der Velde 1989). Anecdotal evidence, however, suggests that the introduction of these supposedly less-expensive means of interaction has increased the total cost of service distribution (Frei and Harker 2000). Among these technologies, online banking is a particularly interesting innovation to study because it represents an area where many firms have pursued strategies aimed at simultaneously reducing costs, increasing revenue, and increasing customer retention with little or no recognition that trade-offs might exist (Hitt et al. 1999).

Using a variety of panel data methods on a large sample of retail banking customers observed over a 30-month period at a large U.S. bank, we test whether changes in service consumption, cost, and customer profitability at the individual level are associated with the adoption of online banking. We find that customer adoption of online banking is associated with (1) *substitution*, primarily from incrementally more costly self-service delivery channels (ATM and voice response unit (VRU)); (2) *augmentation* of service consumption in more costly service delivery channels (branch and call center); (3) a substantial increase in total transaction volume; (4) an increase in estimated average cost to serve resulting from the combination of points (1)–(3); and (5) a reduction in short-term customer profitability. However, we find that

[1] In one of their tests, Hitt and Frei (2002) do exploit a "pseudo time series" based on variation in product adoption dates to test whether the use of online banking is associated with increased product adoption rates. However, their primary analyses of customer profitability, retention, and cross-sell rates are cross-sectional in nature. Empirical results reported in Xue et al. (2007) add to the evidence of Hitt and Frei (2002) by demonstrating that customers with a longer tenure in the online channel tend to be more profitable than both offline customers and online customers with less experience in the channel.

use of online banking is associated with higher customer retention rates over one-, two-, and three-year horizons. The documented relationship between the use of online banking and customer retention remains positive even after controlling for self-selection into the online channel. We also find evidence that future market shares for our sample firm are systematically higher in markets with high contemporaneous utilization rates for the online banking channel. This finding holds even after controlling for contemporaneous market-share, suggesting it is not simply the result of increased market power leading to the acquisition of online banking customers.

The focus of this paper on a specific self-service technology and the use of data from a single firm limit the generalizability of our results. However, the detailed data we are able to obtain from our field site allows a unique opportunity to examine the performance implications of self-service distribution channels in the context of online banking. Future research can make a considerable contribution by examining the performance implications of firm investments in self-service distribution channels for other technologies in other industries. There also remains a significant opportunity to examine how firm investments in capability enhancement and customer management strategies (e.g., pricing, penalties, service tiers, etc.) in existing self-service channels affect the performance of customer relationships in these channels.

The remainder of this paper proceeds as follows. Section 2 reviews related literature from marketing and operations management and develops hypotheses based on this literature. We discuss our research site and data in §3. Section 4 presents the research design and methodology used in this study. Results are presented in §5. We end with a discussion and conclusions in §6.

2. Literature Review and Hypothesis Development

In this section, we draw on findings in the literature on consumer self-service adoption decisions as well as the conceptual literature on customer involvement in services (e.g., Chase 1978, 1981) to argue that the adoption of self-service distribution channels fundamentally changes the economics of service interaction from both the firm's and the customer's perspective. We organize our hypotheses around the implications of self-service adoption for cost structure, customer profitability, and customer retention.

2.1. Cost Structure

The implications of customer involvement in the "production" of services have been discussed in the operations management literature for more than two decades, starting with the work of Chase (1978, 1981), Sasser (1976), and Lovelock and Young (1979). Customer involvement in the service production process implies that adoption of self-service technologies can affect the economics of service production from both the firm's *and* the customer's perspective. The overall cost-structure implications for firms depend not only on how such technologies affect the marginal cost of providing service but also on how such technologies affect customers' consumption of service resources. The use of self-service technologies may result in a reduction in the consumption of service resources *per service interaction*, but they may also affect the customers' demand for service in ways that increase the overall demand for service resources.

Self-service channels are widely regarded as having the potential to lower the marginal cost of service interaction from the firm's perspective by substituting variable cost labor for relatively fixed-cost technology assets (Sasser 1976). Self-service technologies may also lower the marginal cost of service interaction from the customer's perspective through increased convenience, accessibility, and/or reductions in wait times (Curran et al. 2003, Bitner et al. 2000, Marshall et al. 1988, Zeithaml and Gilly 1987). A lower marginal interaction cost from the customer's perspective can affect a firm's cost structure by changing both the overall customer demand for service interactions and the relative rates of substitution from alternative service delivery channels.

In the context of the specific technology of online banking, banks hope to achieve lower costs through a "substitution effect" in which customers migrate transactions from relatively more costly offline channels to the online channel. Cost reductions would then follow in two specific ways. First, steps performed by decentralized labor in the branches could be performed by centralized labor or automated with technology. Second, customers could perform process steps that the firm had previously performed. Both of these changes would result in a lower use of service resources and, hence, cost per interaction, thereby lowering overall distribution costs. However, this channel can significantly lower the cost of interaction from the customer's perspective, leading to a higher demand for service transactions. Customers interacting through the online channel may not incur the opportunity costs (e.g., time) that stem from, for instance, traveling to the bank branch or ATM and waiting in queues. This raises the possibility of a "volume effect," in which total transaction volume increases because of increased demand for transactions in the online channel more than offset any associated reductions in transaction demand in offline channels.

Additionally, even the degree to which substitution of service demand from offline channels will occur is unclear for at least two reasons. First, substitution of service demand between online and offline channels may be limited to the extent that the mix of services available across a firm's portfolio of self-service and employee assisted-service channels is not constant. For example, not all banking transactions can be performed in all channels (e.g., not all transactions are substitutable). Paper-based transactions such as withdrawals and deposits cannot be performed via online banking. In the banking setting, substitution is most likely to occur from offline self-service delivery channels, where the mix of available services is most similar to that offered by online banking (e.g., automated call centers).

Second, self-service technologies allow customers to control service delivery in a manner that more closely meets their needs (Dabholkar 1991). In a multichannel setting, increased customer control of the service production process may allow the customer to customize her portfolio of interactions with the service firm across channels (Bitner et al. 2000). This is consistent with survey-based research, which has found that the importance attached to face-to-face contact actually increased significantly as the importance attached to remote interactions increased. This result suggests that banking customers want increasing access to all available delivery channels and do not necessarily regard them as mutually exclusive or substitutable (Durkin et al. 2003). Moreover, additional survey-based research suggests that electronic channels may allow banking customers to become more efficient "money managers" (Barczak et al. 1997). Because a primary function of online banking is to allow customers continuous access to detailed information on their accounts, adoption of this self-service technology may lead to increased information monitoring and, in turn, more active account management in offline assisted-service channels such as branches and call centers, where employees are available to field inquiries and a broader mix of services is available. This raises the possibility that online banking could have an *augmentation* effect rather than a *substitution* effect in assisted-service channels.

Thus, self-service technologies such as online banking—which lower the cost per transaction from the customer's perspective—can lead to either a "substitution" effect (customers shift transactions from offline channels to the lower-cost online channel) or an "augmentation" effect (customers increase transaction consumption in offline channels). Based on the arguments above, to the extent that these effects are present, the substitution effect is most likely to be found in offline self-service channels, whereas either substitution or augmentation effects are distinct possibilities in offline assisted-service channels. Moreover, either of these potential effects from adoption of the online channel can coincide with a "volume" effect (customers facing a lower implicit cost of transacting via the online channel increase overall service consumption). If *substitution* effects dominate in offline channels, then a volume effect could arise if increased demand for transactions in the online channel more than offsets any associated reductions in transaction demand in offline channels. If *augmentation* effects dominate in offline channels, then a volume effect would arise naturally, because of increased demand for transactions in both offline and online channels.

To examine these potential service demand effects, we test the following hypotheses. Because of the difficulty in making directional predictions on changes in transaction demand in some channels, and to clarify when we do and do not make such predictions, we state all hypotheses in both null and alternative form.

Hypothesis 1_0 ($H1_0$). *Transactions in offline self-service channels do not change following the adoption of the online channel.*

Hypothesis 1_A ($H1_A$). *Transactions in offline self-service channels decrease following the adoption of the online channel ("Substitution Effect").*

Hypothesis 2_0 ($H2_0$). *Transactions in offline assisted-service channels do not change following the adoption of the online channel.*

Hypothesis 2_A ($H2_A$). *Transactions in offline assisted-service channels change following the adoption of the online channel ("Substitution Effect" or "Augmentation Effect").*

Hypothesis 3_0 ($H3_0$). *Total transaction volume does not change following the adoption of the online channel.*

Hypothesis 3_A ($H3_A$). *Total transaction volume increases following the adoption of the online channel ("Volume Effect").*

Any realized cost reduction from the customer adoption of self-service channels depends on the extent to which customers substitute transactions from (or augment transactions in) traditional offline channels, the degree of any associated increases in overall transaction volume, and the estimated cost of providing service through different channels. We investigate how the substitution, augmentation, and volume effects combine to affect overall cost service under reasonable assumptions regarding the cost per transaction for offline and online channels. In particular, we estimate the full cost implications of changes in individual customer behavior surrounding the adoption of online banking by combining our estimates of changes in transaction consumption by channel with reasonable estimates of the cost of performing transactions in each channel.

2.2. Customer Profitability

Customer involvement in services also implies that self-service channels may alter the customer's *marginal benefits* from service interaction through enhanced control and perceived service quality (Dabholkar 1991, 1996; Bitner et al. 2000). A greater ability for the customer to control and customize the service experience may lead to higher customer satisfaction (Meuter et al. 2000) and hence higher rates of repurchases and revenues for the firm. Alternatively, greater control over the service experience may allow customers who adopt self-service channels to more closely manage their relationships with service firms and to gain similar levels of service consumption at a lower price. Both of these potential effects are possibilities in the specific case of the online banking self-service channel.

Banks have increasingly turned to profitability enhancement as a rationale for ongoing investments in their online banking capabilities. They believe that the added convenience of the online channel will encourage customers to consolidate more of their activity in one bank through increasing both the number of products held (cross-selling) and the average balance held per product (Hitt et al. 1999, Hitt and Frei 2002, Shevlin et al. 2002, Hoffman 2002). Customer adoption of online banking may lead to either or both of these benefits to the extent that greater control over the service experience from multiple points of access to the same services leads to an increase in perceived service quality.

However, Hitt and Frei (2002) found in their sample of banks that increased product adoption is not a strong driver of the difference in estimated value between electronic and traditional banking customers. In addition, many standard checking and savings accounts earn little to no interest for consumers. Researchers have puzzled over why consumers keep assets in such low-return accounts while simultaneously holding high levels of debt, for instance, on credit cards (Gross and Souleles 2002). One potential explanation is the existence of some form of transaction costs, such as the inconvenience associated with closely managing balances in bank accounts. The increased convenience and control associated with online banking may reduce such transaction costs, allowing customers to more efficiently manage their money (Barczak et al. 1997) by transferring excess balances more frequently to higher-yield accounts within the same institution or among multiple institutions. Either case could yield a reduction in net-interest revenue. Alternatively, customers holding accounts with minimum balance requirements could use the added convenience and control to manage balances just above the minimum, thereby potentially avoiding fees.

Because a range of effects are possible, we examine the customer-profitability implications of online banking by testing the following hypothesis (stated in both null and alternative form):

Hypothesis 4_0 ($H4_0$). *There is no change in customer profitability following adoption of the online channel.*

Hypothesis 4_A ($H4_A$). *There is a change in customer profitability following adoption of the online channel.*

2.3. Customer Retention

Customers incur implicit *fixed costs* from adopting self-service technologies. These implicit costs include the costs of learning to use a new technology as well as the costs of establishing a relationship through a new channel (Klemperer 1987). Although these costs are sunk once the investment in a self-service relationship by the customer is made, they are relevant to the customer when considering the choice of remaining with a service provider or incurring the same costs to establish a similar relationship with another provider. Thus, customer adoption of self-service technologies may result in long-term benefits to the firm through higher customer retention rates.

Because acquisition expenses associated with new accounts are so high, financial services firms are increasingly looking to electronic channels to increase customer retention rates. Online channels may create additional customer switching costs and improve retention either because of increased product utilization or because of implicit switching costs such as those created by learning to use a new technology (Chen and Hitt 2002). However, customer use of online banking may reduce the importance of a bank's physical presence in any given local market, making customers more willing to switch to alternative providers with more favorable fees and interest rates. To investigate these effects, we test the following hypothesis (stated in both null and alternative form):

Hypothesis 5_0 ($H5_0$). *There is no association between customer retention and the use of online banking.*

Hypothesis 5_A ($H5_A$). *There is an association between customer retention and the use of online banking.*

Some evidence exists in the literature that the use of online banking is associated with customer retention rates (Hitt and Frei 2002, Xue et al. 2007). However, prior research is silent on whether this result is due to a particularly loyal segment of customers selecting into the channel or is a result of increased switching costs, enhanced service quality, or both (Dabholkar 1991, Bitner et al. 2000). We attempt to estimate a causal link between online banking and customer retention by testing H4 after controlling for customer self-selection into the online banking channel.

2.4. Market Outcomes

A direct corollary of our customer-level hypotheses is that use of online banking among a firm's customer base may be associated with market-level performance. If the online banking channel attracts more profitable customers and/or decreases the likelihood that they defect to competitors, then a firm should have higher market shares in markets where it has achieved higher rates of use of online banking among its customer base (higher "online banking penetration rates"). To investigate the extent to which online banking is associated with market-level performance outcomes, we test the following hypothesis:

Hypothesis 6_0 ($H6_0$). *There is no association between market share and the degree of online banking penetration among a firm's customer base.*

Hypothesis 6_A ($H6_A$). *Market share is increasing in the degree of online banking penetration among a firm's customer base.*

3. Research Site and Data Collection

3.1. Research Site

Our research site (hereafter referred to as "National Bank") is one of the largest diversified financial service firms in the United States It serves millions of customers through more than 3,000 branches in more than 20 states and also services customers through electronic delivery channels such as telephone banking, ATMs, and the Internet. The bank provides a variety of traditional financial products and services, in line with those that could be found at other banks of similar size and scope, and considers its retail deposit customers its core customer base. Because of its size and operation across multiple states, National Bank serves customers across a broad range of demographic profiles, making it unlikely that its customers would differ substantially from those of most large traditional banks. National Bank was a top performer among its industry peer group during the timeframe of this study (2003–2007), earning annual stock returns that averaged approximately 6.5% higher than its competitors over this period.[2]

Throughout the past decade, the bank has pursued a variety of alternative distribution strategies to lower costs. These strategies have ranged from colocation of branches (e.g., supermarket branches) to active programs for migrating branch traffic to ATMs. The impetus for most of these strategies came from either the bank's own internal data or industry data that estimated huge cost differentials for servicing a transaction through traditional branches versus nontraditional branch formats and, in particular, electronic distribution channels.

[2] *Source*. MorningStar. Industry peer group used for comparison: Super Regional Banks.

3.1.1. Online Banking at Our Research Site. Our research site offers a variety of services through its online channel, including the ability to query account history, open new accounts, perform balance transfers, and pay bills electronically. The company was an early innovator in electronic banking, being among the first group of financial institutions to introduce online banking through the Internet. The bank's strategy for the online channel largely mirrors the three-part value proposition discussed in the previous section: cost reduction, revenue enhancement, and customer retention. Consistent with this strategy, the bank has aggressively encouraged customer migration to the online channel to reduce costs and increase the profitability of its customer base. Fees are not charged for the basic online banking service, reflecting the bank's desire to encourage adoption in the hopes of realizing cost, revenue, and retention benefits.

3.2. Data Collection

The primary data for this study consist of a random sample of 100,000 customers who enrolled in the online banking channel during 2006. We have constructed an unbalanced monthly panel data set on these customers for the 30-month period ranging from December 2004 to May 2007 consisting of monthly transactions disaggregated by channel, number of accounts by type of product (checking, loan, or investment), balances by product type, customer profitability, tenure with the bank, and age.

To examine the customer retention effects of online banking, we use a second data set consisting of a random sample of 100,000 customers drawn from the population of all National Bank customers (both online and offline) as of the end of December 2003. This second data set consists of these customers' online channel enrollment status, number of online transactions performed during 2003, tenure, age, number of accounts, and balances by product type. In this second data set, all these variables are defined as of year-end 2003. However, we also observe each customer's relationship status (e.g., retained or defected) as of year-end 2004, 2005, and 2006. This allows us to investigate customer retention over a multiyear horizon.

3.2.1. Transactions by Channel. For each customer, we observe the total number of monthly transactions through the online banking, branch, ATM, call center, and VRU channels.[3] Access to transaction data by channel allows us to separately test hypotheses about the effect of online banking on service consumption in offline self-service and assisted-service channels (H1, H2). Table 1 shows the distribution of the types of transactions performed through

[3] The VRU is an automated call center.

Table 1 Distribution of Transactions by Channel During June 2006

	Transactions (%)	Cumulative (%)
Branch		
Deposit	58.80	58.80
Cash check	27.25	86.05
Verify funds	6.71	92.76
Payment	4.24	97.01
Purchase	2.85	99.85
Withdrawal	0.12	99.97
Miscellaneous	0.03	100.00
ATM		
Withdrawal	65.21	65.21
Inquiry	18.04	83.25
Deposit	14.80	98.04
Transfer	1.30	99.34
Purchase	0.58	99.92
Payment	0.08	100.00
Online		
Query history	51.03	51.03
View basic account information	38.83	89.85
Payment	5.48	95.33
Transfer	4.06	99.40
Download financial information	0.60	100.00

Notes. This table shows the distribution of transaction types for each of the branch, ATM, and online channels. The percentages reported represent all transactions performed in each channel at National Bank during June 2006. Because of data limitations, similar breakdowns cannot be provided for either of the phone channels (VRU or call center).

the branch, ATM, and online channels for National Bank's entire customer base during June 2006.[4] The table shows that the branch is used heavily for monetary transactions (86% of branch transactions involve deposits or cashed checks), the ATM is used for both monetary and information-based transactions (98% of ATM transactions are deposits, withdrawals, or account inquiries), and the online banking channel appears to be used primarily to monitor account information (approximately 90% of online transactions are account inquiries).

Table 1 suggests that the mix of transactions performed is fundamentally different across these channels. Not all transactions are substitutable across channels. However, inquiry-based transactions such as balance inquiries at ATMs or funds verifications in branches are directly substitutable via online banking. In addition, transfers of funds between accounts performed in the branch will be counted as a withdrawal from one account and a deposit into another. Thus, online transfers can substitute for some deposit- and withdrawal-based transactions in the branch.

3.2.2. Customer Profitability. The primary performance measure investigated in this paper is National Bank's measure of customer profitability (*PROFIT*). *PROFIT* is defined as net interest income plus fees and service charges less product unit costs and provisions for loan losses. The unit costs for each product type in each channel are determined by the bank's activity-based costing system and consist of allocated overhead related to items such as personnel, supplies, telephone, equipment, occupancy, and processing. Unit costs, interest, and fee revenues in *PROFIT* are calculated across all deposit, loan, and investment products a customer holds and thus capture a measure of performance of the full customer relationship with the firm.

It is important to note that the costs in this profitability calculation are allocated at the product level, with each product having an associated unit cost that can be thought of as the average cost of supporting a customer in a given product. As a result, estimated costs are not driven by customer behavior, but rather, customer-level costs are determined solely by the customer's choice of product portfolio. This is a limitation of our study, as changes in this measure of customer profitability around the adoption of online banking will only partly reflect true underlying changes in customer behavior through the revenue component. However, it is the best measure of the full profitability of the customer relationship at the firm we study. Moreover, this measure of customer profitability will capture the extent to which the adoption of online banking is associated with changes in the profitability of the average customer in a given product portfolio. Later in the paper, we estimate the full cost implications of changes in individual customer behavior surrounding the adoption of online banking by combining our estimates of changes in transaction consumption by channel with reasonable estimates of the cost of performing transactions in each channel.

3.2.3. Customer and Account Characteristics. For each customer, we observe the number of retail deposit, loan, and investment accounts they hold (*NDEP, NLOAN, NINVEST*) as well as end-of-month balances in those accounts (*BALDEP, BALLOAN, BALINVEST*). We also observe length of the relationship with the bank, measured in years (*TENURE*), as well as the age for each customer.

4. Research Methodology

Our basic approach to testing H1–H4 is to measure how service consumption and customer profitability change, relative to a control group, after customers adopt the online banking channel. As a starting point for constructing our control group, we exploit the relatively large group of customers at our research site who enroll in, but do not subsequently use, the online banking channel. These "inactive enrollers" likely result from the bank's marketing practices, whereby

[4] Because of data limitations, we are unable to perform a similar breakdown for call center and VRU transactions.

current customers are actively encouraged to sign up for the online channel if they have not. The large number of such customers at our research site is consistent with prior research, which suggests that a substantial portion of customers who adopt online services discontinue or do not use the service after they adopt it (Parthasarathy and Bhattacherjee 1998). Survey evidence specific to online banking customers also suggests that there is, in general, a substantial segment of customers who have activated online accounts but use the service infrequently (Sarel and Marmorstein 2003).

An alternative starting point for constructing a control group would be the set of customers who never enroll for access to the online banking channel during our sample period. However, in untabulated analyses, when compared with "inactive enrollers," this group demonstrated larger differences with active adopters in levels and trends in transaction demand across channels as well as customer profitability. Given the bank's active marketing efforts to enroll customers in the online channel, much of which happen at the point of customer contact, it is not surprising that customers who never enroll in online banking would have relatively low product and transaction demand. These customers interact with the bank less frequently, giving the bank less opportunity to actively encourage enrollment in the online channel. Thus, using "inactive enrollers" as the starting point for constructing our control group yields a set of customers who are never truly exposed to the event of interest (active adoption of the online channel), but naturally have similar levels of product and transaction demand as well as customer profitability.

We further refine this control group by selecting a subset of propensity score-matched "inactive enrollers." We used a logistic propensity score model to estimate the probability of a customer using[5] online banking within six months subsequent to a given enrollment month as a function of tenure; the average number of products and balances held over the six months prior to enrollment; the average number of transactions by channel in the six months prior to enrollment; changes in the number of transactions by channel over the six months prior to enrollment; and changes in the number of products and balances held over the six months prior to enrollment. By modeling the propensity to become an active adopter in this way, we are attempting to identify a control group that is similar to active adopters in both levels and changes in preadoption characteristics.

[5] We define a customer as using the channel if they perform one or more transactions in the online channel within six months of enrollment for access to online banking. Later in the paper, we further distinguish among online adopters in terms of those who use the channel "passively" versus "actively."

For our tests of H1–H4, we use the following strategy to select the final sample for analysis: Starting with the random sample of 100,000 customers who enrolled in online banking between January and December 2006, we select the sample of all customers for whom we have at least six months preadoption and six month postadoption data. This yields a sample of 80,658 customers. Of these customers, 40,631 are classified as "inactive enrollers" (no recorded transaction activity in the online channel postenrollment) with the remaining 40,027 classified as "adopters" (at least one recorded transaction in the online channel postenrollment). To facilitate a matched control group for adopters, we also randomly sampled an additional 50,000 inactive enrollers from National Bank's customer database, yielding a sample of 90,631 inactive enrollers as candidates for our matched control sample. For each adopter, we then identified the matched inactive enroller with the closest estimated propensity to actively use the online banking channel subsequent to enrollment. This procedure yields a sample of 40,027 adopters and a control group of 40,027 inactive enrollers. These two groups constitute the sample used for all tests of H1–H4.

As will be demonstrated in the sections that follow, our propensity-matched set of "inactive enrollers" has several properties that make them a natural candidate as a control group for studying the behavior of "adopters" including demonstrating broadly similar patterns in behavior prior to enrollment in the online banking channel. Our analysis approach includes standard "difference-in-difference" estimation as well as econometric specifications that readily account for unobserved fixed differences in *levels* of transaction behavior and profitability between customers and time periods (months and years). The major threat to our strategy for identifying the effect of online banking on customer behavior is differential *trends* in behavior across customers. In particular, our approach would be invalid if transaction behavior and customer profitability were trending differently between adopters and our control group before enrollment in the online banking channel. Untabulated results reveal no difference in preenrollment trends in behavior for any of the performance measures used in this study.

4.1. Substitution/Augmentation (H1 and H2) and Volume (H3)

We test H1 and H2 in two different but complementary ways. First, we measure differences in the change in transaction consumption before and after the adoption of online banking between adopters and the control group. These simple difference-in-difference estimates provide a useful starting point for measuring behavioral change around the adoption of online banking, but may not adequately control for differential postenrollment trends between adopters and the control group caused by changing product portfolios, balances, and other factors over time.

Our second approach supplements these estimates with a more detailed econometric specification that controls for these potentially confounding factors. We face two key specification issues in this approach: (1) the number of transactions per month for a given customer is discrete and is frequently zero, particularly when measured for each channel separately; and (2) there are likely to be persistent (fixed) differences across customers in monthly transaction volume related to unobservables such as access to technology as well as income and other demographic characteristics, which need to be controlled for. We deal with both issues via the conditional fixed-effects Poisson model of Hausman et al. (1984). In the basic Poisson model, the probability of observing y_{it} transactions in a given offline channel for customer i at time t is

$$P(y_{it}) = \frac{e^{-\lambda_{it}} \lambda_{it}^{y_{it}}}{y_{it}!},$$

where λ_{it}, the Poisson parameter, is the expected value of y_{it}. We test H1 by modeling this parameter as

$$\begin{aligned} E(y_{it}) = \exp(&\beta_0 + \beta_1 POST_{it} + \beta_2 POST_{it} \times PASSIVE_i \\ &+ \beta_3 POST_{it} \times ACTIVE_i \\ &+ \gamma EnrollMonth_{it} + X_{it}\delta + \alpha_i), \end{aligned} \tag{1}$$

where α_i is the individual customer fixed effect and X_{it} represents a vector of time-varying control variables.[6] $EnrollMonth_{it}$ takes on a value of 1 if customer i enrolls in the online channel in month t and equals 0 for all nonenrollment months. The inclusion of this indicator is intended to capture transient effects occurring during the enrollment month. For example, customers tend to visit the branch or phone the call center to set up access to the online channel, which yields a spike in transaction activity during the month of enrollment.

To test whether different levels of postadoption activity in the online channel give rise to different effects on transaction patterns in offline channels, we further segment adopters into two groups: those who perform fewer than the median number of online transactions in the six months subsequent to enrollment (passive adopters) and those who perform more than the median number of online transactions in the six months subsequent to enrollment (active adopters).[7] *PASSIVE* and *ACTIVE* are indicators for these two groups, respectively. Intuitively, segmentation of our sample into these groups allows our estimates of any substitution or augmentation effects around the adoption of online banking to vary with how extensively the customer has used this technology.[8]

For each customer in the sample, *POST* is an indicator taking on a value of 1 for all post-online-enrollment months and 0 otherwise. This variable is our primary focus for testing H1 and H2. The coefficient β_1 captures any changes in average transaction consumption in offline channels for the control group of inactive enrollers. If adoption of the online banking channel leads to substitution from (augmentation in) offline channels, then we expect β_2 and β_3 to be negative (positive), as these coefficients capture average changes in transaction consumption in offline channels *relative to the control group* for passive and active adopters, respectively. Furthermore, we expect $|\beta_2| < |\beta_3|$, as any substitution or augmentation effects of the online channel should be more prevalent among adopters who are most active in the channel.

To fully examine substitution and augmentation among channels, we estimate Equation (1) separately for transactions through each offline channel (branch, ATM, VRU, and call center), as well as for the total

[6] The exponential form of the Poisson model ensures nonnegativity for λ and allows estimation of the parameters through maximum likelihood in the standard way. In estimation the fixed effect, γ, is not estimated directly, but rather is conditioned out by modeling the event in the likelihood function as the sequence of transactions for a customer conditional on total transactions for that customer over time. This yields a likelihood function that is globally concave and readily maximized (see Hausman et al. 1984 or Becker and Henderson 2000 for details). We also ran all analyses using the negative binomial fixed-effects count data model without substantive changes in the results.

[7] Among adopters, the mean (median) number of online transactions performed in the six months subsequent to enrollment in the online banking channel is 28.1 (18), with a standard deviation of 35.8. Adopters in the bottom and top deciles have mean levels of online transactions of 4.5 and 64.5, respectively, in the six months subsequent to enrollment in the online banking channel.

[8] Because the *PASSIVE* and *ACTIVE* variables are simply indicators for which particular sample a customer belongs to, main effects of these variables are not estimated, because they would represent the average difference over time among the passive, active, and control samples. Such main effects cannot be estimated in fixed-effects panel data models because these econometric methods eliminate individual fixed effects, which would subsume any such average main effects. Our panel data methods essentially "wash out" these fixed average differences between the different samples so that our estimates of the online adoption effects are not confounded by unobserved heterogeneity across customers. Our approach of interacting time-constant and time-varying variables in a fixed-effects framework is consistent with prior literature in a wide variety of contexts (Ashenfelter and Rouse 1998, Becker and Henderson 2000, Gross and Souleles 2002, Wooldridge 2002, Lapré and Tsikriktsis 2006, Campbell 2008). However, the estimates of the postadoption effects reported in Tables 3, 4, and 6 are directionally and substantively similar when alternative specifications are used that directly include *PASSIVE* and *ACTIVE* as control variables without accounting for customer fixed effects.

number of transactions in all offline channels. We test the volume effect (H3) by replacing y_{it} in Equation (1) with the total volume of transactions across all channels (including online banking transactions).

We include in X_{it} the number of accounts by product type (*NDEP, NLOAN*, and *NINVEST*), as well as balances by product type (*BALDEP, BALLOAN*, and *BALINVEST*), in all specifications to avoid attributing any changes in transaction activity to postadoption use of online banking that are actually due to the adoption of additional products.[9] We also include in X_{it} year and month indicators to control for seasonality and general time trends. Standard errors are adjusted for heteroskedacticity across customers as well as serial correlation within customers in all specifications prior to inference (Petersen 2009).

4.2. Customer Profitability (H4)

We test H4 using a similar approach to our tests for H1–H3, including the use of both standard difference-in-difference and econometric estimation. Because the particular estimation issues that arise from the discrete nature of the dependent variables used in Equations (1) and (2) do not arise for the measures of financial performance used in this study, we test the effect of adoption of the online channel on customer profitability (H4) using the following linear specification:

$$\begin{aligned} P_{it} &= \rho P_{it-1} + \lambda_1 POST_{it} + \lambda_2 POST_{it} \times PASSIVE_i \\ &\quad + \lambda_3 POST_{it} \times ACTIVE_i + \gamma EnrollMonth_{it} \\ &\quad + v_i + \mu_{it}, \end{aligned} \tag{2}$$

where P_{it} denotes *PROFIT*, v_i is the customer-specific fixed effect, and μ_{it} is a random error term. We include past performance to control for trends in performance unrelated to the adoption of online-banking. We estimate Equation (2) in first-differences to eliminate the customer-specific fixed effect. The use of differences controls for individual effects in the levels of these performance metrics. Equation (2) is estimated using two-stage least squares, with P_{it-2} as an instrument for the lagged first-difference in *PROFIT*, ΔP_{it-1}, because of the endogeneity of the lagged dependent variable in the first-differenced model (Anderson and Hsiao 1982, Nickell 1981).[10] We do not include controls for number of products or balances, as these are components of the customer profitability measure, and either or both of these may be the actual sources of any observed changes in profitability around the adoption of online banking.[11] Standard errors are adjusted for heteroskedacticity across customers as well as serial correlation within customers in all specifications prior to inference.

4.3. Retention (H5)

We test H5 by using probit regression to estimate the following cross-sectional model on our random sample of 100,000 customers (both online and offline) as of year-end 2003:

$$\begin{aligned} &\Pr(RETAIN_i = 1 \mid \cdot) \\ &\quad = f(\gamma_0 + \gamma_1 ONLINEUSE_i + \gamma_2 TENURE_i \\ &\qquad + \gamma_3 AGE_i + X_i\beta). \end{aligned} \tag{3}$$

RETAIN is an indicator variable that takes a value of 1 if a customer as of December 31, 2003, remains with the bank one year later. We also investigate retention over two- and three-year horizons by redefining *RETAIN* to take on a value of 1 if a customer remains as of year-end 2005 and 2006, respectively. *ONLINEUSE* is the average number of monthly transactions performed by the customer in the online channel during 2003 and will be 0 for all customers who are not enrolled in the online channel. The sign and significance of γ_1 is the basis for testing H5. The probability of retention is expected to increase over the tenure of relationships as customers consolidate more business with one provider or simply because of switching costs inherent in an established relationship. *AGE* is included to control for differences among age groups in the propensity to remain with the bank.[12] X_i is a vector of further control variables, including the number of accounts held by type (*NDEP, NLOAN, NINVEST*), balances in those accounts (*BALDEP, BALLOAN, BALINVEST*), and the

[9] Untabulated analyses suggest that the number of accounts increases on average for adopters *prior* to going online. This is consistent with the bank's marketing practices, whereby when existing customers open new accounts, they are actively encouraged to sign up for the online channel. Results are very similar when the number of accounts and account balances are not included. We also ran the analyses on a subsample of customers who experienced no change in their product portfolio over the entire sample period and obtained similar results. This suggests that the effects we attribute to use of online banking are not driven by changes in product holdings coincident with the adoption of online banking.

[10] The error term in the first-differenced version of Equation (2) is a first-differenced error term from the corresponding levels model and will be correlated with the lagged dependent variable by construction. This leads to biased coefficient estimates (Nickell 1981). Instrumenting with the twice-lagged level of the dependent variable is a valid approach for overcoming this problem under the assumption of no second-order serial correlation.

[11] We also ran the analyses on the subsample of customers who experienced no change in their product portfolio over the entire sample period and obtained similar results, suggesting that the profitability effects we attribute to the use of online banking are not driven by changes in product holdings that coincide with the adoption of online banking.

[12] Results are robust to the inclusion of higher-order terms of *TENURE* and *AGE*.

level of competition faced by National Bank in a customer's local market (measured as the percentage of deposits in the market controlled by National Bank's competitors). All control variables are measured as of December 31, 2003.[13]

Any documented increase in retention associated with the online banking channel may be the result of a particularly loyal segment of customers self-selecting into the online channel rather than indicating that online banking increases retention rates through increased switching costs or enhanced service quality. As a consequence of this self-selection, the online indicator and use variables in Equation (3) are endogenous. We also consider a linear version of Equation (3)

$$RETAIN_i = \gamma_0 + \gamma_1 ONLINEUSE_i + \gamma_2 TENURE_i + \gamma_3 AGE_i + X_i\beta + \varepsilon_i \tag{4}$$

and allow for potential correlation between $ONLINEUSE_i$ and ε_i.

To address this potential endogeneity, we estimate Equation (4) using two-stage least squares with variables measuring the availability and prevalence of high-speed Internet access in a customer's zip code serving as instruments for *ONLINEUSE*. The data on high-speed Internet access comes from the Federal Communications Commission (FCC).[14] The FCC data report (1) whether a particular zip code has any companies providing high-speed broadband services such as DSL or cable modem access; (2) whether a zip code has between one and four providers of these services; and (3) for those zip codes with more than four providers, the total number of providers of these services. Because of the nature of the FCC data, we instrument the online dummy with a dummy indicating between one and four high-speed Internet access providers in a customer's zip code, a dummy indicating four or more providers, and the number of providers for customers in zip codes with four or more high-speed Internet access providers. These variables are expected to be determinants of the decision to use online banking, because the availability of high-speed Internet access should increase the convenience of performing online banking transactions. Moreover, availability of high-speed Internet access within a customer's zip code is unlikely to be a determinant of a customer's decision to remain with the bank independent of the decision to utilize online banking (i.e., these instruments are unlikely to be correlated with the error term ε_i). In first-stage regressions, each of these variables is significant ($p < 0.01$), with the probability of online use increasing in the availability and number of high-speed Internet access providers. The first-stage R^2 is approximately 0.09, which is relatively large in the context of related consumer-level studies in the banking industry (Hitt and Frei 2002, Gross and Souleles 2002).

4.4. Market Outcomes (H6)

We test H6 by estimating the following model:

$$MarketShare_{mt+1} = \gamma_0 + \rho MarketShare_{mt} + \gamma_1 OnlineRate_{mt} + \varepsilon_{mt+1}, \tag{5}$$

where "m" denotes markets and "t" denotes years, respectively. National Bank operates branches across 369 internally defined banking markets that consist of contiguous zip codes. *MarketShare* is the share of all bank account deposits in a banking market that are controlled by National Bank. Data on market-level deposits come from the Federal Deposit Insurance Corporation's Summary of Deposits database. *OnlineRate* denotes online penetration among National Bank's customer base in a given market and is defined as the proportion of all of National Bank's consumer accounts in that market that are linked to the online banking channel.[15] There may be a simultaneous relationship between market share and online penetration rates if increased market power enhances the firm's ability to acquire more accounts from the relatively profitable segment of online banking customers.

To eliminate this alternative explanation, we control for current market share. H6 would be supported if online penetration rates among the firm's customer base are associated with future market shares after controlling for current market share ($\gamma_1 > 0$). We also estimate a version of (5), where all variables are first-differenced to further control for unobserved heterogeneity across markets. We have access to National Bank's online banking penetration rates across markets only for year-end 2002 and 2003, limiting our analysis to these two years. In the first-difference specification, we use two-stage least squares, with $MarketShare_{m,t-1}$ as an instrument for $\Delta MarketShare_{mt}$, because of the endogeneity of the lagged dependent variable in the first-differenced model (Anderson and Hsiao 1982, Nickell 1981).

[13] In untabulated results, we also included a full set of market area dummies to control for geographic characteristics that may be systematically related to retention, such as branch and ATM density within a customer's market area, without any substantive changes in the results.

[14] FCC form 477 data are available at http://www.fcc.gov/wcb/iatd/comp.html. The FCC collects these data to determine the extent of local telecommunications competition and deployment of broadband services.

[15] An account is linked to the online banking channel if the customer has adopted the channel and set up the account to be accessed online.

5. Results

5.1. Substitution and Augmentation Effects (H1 and H2)

Before discussing tests of H1 and H2 in detail, we begin with a few observations from Figures 1(a) and 1(b). These figures plot the mean number of transactions by channel for all customers in our sample with at least 12 months of preadoption and postadoption data. In these figures, channels are grouped into offline "self-service" (ATM and VRU) and offline "assisted-service" (branch and call center) channels. Figure 1(a) shows that, relative to all groups, there appears to be substitution away from other self-service channels on adoption of the online channel by active adopters. Figure 1(b) shows no apparent substantial changes in transaction behavior in "assisted-service" channels. Although there appears to be a peak at the enrollment month, this is likely the result of transient behavior associated with setting up the online channel. Thus, a baseline observation is that substitution appears to occur only from channels that are estimated to be just incrementally more costly than the online channel.

Figures 1(a) and 1(b) also demonstrate some persistent differences in the average level of transaction behavior over time between each group of customers. However, differences in levels of transaction activity between groups are relatively fixed prior to adoption of the online banking channel. These differences in levels can be readily accounted for through the fixed-effects models proposed in §4 or through the use of standard difference-in-difference techniques. That differences in levels of preadoption activity are relatively fixed, and trends in preadoption behavior are similar, between adopters and the control group lends credence to our choice of propensity-matched inactive enrollers as an appropriate control group for passive and active adopters.

Panel A of Table 2 contains estimates of differences in mean transaction activity before and after enrollment in the online banking channel for the control group, passive adopters, and active adopters. The patterns revealed in Table 2 are broadly consistent with those of Figure 1. Transaction volume in offline self-service channels (ATM and VRU) shows a significant decline only for the group of active adopters. Active adopters appear to reduce transactions in offline self-service channels by approximately 1.3 transactions per month on average, with this decline coming exclusively from substitution away from the VRU channel. However, the results in Table 2 point to the potential of an *augmentation* effect of online banking on transaction consumption in offline assisted-service channels (branch and call center). On average, transactions in assisted-service channels

Figure 1(a) **Transactions in Offline Self-Service Channels: ATM and VRU**

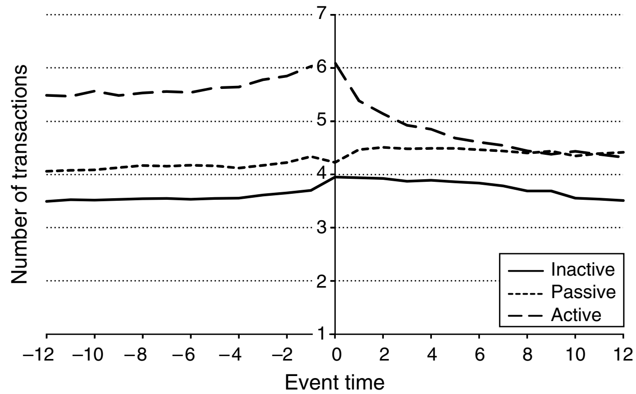


Figure 1(b) **Transactions in Offline Assisted-Service Channels: Branch and Call Center**

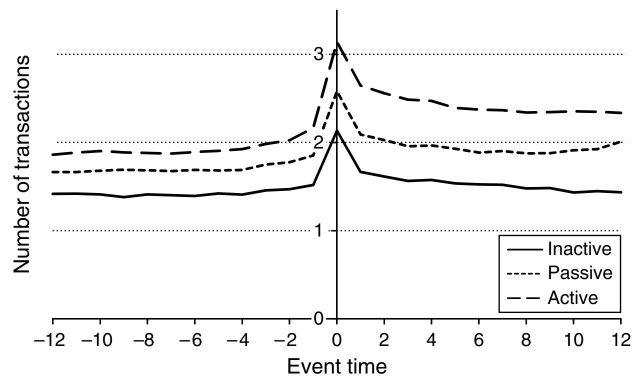
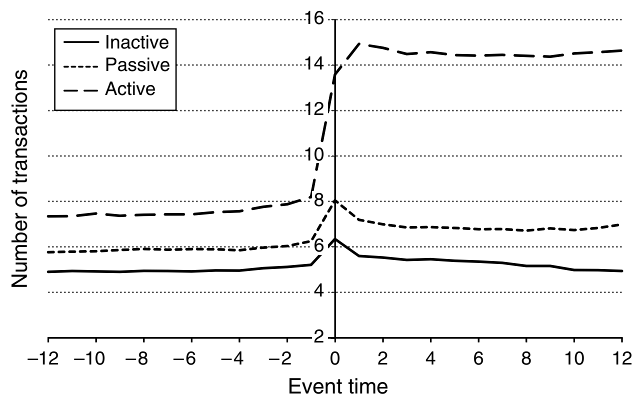


Figure 1(c) **Total Transaction Volume: Online and Offline Channels**



Notes. Each figure shows the mean number of transactions through each set of channels for customers who adopted online banking during 2006. Time is recorded in event time, with "0" in each graph corresponding to the month of adoption. Passive (active) users are defined as adopters with average post-adoption online transactions per month below (above) the median number of monthly online transactions for all adopters, with at least one postadoption transaction through the online channel.

increase for inactive enrollers as well as both passive and active adopters. Moreover, the change in transaction volume in these channels for active adopters is larger than the change for both inactive enrollers

Table 2 Descriptive Statistics for Online Adopters

	Means with standard deviations in parentheses								
	Control group (propensity-matched inactive enrollers)			Passive adopters			Active adopters		
	Before	After	Change	Before	After	Change	Before	After	Change
Panel A: Transactions									
Branch	1.24	1.34	0.10*	1.51	1.73	0.23*, +	1.75	2.28	0.53*, +, ++
	(2.14)	(2.23)	(1.24)	(4.96)	(5.25)	(1.53)	(2.82)	(3.85)	(2.49)
Call center	0.18	0.22	0.04*	0.19	0.24	0.04*	0.31	0.35	0.04*
	(0.64)	(0.74)	(0.55)	(0.53)	(0.57)	(0.48)	(3.25)	(1.46)	(1.94)
ATMs	2.12	2.30	0.18*	2.48	2.70	0.23*, +	3.41	3.54	0.14*, ++
	(4.71)	(5.02)	(2.70)	(4.31)	(4.42)	(2.84)	(5.26)	(4.42)	(3.74)
VRU	1.41	1.57	0.1*	1.51	1.40	−0.11*, +	2.90	1.45	−1.45*, +, ++
	(4.42)	(4.78)	(2.37)	(4.19)	(4.25)	(2.53)	(6.28)	(4.05)	(4.52)
Total assisted-service (branch and call center)	1.42	1.56	0.14*	1.70	1.97	0.27*, +	2.06	2.63	0.58*, +, ++
	(2.36)	(2.49)	(1.41)	(5.05)	(5.33)	(1.66)	(4.38)	(4.19)	(3.24)
Total self-service (ATM and VRU)	3.53	3.87	0.34*	3.98	4.10	0.12*, +	6.31	4.99	−1.32*, +, ++
	(7.05)	(7.53)	(3.76)	(6.55)	(6.64)	(3.97)	(8.85)	(6.41)	(6.19)
Total offline (assisted-service and self-service)	4.95	5.43	0.48*	5.69	6.07	0.39*, +	8.36	7.62	−0.74*, +, ++
	(8.17)	(8.74)	(4.33)	(8.69)	(8.89)	(4.62)	(10.47)	(7.92)	(7.45)
Total transaction volume (offline and online)	4.95	5.43	0.48*	5.69	7.46	1.77*, +	8.36	17.53	9.17*, +, ++
	(8.17)	(8.74)	(4.33)	(8.69)	(8.96)	(4.99)	(10.47)	(11.57)	(10.67)
Panel B: Customer profitability									
Customer profitability	22.89	30.85	7.96	23.32	28.17	4.85	20.34	28.07	7.73
	(70.22)	(74.13)	(74.02)	(68.27)	(91.78)	(74.75)	(62.66)	(66.81)	(52.67)

Notes. This table shows mean levels and changes of selected variables before and after enrollment in online banking for inactive enrollers (no transactions in the online channel subsequent to enrollment in the channel), passive adopters (fewer than the median number of transactions in the online channel subsequent to enrollment in the channel), and active adopters (greater than the median number of transactions in the online channel subsequent to enrollment in the channel), respectively.

*Denotes significantly different than 0 at least at the 10% level.

+Denotes that the change in the selected variable is significantly different from the change for inactive enrollers at least at the 10% level.

++Denotes that the change in the selected variable is significantly different from the change for passive adopters at least at the 10% level.

and passive adopters (0.58 compared to 0.27 and 0.14, respectively). These differences-in-differences for active adopters relative to both groups are statistically significant at the 1% level. Thus, active users of the online channel appear to increase activity in costly offline assisted-service channels relative to passive and nonusers of the channel.

Turning to our formal tests of H1 and H2, Table 3 shows results from estimation of Equation (1). Results are largely consistent with those shown in Figure 1 and Table 2. The coefficient estimates on *POST* × *PASSIVE* and *POST* × *ACTIVE* in columns 2 and 3 demonstrate that after adoption of the online channel, transactions in the branch channel increase for passive adopters, relative to the control group (coefficient = 0.035; $p < 0.001$), and that transactions in the branch *and* call center channels increase for active adopters, relative to both passive adopters and the control group (coefficients = 0.083, 0.034 for branch and call center, respectively; $p < 0.001$, $p < 0.05$, respectively). These results point to an *augmentation* effect of self-service adoption in assisted-service channels.

In contrast, the coefficient estimates on the postadoption indicators in columns 4–5 of Table 3 demonstrate substitution away from the ATM and VRU channels, respectively. The channel demonstrating the largest postadoption substitution effect is the VRU. The estimates of the substitution effect for active adopters in the VRU channel suggest that, on average, after adoption, transactions in this channel will decline by 41% and 59% relative to passive adopters and the control group, respectively.[16] There appear to be smaller rates of substitution from the ATM channel. For active adopters, the coefficient estimates for this channel suggest a reduction in ATM transactions

[16] The postadoption substitution effect for active adopters in any postadoption period, relative to the control group, can be computed as $100 * [\exp(\beta_1 + \beta_3) - \exp(\beta_1)]$. The first expression is simply the percentage of change in VRU transactions after adoption of online banking for the average active adopter, whereas the second expression represents the implied percentage of change for inactive enrollers *if all else is equal*. Similarly, the same effect for active adopters relative to passive adopters can be computed as $100 * [\exp(\beta_1 + \beta_3) - \exp(\beta_1 + \beta_2)]$.

Table 3 Substitution Between Offline and Online Service Channels

	Total offline	Branch	Call center agent	ATM	VRU	Total transaction volume
POST	0.037***	0.020	0.104***	0.021*	0.063***	0.017
	(4.24)	(1.27)	(5.15)	(1.86)	(3.38)	(0.07)
POST × *PASSIVE*	−0.050***	0.035**	0.007	−0.025**	−0.185***	0.056***
	(6.62)	(2.05)	(0.01)	(2.12)	(10.19)	(6.26)
POST × *ACTIVE*	−0.236***, a	0.083***, a	0.034**, a	−0.105***, a	−0.816***, a	0.245***, a
	(21.88)	(5.74)	(2.03)	(7.53)	(29.87)	(32.65)
Number of deposit accounts	0.233***	0.253***	0.366***	0.246***	0.153***	0.252***
	(23.34)	(31.66)	(19.68)	(27.54)	(15.29)	(32.76)
Number of loan accounts	0.047***	0.066***	0.121***	0.046***	−0.016	0.028
	(4.76)	(6.45)	(3.24)	(3.25)	(0.12)	(0.17)
Number of investment accounts	−0.012	−0.010	0.028	−0.014**	−0.043	−0.010***
	(1.35)	(1.00)	(1.27)	(2.01)	(1.59)	(2.62)
Deposit account balances ($000s)	0.00001	0.00002***	0.00006***	−0.00001***	−0.00005***	0.00001
	(1.49)	(3.13)	(2.83)	(2.96)	(3.47)	(0.77)
Loan account balances ($000s)	−0.00002***	−0.00001	−0.00004	−0.00002**	−0.00001	−0.00002*
	(2.83)	(0.98)	(1.56)	(2.55)	(1.44)	(1.87)
Investment account balances ($000s)	0.00001	0.00001	0.00003	−0.00004	−0.00003	0.00001
	(1.19)	(1.19)	(0.86)	(0.60)	(1.12)	(1.13)
EnrollMonth	0.123***	0.240***	0.793***	−0.007	0.077***	0.218***
	(21.72)	(34.49)	(37.89)	(1.43)	(6.01)	(41.70)
Year indicators	+++	+++	+++	+++	+++	+++
Month indicators	+++	+++	+++	+++	+++	+++
R^2 *within* (%)	13.38	17.14	1.42	4.30	7.69	25.86
Number of observations	1,370,661	1,342,716	1,031,823	1,108,415	796,420	1,378,215

Notes. Absolute values of z-statistics based on standard errors adjusted for correlation within customers over time are in parentheses. *EnrollMonth* = 1 for month of adoption, 0 otherwise. *POST* = 1 for postadoption months and 0 otherwise. *PASSIVE* = 1 for adopters with fewer than the median number of postadoption online transactions and 0 otherwise. *ACTIVE* = 1 for adopters with more than the median number of postadoption online transactions and 0 otherwise. +++ denotes jointly significant at the 1% level using Chi-squared test. R^2 *within* denotes the R^2 from a traditional fixed-effects regression and captures the proportion of *within-customer* variation in each dependent variable over time that is explained by *within-customer* variation over time in the independent variables.

[a]Denotes that the coefficient for active adopters is significantly different than that for inactive adopters at least at the 10% level.

*$p < 0.10$; **$p < 0.05$; ***$p < 0.01$.

of 8% and 10% on average, relative to both inactive adopters and the control group, respectively. The net effects of these results are 17% and 22% reductions in total offline transactions for active adopters relative to passive adopters and the control group, respectively. Overall, these results provide support for $H1_A$ and $H2_A$, demonstrating *substitution* from offline self-service channels (ATM and VRU) and *augmentation* in offline assisted-service channels (branch and call center). These two effects yield a net substitution effect in total offline transactions, because the rate of substitution in offline self-service channels is greater than the rate of augmentation in offline assisted-service channels.

5.2. Volume Effect (H3)

Figure 1(c) is similar to Figures 1(a) and 1(b), but plots *total* transaction volume in all channels (including the online channel) for each subsample. This figure suggests a substantial volume effect for active adopters: the mean number of total transactions appears to climb from less than 8 to more than 14 for active adopters. The differences in preadoption versus postadoption means in total transaction volume reported in panel A of Table 2 confirm the evidence in Figure 1(c), with total transactions increasing by 9.17, 1.77, and 0.48 for active adopters, passive adopters, and inactive enrollers, respectively. The increase in transaction volume for active adopters is significantly different than the increases for both passive adopters and inactive enrollers at the 1% level.

Column 6 of Table 3 shows the results from estimation of Equation (1) with total transaction volume (including online transactions) as the dependent variable. These estimates suggest that on average after adoption, transaction volumes increase by about 22% and 28% *all else being equal* for active adopters relative to both passive adopters and the control group, respectively. This substantial increase in total transaction volume following the adoption of online banking channel provides support for $H3_A$.

Table 4 Postadoption Trend Analysis of Substitution Between Offline and Online Service Channels

	Total offline	Branch	Call center agent	ATM	VRU	Total transaction volume
POST1	0.055	0.037	0.082***	0.026	0.103	0.003
	(0.13)	(0.43)	(3.32)	(0.39)	(0.09)	(3.52)
POST1 × *PASSIVE*	0.007	0.062***	0.125***	0.025	−0.096***	0.082***
	(1.38)	(4.94)	(3.04)	(0.38)	(6.26)	(8.29)
POST1 × *ACTIVE*	−0.098***, a	0.147***, a	0.217***, a	−0.005***, a	−0.541***, a	0.343***, a
	(13.65)	(8.29)	(5.44)	(2.63)	(25.26)	(38.26)
POST2	0.041	−0.005	0.109	0.011	0.119	0.044
	(0.87)	(1.57)	(0.33)	(1.67)	(0.69)	(1.43)
POST2 × *PASSIVE*	−0.011***	0.056***	−0.003	0.011***	−0.121***	0.067***
	(4.02)	(10.76)	(0.23)	(2.81)	(22.56)	(4.97)
POST2 × *ACTIVE*	−0.177***, a	0.126***, a	0.092***, a	−0.049***, a	−0.763***, a	0.328***, a
	(18.82)	(6.49)	(2.74)	(5.14)	(27.97)	(32.00)
POST3	0.047***	0.001***	0.111	0.012	0.137	0.045***
	(3.04)	(3.27)	(0.15)	(1.68)	(1.45)	(5.22)
POST3 × *PASSIVE*	−0.062***	0.024***	−0.044	−0.021***	−0.217***	0.060***
	(8.55)	(3.25)	(1.01)	(3.21)	(10.28)	(3.53)
POST3 × *ACTIVE*	−0.234***, a	0.079***, a	0.049***, a	−0.091***, a	−0.852***, a	0.259***, a
	(22.76)	(3.29)	(5.28)	(8.98)	(28.50)	(24.15)
POST4	0.034***	−0.015***	0.10	−0.001***	0.128***	0.031***
	(4.66)	(4.01)	(0.65)	(2.13)	(3.14)	(5.48)
POST4 × *PASSIVE*	−0.073***	0.030***	−0.039	−0.038***	−0.244***	0.062***
	(8.87)	(2.47)	(0.88)	(3.80)	(10.52)	(4.59)
POST4 × *ACTIVE*	−0.254***, a	0.054***, a	0.036***, a	−0.112***, a	−0.864***, a	0.208***, a
	(22.75)	(2.43)	(6.64)	(8.79)	(27.67)	(41.08)
Number of deposit accounts	0.238***	0.256***	0.372***	0.259***	0.152***	0.261***
	(32.66)	(31.55)	(19.62)	(27.48)	(15.22)	(32.71)
Number of loan accounts	0.049***	0.070***	0.120***	0.043***	−0.003	0.032***
	(4.91)	(6.52)	(3.34)	(3.34)	(0.01)	(4.33)
Number of investment accounts	−0.002	−0.001	0.016	−0.029	−0.017	−0.002
	(1.33)	(1.00)	(1.31)	(1.48)	(1.55)	(0.86)
Deposit account balances ($000s)	0.00002	0.00002***	0.0004***	−0.00007***	−0.00003***	0.00005***
	(1.61)	(3.10)	(2.80)	(3.00)	(3.50)	(1.65)
Loan account balances ($000s)	−0.0002***	−0.0002	−0.0003	−0.0003***	−0.0001	−0.0002***
	(2.95)	(1.04)	(1.63)	(2.62)	(1.54)	(2.18)
Investment account balances ($000s)	−0.00004	−0.00003	0.00001	−0.00006	−0.0005	−0.00004
	(1.25)	(1.20)	(0.93)	(0.54)	(1.26)	(1.18)
EnrollMonth	0.159***	0.268***	0.822***	0.013***	0.143***	0.210***
	(21.72)	(33.52)	(37.43)	(2.45)	(4.71)	(32.71)
Year indicators	+++	+++	+++	+++	+++	+++
Month indicators	+++	+++	+++	+++	+++	+++
R^2 *within* (%)	14.90	19.80	1.50	4.40	8.10	28.10
Number of observations	1,370,661	1,342,716	1,031,823	1,108,415	796,420	1,378,215

Notes. Absolute values of z-statistics based on standard errors adjusted for correlation within customers over time are in parentheses. *EnrollMonth* = 1 for month of adoption, 0 otherwise. *POST1*, *POST2*, *POST3*, and *POST4* = 1 for post adoption months 1–3, 4–6, 7–9, and 10–12, respectively, and 0 otherwise. *PASSIVE* = 1 for adopters with fewer than the median number of postadoption online transactions and 0 otherwise. *ACTIVE* = 1 for adopters with more than the median number of postadoption online transactions and 0 otherwise. +++ denotes jointly significant at the 1% level using Chi-squared test. R^2 *within* denotes the R^2 from a traditional fixed-effects regression and captures the proportion of within-customer variation in each dependent variable over time that is explained by within-customer variation over time in the independent variables.

[a]Denotes that the coefficient for active adopters is significantly different than that for inactive adopters at least at the 10% level.

**$p < 0.05$; ***$p < 0.01$.

5.3. Trends in Substitution, Augmentation, and Volume Effects

The substitution, augmentation, and volume effects documented in Tables 2 and 3 capture average changes in transaction behavior around enrollment in the online channel for passive and active adopters relative to the control group. However, they do not provide evidence on the extent to which these effects persist or change over time. To provide evidence on any potential trends in these various effects, we report results in Table 4 from estimation of a version of Equation (1) in which we replace the single *POST* indicator variable with four separate indicators, $POSTk$ ($k = 1, 2, 3, 4$), representing post-online-enrollment months 1–3, 4–6, 7–9, and 10–12, respectively.[17] The pattern of the coefficient estimates on the $POSTk \times ACTIVE$ coefficients ($k = 1, 2, 3, 4$) in Table 4 suggests that the relative increase in branch and call center transactions (augmentation effects), the relative decrease in ATM and VRU transactions (substitution effects), and the relative increase in overall transaction volume (volume effect) for active adopters persist throughout the postadoption period.[18]

5.4. Cost Structure Implications of Substitution, Augmentation, and Volume Effects

The net cost implications of the substitution, augmentation, and volume effects documented above depend on the extent of upward or downward adjustment of resources to accommodate changes in transaction demand across channels. Based on internal activity-based costing studies of the level and cost of resources required to support transactions in different channels, National Bank estimates that when the cost of a transaction in the branch is normalized to be 1, the cost of supporting similar transactions in the call center, ATM, or online channel is 0.94, 0.31, 0.18, and 0.09, respectively.[19] Table 5 shows that taking the preadoption mean number of transactions by channel for active adopters as our benchmark, National Bank's transaction cost estimates, combined with the documented substitution, augmentation, and volume effects shown in Table 3, suggest that estimated monthly cost to serve will *increase* by approximately 18% for the average active adopter after adopting the online channel.[20]

Table 5 **Estimate of Change in Normalized Cost to Serve for Active Adopters**

Channel	Normalized cost ($)	Preadoption mean transactions	Preadoption normalized cost ($)	Change (%)	Postadoption normalized cost ($)
Branch	1.00	1.75	1.75	9	1.90
Call center	0.94	0.31	0.29	4	0.30
ATM	0.31	3.41	1.06	−10	0.95
VRU	0.18	2.9	0.52	−59	0.21
Online	0.09	0	0.00	N/A	0.90
Total			3.62		4.27

Notes. This table shows the estimated change in normalized cost to serve for the sample of active adopters. The unit cost of performing a transaction in each channel is normalized by the unit cost of a branch transaction to preserve confidentiality in National Bank's cost estimates. Preadoption mean transactions by channel are taken from Table 2. The estimates of percentage change in transactions attributable to adoption of online banking for each channel are computed using the coefficient estimates from Table 3. The postadoption normalized cost estimate in the final column assumes the average level of monthly postadoption transactions for active adopters of 10 per month.

Although many of the costs associated with automated channels such as the ATM, VRU, and online banking are largely fixed in the short term, the levels of some costly resources required for these channels do adjust with customer transaction activity over the short to medium term. An increase in transactions at ATMs, for instance, requires more frequent cash replenishment activity. Also, deposits at ATMs consume central processing resources. As more customers sign up for the online channel, National Bank must increase call center staff to handle inquiries about the channel. In addition, National Bank's online channel stores up to 60 days of account activity for each account. Increases in the number of users and their associated transactions drive the need for more disk space to efficiently store all their information and to maintain service levels. As transaction demand in the online channel has grown over the last several years, National Bank has steadily invested in increasing storage and processing capacity in the online banking channel.

However, other costs, such as equipment and occupancy, are fixed in the short term. Even if transactions shift from offline to online banking channels, National Bank will only realize the cost savings from this shift

[17] Formally, this specification takes the following form:

$$E(y_{it}) = \exp\biggl(\beta_0 + \sum_{k=1}^{4}[\beta_k POSTk_{it} + \beta_k^{\text{Passive}} POSTk_{it} \times PASSIVE_i + \beta_k^{\text{Active}} POSTk_{it} \times ACTIVE_i] + \gamma EnrollMonth_{it} + X_{it}\delta + \alpha_i\biggr).$$

[18] These coefficient estimates suggest that differences in branch and call center transactions for active adopters relative to passive adopters and the control group are declining over the sample period. To check this, we repeated the analyses in Table 4 using only the cohort of customers who signed up for the online channel during January 2006 and remained customers to the end of our sample period (May 2007). This is the group of customers for which we have the maximum postadoption observations (16 months). For this cohort, branch and call center transactions remain higher for active adopters relative to both passive adopters and the control group 13–16 months after adoption. Moreover, this relative difference in transaction activity in postadoption months 13–16 is not significantly different than the relative difference for postadoption months 10–12. Thus, we find no evidence that postadoption transaction levels in the branch channel for active adopters converge to the levels of either passive adopters or the control group.

[19] We normalize the estimated cost of a branch transaction to be 1 to maintain confidentiality of National Bank's cost-to-serve estimates.

[20] Note that these cost estimates are not confounded with capacity utilization. Our research site allocates costs based on estimates of transaction *capacity* rather than *actual volume*. Therefore, unit cost estimates remain constant regardless of capacity utilization. Proponents of this approach argue that it provides a better picture of the costs of resources used versus the cost of unused capacity—with the latter including any costs from actual transaction volumes being lower than transaction capacity (Cooper and Kaplan 1999).

if it can eliminate unused resources in the offline channels. Likewise, costs will only increase if capacity is adjusted upward in channels that experience an increase in demand for transactions. By including short-term fixed costs in the unit transaction cost estimates, executives at National Bank are implicitly assuming that resources will be adjusted upward or downward over the medium to long term in response to changes in transaction activity. These unit costs may overstate any cost savings from shifting transactions to the online banking channel if the corresponding resources are not shifted. Similarly, they may overstate any cost increases caused by increased demand for transactions in the online channel if resources used to support this channel remain fixed as transaction demand grows. However, this latter case seems unlikely, given the patterns of increasing investment in storage and processing capacity in the online banking channel commensurate with increasing demand for transactions in this channel.[21] Overall, our estimates suggest that increased transaction activity in the online channel, coupled with small rates of substitution from other self-service channels (ATM and VRU) and small rates of augmentation in assisted-service channels (branch and call center), combine to yield a substantial increase in overall demand for service transactions ("volume effect") and a net increase in customer-level cost of service around the adoption of the online banking channel.

5.5. Customer Profitability (H4)

Panel B of Table 2 contains estimates of differences in mean customer profitability before and after enrollment in the online banking channel for inactive enrollers, passive adopters, and active adopters. These estimates provide no evidence of any change in profitability corresponding to the adoption of online banking. All groups show an increase in profitability around enrollment in the online banking channel. However, in no case is this change significantly different than 0 at conventional levels. Moreover, although the change in profitability for active and passive adopters is smaller than the corresponding change for inactive enrollers, none of these changes is significantly different from another at the 10% level.

Turning to our formal tests of H4, column 1 of Table 6 shows results from the estimation of Equation (2). The coefficient estimates on the *POST* × *PASSIVE* and *POST* × *ACTIVE* indicators demonstrate that after adoption of the online channel, customer

[21] For the two years preceding this study, the total number of transactions performed in the online banking channel grew by 150%, while total costs attributed to the channel increased by 50%. This is consistent with the presence of some short-run fixed costs coupled with a nontrivial upward adjustment of resources commensurate with increased demand for transactions in the channel.

Table 6 **Effects of Online Adoption on Customer Profitability**

	(1)	(2)
$PROFIT_{t-1}$	0.026***	0.026***
	(91.94)	(93.44)
POST	0.681	
	(0.39)	
POST × *PASSIVE*	−1.41**	
	(2.19)	
POST × *ACTIVE*	−1.21**	
	(2.12)	
POST1		0.618
		(0.22)
POST1 × *PASSIVE*		0.319
		(0.31)
POST1 × *ACTIVE*		1.067
		(1.47)
POST2		0.290
		(0.35)
POST2 × *PASSIVE*		−1.349
		(0.75)
POST2 × *ACTIVE*		−0.447
		(0.24)
POST3		0.421
		(0.08)
POST3 × *PASSIVE*		−2.598***
		(2.58)
POST3 × *ACTIVE*		−2.112***
		(2.80)
POST4		1.232
		(0.04)
POST4 × *PASSIVE*		−2.567***
		(2.62)
POST4 × *ACTIVE*		−2.297*
		(1.74)
EnrollMonth	−2.99***	−2.952***
	(8.21)	(6.95)
Constant	15.96***	19.93***
	(20.23)	(9.70)
Year indicators	+++	+++
Month indicators	+++	+++
R^2 *within* (%)	81	83
Number of observations	1,199,206	1,199,206

Notes. Absolute values of t-statistics based on standard errors adjusted for correlation within customers over time are in parentheses. *EnrollMonth* = 1 for month of adoption, 0 otherwise. *POST* = 1 for postadoption months and 0 otherwise. *POST1*, *POST2*, *POST3*, and *POST4* = 1 for postadoption months 1–3, 4–6, 7–9, and 10–12, respectively. *PASSIVE* = 1 for adopters with fewer than the median number of postadoption online transactions. *ACTIVE* = 1 for adopters with more than the median number of postadoption online transactions. +++ denotes jointly significant at the 1% level using Chi-squared test. R^2 *within* denotes the R^2 from a traditional fixed-effects regression and captures the proportion of within-customer variation in each dependent variable over time that is explained by within-customer variation over time in the independent variables.

* $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$.

profitability decreases for both passive and active adopters relative to the control group (coefficients = −1.41, −1.21; $p < 0.05$). Taking the preadoption mean levels of profitability for passive and active adopters reported in Table 2 as our benchmark, these negative coefficient estimates suggest that monthly customer profitability will *decline* on average by approximately 6% for both groups relative to the control group after adoption of the online channel. Results from estimation of an alternative version of Equation (2) in which we replace the single *POST* indicator variable with four separate indicators, *POSTk* ($k = 1, 2, 3, 4$), representing post-online-enrollment months 1–3, 4–6, 7–9, and 10–12, respectively, are reported in column 2. Taking the preadoption mean levels of profitability for passive and active adopters reported in Table 2 as our benchmark, the pattern of the coefficient estimates on the $POSTk \times ACTIVE$ coefficients ($k = 1, 2, 3, 4$) suggests that the relative decline in profitability for passive and active adopters takes at least six months to materialize and that profitability will *decline* by approximately 11% for both groups relative to the control group within 10–12 months of adoption of the online channel. Overall, these results raise the possibility of the online channel allowing more efficient money management by customers, with the net effect of reducing fees paid to the bank and/or requiring higher (lower) rates of interest to be paid on deposit (loan) accounts.[22]

5.6. Retention (H5)

Table 7 contains summary statistics for the December 2003 cross-sectional sample of online and offline customers for use in our retention analyses. Before turning to our formal tests of H5, several observations about the data in Table 7 are worth noting. Simple comparisons of means between online and offline customers reveal that online customers tend to be younger, have less tenure with the bank, hold more deposit and loan accounts and fewer investment accounts, and—most interestingly—tend to have higher profitability than offline customers on average. All differences in means between online and offline customers in Table 7 are significant ($p < 0.10$ in all cases using two-tailed t-tests). Consistent with prior studies (Hitt and Frei 2002, Xue et al. 2007), the statistics reported in Table 7 provide evidence that online customers are different than offline customers along a variety of dimensions. However, our tests of H1–H4 suggest that these performance-related differences are the result of preexisting differences in the online and offline customer populations rather than the result of behavioral change due to the adoption of online banking. Our tests of H1–H4 provide evidence that customers adopting and using the online channel become more costly to serve in the longrun and less profitable in the shortrun, even before considering the allocation of transaction costs. Whether these effects are in any way compensated by increased retention of a relatively profitable segment of customers depends on the relationship between customer retention and the use of the online channel.

Table 7 Descriptive Statistics by Online Status for a Random Sample of Customers as of January 2004

	Offline customers ($N = 69{,}871$)		Online customers ($N = 30{,}129$)	
	Mean	Std. dev.	Mean	Std. dev.
Retention—1 year	0.86	0.35	0.90	0.30
Retention—2 years	0.78	0.42	0.84	0.37
Retention—3 years	0.71	0.45	0.79	0.41
Tenure	10.33	12.25	8.29	7.54
Age	45.34	20.77	38.90	13.79
Number of deposit products	1.02	0.97	1.79	1.23
Number of loan products	0.32	0.58	0.53	0.75
Number of investment products	0.11	1.94	0.04	0.30
Deposit account balances	8,781	53,778	10,530	58,718
Loan account balances	3,240	17,911	4,127	19,487
Investment account balances	1,935	29,204	483	6,587
Annual customer profitability	196.8	1,056	217.9	1,037

Notes. "Offline" customers = customers who have not adopted online banking as of December 2003. "Online" customers = customers who have adopted the online channel as of December 2003. All differences in means between these groups are significant at least at the 10% level using t-tests.

Table 7 demonstrates that one-, two-, and three-year retention rates for online customers are significantly higher than those for offline customers (all differences significant at the 1% level). Within three years, 79% of online customers remain with the bank, whereas only 71% of offline customers do so. However, as noted above, online customers are systematically different than offline customers in ways that may be associated with these differential retention rates independent of the use of online banking (e.g., holding more products). We control for these observed differences in our estimation of Equation (3).

The first columns in Table 8 show the results from estimating Equation (3) using one-, two-, and three-year retention rates, respectively. After controlling for tenure, age, number/type of products, balances, and competition in the local market area, use of the online channel is positively and significantly associated with one-, two-, and three-year retention rates at the 1% level. To benchmark the estimated coefficients, the

[22] We reran the analysis of customer profitability on the set of customers who experienced no change in their product portfolio over the sample period and found substantively similar results. This suggests that our finding of a reduction in customer profitability associated with increased postadoption use of the online channel is not due to customers simply shifting balances into products with higher unit costs, but is more likely due to such revenue effects.

Table 8 Marginal Effects Probit Estimates of Retention with Online Status Using Cross-Sectional Sample of 100,000 Customers Observed at Year-End 2003, 2004, 2005, and 2006

	Marginal effects probit estimates			Self-selection test
	Retention 1 year	Retention 2 years	Retention 3 years	2SLS
ONLINEUSE	0.001***	0.001**	0.002***	0.002**
	(2.76)	(2.32)	(3.62)	(2.04)
TENURE	0.003***	0.005***	0.005***	0.005***
	(17.98)	(23.86)	(23.91)	(16.89)
AGE	−0.001***	−0.001***	−0.001***	−0.001***
	(4.66)	(6.47)	(9.28)	(3.32)
Number of deposit products	0.052***	0.070***	0.076***	0.061***
	(36.22)	(40.64)	(40.98)	(9.00)
Number of loan products	0.039***	0.048***	0.053***	0.041***
	(18.37)	(18.61)	(18.74)	(7.79)
Number of investment products	−0.001	0.023***	0.014***	0.008**
	(0.28)	(5.25)	(3.64)	(2.56)
Deposit account balances ($000s)	0.0001***	0.0001***	0.0001***	0.0001
	(2.83)	(2.88)	(2.69)	(0.23)
Loan account balances ($000s)	−0.0002***	−0.0004***	−0.0006***	−0.0007***
	(4.68)	(6.52)	(7.19)	(5.20)
Investment account balances ($000s)	0.00007	0.00008	0.00006	−0.00006
	(1.48)	(0.41)	(0.74)	(0.47)
COMPETITION	−0.047***	−0.076***	−0.067***	−0.075**
	(4.54)	(5.79)	(4.53)	(2.21)
Psuedo R^2 (%)	6.1	6.1	5.2	
Adjusted R^2 (%)				4.9

Notes. Absolute values of *t*-statistics are in parentheses. Estimated coefficients reported as marginal effects at the mean value of all variables. *ONLINEUSE* = average number of online transactions performed by the customer per month during 2003. *TENURE* = length of time (in years) since customer established first account relationship with the bank, measured as of year end 2003. *AGE* = age of customer (in years) measured as of year-end 2003. *COMPETITION* = percentage of deposits controlled by other banks in the market in which the customer resides.

**$p < 0.05$; ***$p < 0.01$.

unconditional probability of retention in three years for offline customers in the sample is 71%, representing a three-year customer attrition rate of 29%. Our estimates suggest that an active online customer, averaging approximately 10 transactions per month, would have a 2% higher three-year retention rate than an offline customer, *all else being equal*. This represents a 7% (0.02/0.29) decrease in the attrition rate.

The results from estimation of (4) via two-stage least squares are shown in the last column of Table 8. For brevity, we only report results using three-year retention rates, because results are qualitatively similar for one- and two-year retention rates. The two-stage estimate of the *ONLINEUSE* coefficient remains positive, significant, and similar in magnitude to the marginal effects probit estimates even after controlling for self-selection into the online channel. This result suggests a potential causal link between online banking and customer retention and points to customer retention as an important value driver for the self-service channel of online banking.

Table 9 Market Share and Online Banking Penetration Market-Level Regressions on Cross-Sectional Sample of 369 Banking Markets

	Dependent variable = $MarketShare_{t+1}$	
	Levels	Changes
$MarketShare_t$	0.939***	0.291*
	(105.37)	(1.88)
$OnlineRate_t$	0.025**	0.021**
	(2.25)	(2.12)
Constant	−0.003	−0.002
	(0.89)	(1.07)
Adjusted R^2	0.97	0.02

Notes. Absolute values of *t*-statistics are in parentheses. *MarketShare* = share of deposits in banking market controlled by National Bank. *OnlineRate* = proportion of National Bank accounts that are linked to the online banking channel in a market. "*t*" = 2004. Column 2 reports estimates of a changes specification where the change in *MarketShare* from 2003 to 2004 is regressed on the changes in *MarketShare* and *OnlineRate* from 2002 to 2003.

*$p < 0.10$; **$p < 0.05$; ***$p < 0.01$.

5.7. Market-Level Outcomes (H6)

Table 9 provides the results from estimation of Equation (5). Column 1 shows that increases in market-level online banking penetration rates among the firm's customer base (*OnlineRate*) are positively and significantly ($p < 0.05$) associated with future market share even after controlling for current market share. Column 2 demonstrates that these findings hold when Equation (5) is estimated in first-differences, suggesting that the results are not caused by time-constant-omitted correlated variables across markets.

The mean and standard deviation for *OnlineRate* in our sample are 33.8% and 14.3%, respectively. The mean change in *OnlineRate* in our sample from year-end 2003 to year-end 2004 is also approximately 14%. The coefficient estimates in columns 1 and 2 show that a change of 14% in *OnlineRate* in the current year is associated with an approximate 0.4% increase in market share the subsequent year. Though the magnitude of the relationship between market shares and online penetration rates appears small, it is worth noting that this increase compares relatively favorably against the average change in market shares for National Bank (−0.3% over the same period). Overall, the evidence in Table 9 provides support for the notion that online banking penetration is associated with market-level outcomes (H6).[23]

[23] Market shares and online penetration rates may share common unobserved trends over time, raising the possibility that our results are due to spurious correlation. However, our analysis has several features that substantially mitigate against this possibility. First, our analysis uses panel data rather than a single time series. The use of panel data over several markets lowers the possibility of spurious correlation, as trends vary over markets and therefore common

6. Discussion and Conclusions

The performance consequences of self-service delivery channels has been a relatively unexplored area in the prior literature in service operations and services marketing. In this paper, we investigate one self-service technology—online banking—that many firms are deploying with the aim of simultaneously achieving benefits in the form of lower service costs, increased revenues, and higher customer loyalty.

We find that customer adoption and use of online banking is associated with (1) *substitution* primarily from incrementally more costly self-service delivery channels (ATM and VRU); (2) *augmentation* of service consumption in more costly assisted-service delivery channels (branch and call center); (3) a substantial increase in total transaction volume; (4) an increase in estimated average cost to serve resulting from the combination of points (1)–(3); and (5) a reduction in short-term customer profitability. However, we find that the use of online banking is associated with higher customer retention rates over one-, two-, and three-year horizons, with the association increasing in the length of the horizon. These latter findings hold even after controlling for self-selection into the online channel, suggesting the potential for a causal relationship between online banking and customer retention. We also find evidence that future market shares for our sample firm are systematically higher in markets with high contemporaneous utilization rates for online banking. This finding holds even after controlling for contemporaneous market share, suggesting it is not simply the result of increased market power leading to the acquisition of online banking customers.

These findings have a number of implications for service operations management research and practice. First, technologies that lower the firm's cost of service delivery also potentially alter the economics of service consumption from the customer's perspective. Our results suggest that this is an important consideration in evaluating the likely benefits of technology investments directed at service delivery. In our setting, lowering the customer's costs of interaction appears to have the unintended consequence of increasing service consumption and thus reducing estimated short-term customer profitability.

trends in the data are less likely to occur. Second, our results hold when transforming the data to first differences prior to estimation. First-differencing the data reduces the risk of spurious correlation that can arise in nonstationary time series. Finally, and perhaps most important, our analysis relates future market share to current online penetration rates after controlling for the current level of market share. That the relationship between current online penetration and future market share holds even after controlling for the contemporaneous correlation between current online penetration rates and current market share makes it unlikely that our results are driven by spurious correlation between these two series.

Second, and more important, the result that the estimated long-run average cost to serve increases around the adoption and use of online banking suggests that traditional costing methods alone may not be appropriate for decision making in settings where customer interaction is important in determining cost. Accounting and operations management texts (Cooper and Kaplan 1999, Fitzsimmons and Fitzsimmons 2001) recognize the importance of considering customer interaction in the design of performance measurement systems in service firms. The results in this paper demonstrate that the overall cost impact of new service delivery technologies depends not only on the estimated unit cost of a service transaction using that technology but also on the effect of the technology on overall service consumption. Thus, the design of performance measurement systems for evaluating distribution strategies should explicitly consider how the use of one service delivery technology affects service consumption and costs across all delivery channels.

Finally, our results suggest that important tradeoffs may exist among multiple performance measures, such as short-term customer profitability, customer retention, and market share, highlighting the potential importance of a long-term "customer asset" view for evaluating investments in service delivery technologies (Hogan et al. 2002). In the context of online banking, our results suggest that customers may capture the gains from this technology in the short term but that these gains to the customer may translate into higher customer satisfaction and, in turn, higher customer retention rates. This could lead to potential long-term gains for firms. The provision of online banking services may be a competitive necessity, but many banks, including our research site, are allocating resources toward actively migrating customers to the online banking channel under the assumption that cost, revenue, and retention benefits will follow. When coupled with the finding in prior literature that more profitable customers tend to *select* into online banking (Hitt and Frei 2002), our results suggest that the primary benefit of the online banking channel may be in attracting and retaining more profitable customers rather than in increasing the profitability of existing customers.

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