The Cost Structure and Customer Profitability Implications of Electronic Distribution Channels: Evidence from Online Banking

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Abstract

This paper uses the context of online banking to investigate the consequences of employing technology to alter customer interactions with the firm. Using a sample of retail banking customers observed over an 18-month period at a large U.S. bank, I test whether changes in service consumption, revenue, cost, and customer profitability are associated with the adoption and use of online banking. I 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 voice response unit) with little or no substitution from more costly service delivery channels (branch and staffed call center); (2) a substantial increase in total transaction volume; (3) an increase in cost-to-serve resulting from the combination of (1) and (2); and (4) a reduction in revenues consistent with customers using the channel to more closely manage balances and avoid fees associated with minimum balance requirements. These effects combine to yield a net reduction in estimated short-term customer profitability. However, I find that use of online banking is associated with higher customer retention rates. I discuss the implications of these findings for performance measurement in service firms.

1. Introduction

This paper investigates the consequences of employing technology to alter customer interactions with the firm and considers the implications of these consequences for performance measurement in service firms. Firms are increasingly implementing technologies, such as the internet, vendor managed inventory, and electronic data interchange (EDI) with the goals of reducing cost, increasing revenue, and increasing customer retention rates (Anderson and Lanen 2002, Cohen-Kulp 2002, Hitt and Frei 2002). However, the success of strategies for deploying these technologies is dependent upon how customers utilize them. For example, while 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, I examine the impact of one technology, online banking, on customer level cost, revenue, profitability, and retention.

Banking represents an ideal setting to investigate the consequences of using technology 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., ATM's, touch-tone banking, centralized telephone call centers and online banking (Clemons et al. 2002, Frei and Harker 2000)). 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).

However, to my knowledge, existing research has not systematically examined the impact of any of these technologies on service consumption or cost.

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). Existing research in the operations management literature finds that online customers tend to be more profitable than offline customers, but concludes that these differences may be the result of more profitable customers selecting into this technology rather than being caused by its adoption (Hitt and Frei 2002). This is an important distinction since distribution strategies in many retail banks involve allocating resources towards actively migrating customers to online banking under the assumption that cost, revenue, and retention benefits will follow. Hitt and Frei (2002) focus on one of the assumed causal benefits of migrating customers to online banking: increased cross-sales of new products to existing customers. The extent to which adoption and use of online banking translates into benefits in terms of cost, revenue, and retention remains an open empirical issue.

Using a variety of panel data methods on a large sample of retail banking customers observed over an 18-month period at a large U.S. bank, I test whether changes in service consumption, revenue, cost, and customer profitability are associated with the adoption and use of online banking. I 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 voice response unit) with little or no substitution from more costly service delivery channels (branch and staffed call center); (2) a substantial increase in total transaction volume; (3) an increase in cost-to-serve resulting from the combination of (1) and (2); and (4) a reduction in revenues consistent with customers using the channel to more closely manage balances and avoid fees associated with minimum balance requirements. These effects combine to yield a net reduction in estimated short-term customer profitability. However, I find that use of the online channel is associated with higher customer retention rates. These results are robust to a number of alternative specifications.

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

Second, and more important, the result that estimated 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 and monographs (Cooper 1999; 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 cost across all delivery channels.

Finally, my findings run contrary to many of the established business models for deploying online banking in this industry. These models implicitly assume that online banking represents a more efficient way to deliver the same or better service quality. My results suggest that important tradeoffs may exist among multiple performance measures such as customer profitability and customer retention, highlighting the potential importance of a “business model” or “balanced-scorecard” approach in the design of performance measurement systems (Ittner and Larcker 1998; Kaplan and Norton 1996) for evaluating investments in service delivery technologies. In the context of online banking, my 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 leading to potential long term gains for firms.

The remainder of the paper proceeds as follows. Section 2 reviews related literature from accounting and operations management. I discuss my research site and data in section 3. Section 4 presents the research design and methodology used in this study. Results are presented in section 5. I end with a discussion and conclusions in section 6.

2. Background and Hypotheses

Research in the accounting and operations management literatures has documented the impact of complexity on firm performance primarily in the context of manufacturing firms (Anderson 1995; Foster and Gupta 1990; Ittner and MacDuffie 1995; Banker et al 1993; Datar et al. 1993). However, many of the arguments advanced in this literature extend directly to service firms where the variation in demand for organizational resources is tied much more directly to customer behavior (Cooper and Kaplan 1999; Fitzsimmons and Fitzsimmons 2001)[1]. The implication of customer involvement in the "production" of services has been discussed in the operations management literature for more than two decades. For instance, Chase (1978, 1981) characterized customer involvement in production processes in terms of the degree of customer contact and proposed that the potential efficiency of a given service facility is inversely related to the degree of customer contact due to the heterogeneity that customer behavior introduces into the production process. Activity-based costing methods have provided one way to quantify the costs associated with the complexity customers introduce into the production process, and to measure the costs and profitability associated with individual customers (Cooper and Kaplan 1999; Kaplan and Narayanan 2001; Shank and Govindarajan 1994).

Academic research has documented wide variability in the estimated contribution of individual customers to overall profitability across a variety of firms and industries (Foster and Gupta 1990, Foster et al. 1995, Rust et al. 2000). The financial services industry is a leading example of this phenomenon. Customer behavior is a key driver of profitability because customers choose which products to hold, what balances to maintain, which channels to interact through, and how often to interact through them. The application of ABC methods in the banking industry throughout the late-1990's yielded varying estimates on the percentage breakdown of profitable vs. unprofitable customers. Many retail banks were characterized as following an approximate "150/20" rule whereby 150% of profits derived from just 20% of customers (Stoneman 1999). Other findings suggested that only 40% of a retail bank's customers were profitable contributing approximately 300% of overall profits (Council on

[1] Balakrishnan et al. (1996) document the relation between complexity and operating costs in a service setting, and find limited evidence that the effect of complexity of care on operating costs in hospitals increases as direct contact with the patient increases. Balakrishnan et al. (1999) find that capacity adjustment in terms of staffing levels in therapy clinics is related in complex ways to the volume of patients served.

Financial Competition 1996). The differences in the findings of these studies are, of course, largely driven by variation in financial institutions methodologies for allocating costs and calculating profitability at the customer level. However, their differences notwithstanding, they all conclude that the contribution of individual customers to bank earnings varies widely with a small percentage of customer's cross-subsidizing the profitability of the bulk of the customer base. This realization has led banks to employ a variety of strategies for improving customer profitability.

One leading strategy has been to develop, promote and actively encourage migration of transactions out of high cost branch networks and towards perceived lower marginal cost electronic distribution channels. These channels have a long history in banking starting with ATM's in the 1970's, touch-tone banking, centralized telephone call centers and now online banking (Frei and Harker 2000). A review of the related operations management and practitioner-oriented literature reveals essentially three value propositions for online banking: cost reduction, revenue enhancement, and customer retention (Hitt et al. 1999; Hitt and Frei 2002; Prasad and Harker 2000; Shevlin et al. 2002; Hoffman 2002).

Cost Reduction: Banks hope to achieve lower costs through the active migration of customers to online banking in two ways. First, steps performed by decentralized labor in the branches could then be performed by centralized labor or automated with technology. Second, customers could perform process steps that had previously been performed by the firm. Both of these changes would result in a lower cost per interaction, thereby lowering overall distribution costs as customers migrated transactions from relatively more costly offline channels to the online channel. However, innovations such as online banking can significantly lower the cost of interaction from the customer's perspective. Interaction through the online channel will 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 that customers may simply use this increased convenience to consume more transactions. Thus, new technologies, such as online banking, which lower the cost per transaction from the customer's perspective can lead to both a "substitution" effect (transactions shift to the lower cost channel) and an "income" or "volume" effect (customers facing a lower implicit cost to use a service, demand more of that service).

In considering these two effects, it is worth noting that not all banking transactions can be performed in all channels (e.g. not all transactions are substitutable). For instance, paper based transactions such as withdrawals and deposits cannot be performed via online banking. However, it is worth considering substitution from offline channels across all transaction types, even those that are not substitutable, because there may be complementarities among channels. Lower transactions costs associated with online banking may lead to increased information monitoring and, in turn, more active account management in offline channels such as branches, ATM's, and call centers. Complementarities among channels may limit any potential substitution effects, while increases in the volume of service consumption need not occur solely through the online banking channel.

Any realized cost reductions from the introduction of new channels depends heavily on the extent to which customers substitute transactions from traditional channels to electronic channels as well as the degree of any associated increases in overall transaction volume. In order to examine these two effects, I test the following hypotheses:

H1: Transactions in offline channels decrease following the adoption and use of the online channel ("Substitution Effect")

H2: Total transaction volume increases following the adoption of the online channel ("Volume Effect")

Because it is unclear how the substitution and volume effects will combine to affect cost, I test the following hypothesis (stated in null form):

H3: There is no change in cost following the adoption and use of the online channel

Revenue Enhancement: Banks have increasingly turned to revenue 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 both increasing the number of products held (cross-sell), and the average balance held per product. Customer adoption of online banking may lead to either, or both, of these benefits to the extent that 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 banking customers 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 2000). One potential explanation is the existence of some form of transactions costs such as the inconvenience associated with closely managing balances in bank accounts. The increased convenience associated with online banking may reduce such transactions costs allowing customers to more efficiently manage their money 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 to manage balances close to the minimum without falling below it thereby avoiding the probability of incurring fees and simultaneously keeping average balances lower. Thus, in addition to affecting cost (H3), changes in transaction behavior associated with online banking (H1 and H2) may also affect revenue. Since a range of effects are possible, I examine the revenue implications of online banking by testing the following hypothesis (stated in null form):

H4: There is no change in revenue following the adoption and use of the online channel

I also test the following hypothesis (stated in null form) to examine the combined effects of (H1)-(H4):

H5: There is no change in customer profitability following the adoption and use of the online channel

Customer Retention: Because acquisition expenses associated with new accounts are so high, financial services firms are increasingly looking to electronic channels as tools for increasing 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 created by learning to use a new technology (Chen and Hitt, 2001). 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, I test the following hypothesis (stated in null form):

H6: There is no association between customer retention and the use of online banking

3. Research Site and Data Collection

3.1 Research Site

My research site, henceforth referred to as National Bank,[2] is one of the largest diversified financial services firms in the U.S. It serves millions of customers through more than 5,000 branches in approximately 20 states, and also services customers through electronic delivery channels such as telephone banking, ATMs, and the Internet. Although National provides a variety of financial products and services, it considers its retail deposit customers its core customer base.

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

Online Banking at National

National offers a variety of services through their online channel including the ability to query account history, open new accounts, perform balance transfers, and pay bills electronically. National'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 firm has aggressively encouraged customer migration to the online channel in order to reduce costs and increase the profitability of its customer base. Fees are not charged for the basic online banking service, reflecting National's desire to encourage adoption in the hopes of realizing cost, revenue, and retention benefits. National has one of the fastest growing online customer bases in the nation.

3.2 Data Collection

[2] I use the disguised name National Bank due to the confidential nature of the data.

The data for this study consists of a random sample of 525,864 customers drawn as of the end of May 2001 from the population of National's retail deposit customers[3]. I have constructed an unbalanced monthly panel dataset on these customers for the 18-month period ranging from January 2001 to June 2002 consisting of monthly transactions disaggregated by channel, average daily balances, net-interest revenue on balances, fee revenue, total revenue, customer profitability, number of accounts, tenure with the bank, and age.

All data on number of transactions, revenue, cost, and profit are defined over a customer's retail deposit products and exclude performance in asset products such as home mortgages and consumer loans. From the standpoint of testing the effect of online banking on service consumption (H1 and H2) and cost (H3), data on these asset products is likely to be largely irrelevant. Deposit products, such as standard checking and savings accounts generate by far the most transactions in the banking industry, and labor-intensive channels such as branches exist largely to service these types of products. In contrast, asset products, such as consumer loans, are typically not transaction intensive and only incur the ongoing servicing costs of mailing statements and processing payments. A potentially more serious limitation of this lack of data is that it misses important components of customer level revenue. An assumption throughout the banking industry is that online banking represents a channel through which to sell new products to existing customers. As a result of this data limitation, the tests performed in this paper only partially capture the potential revenue and profitability implications of this "cross-sell" effect. However, past research finds that this effect is minimal (Hitt and Frei 2002). In addition, benefits in the form of cross-sales to existing customers, to the extent that they materialize, are likely to come in the longer term. Thus, the analysis performed in this paper

[3] The 525,864 customers represent a random sample based on a fixed percentage of National's total retail customer deposit base. Due to confidentiality restrictions, I cannot reveal this percentage (which, by extension, would reveal

with respect to revenue and profit can be interpreted as examining more immediate effects of online banking on these performance metrics.

Transactions by Channel

For each customer, I observe the total number of monthly transactions through the branch, ATM, call center, and voice response unit[4] (VRU) channels. Additionally, for each customer, I observe the total number of monthly transactions through the online banking channel starting in September 2001.[5] This limits the sample I can use for subsequent analyses since most of my tests are conditional on online adoption *and* use. Table 1 shows the distribution of the types of transactions performed through the branch, ATM, and online channels for National's entire customer base during May 2001.[6] Table 1 demonstrates that the branch is used heavily for monetary transactions (95% of branch transactions involve deposits, withdrawals, or cashed checks), the ATM is used for both monetary and information based transactions (75% of ATM transactions are deposits or withdrawals while 15% are account inquiries), while 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. However, even given these differences, it is unclear how adoption and use of online banking will translate into substitution (H1) from the branch or ATM channels or result in increased volume of service consumption (H2). As discussed in the development of (H1) and (H2), these effects depend not only on the extent to which transactions among channels are directly substitutable, but also on the extent to which customers view transactions among

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the size of National's customer base).

[4] The voice response unit is an automated call center.

[5] National did not begin storing online transactions in its standard transaction databases until September 2001.

[6] Due to data limitations, I am unable to perform a similar breakdown for call center and VRU transactions.

channels as complementary. Furthermore, inquiry based transactions such as balance inquiries at ATM's 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, transfers performed via online banking can substitute for some deposit and withdrawal based transactions in the branch.

Performance Measures

The primary performance measures investigated in this paper are net-interest revenue (NET), fee revenue (FEE), total revenue (REV), transaction expense (COST), and customer profitability (PROFIT). NET represents investment income from deposit balances that National calculates by applying funds transfer pricing rates to individual account balances. FEE includes all fees related to monthly service charges, overdrafts, minimum balances, and other service charges. REV represents total revenue from both net-interest and fees. PROFIT is defined as total revenue less transaction related costs (COST). The unit costs for each transaction type in each channel are determined by National's activity-based costing system and consist of allocated overhead related to items such as personnel, supplies, telephone, equipment, occupancy, and processing. To illustrate differences in unit costs across channels, the unit cost for performing a transfer of funds between accounts is shown for each channel in Table 2. While many of the costs associated with automated channels such as the ATM, VRU, and online banking are largely fixed in the short-term, there are costs associated with these channels that are likely to vary with customer transaction activity over the short to medium-term. An increase in transactions at ATM's for instance requires more frequent cash replenishment activity. Also, deposits at ATM's consume central processing resources. As more customers have signed up for the online channel, National has had to devote call center staff solely to handling inquiries about the channel. In addition, National's online channel stores up to 60 days of account activity for each account linked to the online channel. Increases in the number of users and their associated transactions drive the need for more disk space to efficiently store all of their information.

However, other costs, such as equipment and occupancy, are fixed in the short term. Even if transactions shift from offline channels to the online banking channel, National will only realize the cost savings from this shift if it can eliminate unused resources in the offline channels. By including short-term fixed costs in the unit transaction cost estimates, I am implicitly assuming that resources will be adjusted upward or downward over the medium to long term in response to changes in transaction activity. To the extent that substitution from offline channels does occur and the resources do not fully adjust downward, these unit costs may overstate any cost savings from shifting transactions to the online banking channel.

Customer and Account characteristics

For each customer, I observe the number of retail deposit products they hold (NPROD) as well as average daily balances (BALANCE) in those products. Average daily balance is defined as cumulative daily balance divided by the number of days in the month. I also observe length of the relationship with the bank measured in years (TENURE), as well as the age and zip code for each customer.

Geographic Characteristics

In addition to the customer level data described above, I observe a number of regional variables that can be matched to customer by zip code. In some of my tests, I use these variables as exogenous sources of variation to address potential endogeneity issues. National operates in approximately 400 different market areas. The number of market areas served by National has grown over time due to mergers and acquisitions as well as new bank charters. For each of these markets, I observe online penetration rates, defined as the proportion of all accounts in the market that are linked to the online channel. In addition, at the zip code level I observe data from the Federal Communications Commission (FCC) on the availability of high-speed Internet access.[7] The FCC data reports (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 1 and 4 providers of these services; and (3) for those zip codes with more than 4 providers, the total number of providers of these services.

4. Research Methodology

4.1 Substitution (H1) and Volume (H2)

I face three key specification issues in testing (H1) and (H2): (1) the number of transactions per month for a given customer is discrete and frequently zero, particularly when measured for each channel separately; (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; and (3) pre-adoption trends in the number of transactions performed need to be controlled for. I deal first with (1) and (2) via the conditional fixed-effects Poisson model of Hausman, Hall, and Griliches (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}. I test (H1) by modeling this parameter in the standard way as

$$E(y_{it}) = \exp(\beta_0 + \alpha' time_t + \beta_1 ADOPT_{it} + \beta_2 USE_{it} + \beta_3 NPROD_{it} + \gamma_i) \quad (1)$$

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

where $time_t$ represents a vector of time dummies and γ_i is the individual customer fixed effect.

$ADOPT_{it}$ takes on a value of 1 if customer *i* adopts the online channel in month *t*, and equals 0 for all non-adoption months. The inclusion of this indicator is intended to capture transient effects occurring during the adoption month. For example, customers tend to visit the branch or phone the call center in order to set up access to the online channel which yields a spike in transaction activity during the month of adoption. USE_{it} is measured for each customer as the total number of online banking transactions performed from the first post-adoption month up to and including time t. Therefore, USE_{it} equals zero for all months prior to the first post-adoption month and represents *cumulative* post-adoption use of online banking for customer *i* at time *t*. I include cumulative use to control for learning effects associated with using a new technology. Intuitively, this allows total substitution around the adoption of online banking to vary with how extensively the customer has used this technology. If adoption and use of online banking leads to substitution from offline channels (H1), I expect β_2 to be negative. The estimate of β_2 can also be used to compute quantities of interest such as the post-adoption percentage change in monthly transactions in offline channels conditional on cumulative use of the online channel.

The exponential form of (1) ensures nonnegativity for λ and allows estimation of the parameters through maximum likelihood in the standard way. In estimation the fixed effect, γ, 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, yielding a likelihood function that is globally concave and readily maximized (see Hausman, Hall, and Griliches (1984) or Becker and Henderson (2000) for details). In order to fully examine substitution among channels, I estimate equation (1) separately for transactions through each offline channel (branch, ATM, VRU, and call center) as well as for the total number of transactions in all offline channels. I test the volume effect (H2) using the following analogous specification

$$E(y_{it}) = \exp(\alpha_0 + \delta' time_t + \alpha_1 ADOPT_{it} + \alpha_2 POST_{it} + \alpha_3 NPROD_{it} + \eta_i) \quad (2)$$

Here, y_{it} is *total* volume of transactions across all channels (including online banking transactions) for customer *i* at time *t*. $POST_{it}$ equals 1 for all post-adoption months and 0 otherwise. η_i is the customer specific fixed-effect. If total volume of transactions through all channels increases after adoption of online banking (H2), I expect α_2 to be positive. The estimate of α_2 can also be used to compute quantities of interest such as the post-adoption percentage change in total volume of monthly transactions. I include NPROD in all specifications to avoid attributing any changes in transaction activity to post-adoption use of online banking that are actually due to the adoption of additional products.[8,9]

In order to control for pre-adoption trends in the number of transactions through various channels, I also estimate dynamic versions of (1) and (2) including the lagged number of transactions. It is a nontrivial problem to incorporate lagged dependent variables into nonlinear count data models (Chamberlain 1992; Blundell et. al. 2002). In order to consistently estimate dynamic versions of equations (1) and (2), I use the conditional maximum likelihood approach of Wooldridge (2000).

4.2 Cost (H3), Revenue (H4) and Profit (H5)

Since the particular estimation issues that arise due to the discrete nature of the dependent variables used in equations (1) and (2) do not arise for the measures of financial performance

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[8] While not reported, preliminary analysis suggests that the number of accounts increases on average for adopters *prior* to going online. This is consistent with National's marketing practices whereby when customers open new accounts, they are actively encouraged to sign up for the online channel if they are currently offline customers.

[9] Results are very similar when NPROD is not included. I also ran the analyses on a subsample of customers which experienced no change in NPROD over the entire sample period and obtained similar results.

used in this study, I test the effect of adoption and use of the online channel on cost (H3), revenue (H4) and profit (H5) using the following linear specification:

$$P_{it} = \gamma' time_t + \rho P_{it-1} + \lambda_1 ADOPT_{it} + \lambda_2 USE_{it} + \lambda_3 NPROD_{it} + \upsilon_i + \mu_{it}$$

where P_{it} denotes NET, FEE, REV, COST, or PROFIT respectively, υ_i is the customer specific fixed effect, and μ_{it} is a random error term. I include past performance to control for pre-adoption trends in performance. First-differencing eliminates the customer-specific fixed effect and yields the following equation used for estimation:

$$\Delta P_{it} = \gamma' \Delta time_t + \rho \Delta P_{it-1} + \lambda_1 \Delta ADOPT_{it} + \lambda_2 \Delta USE_{it} + \lambda_3 \Delta NPROD_{it} + \varepsilon_{it} \qquad (3)$$

The use of differences controls for individual effects in the levels of these performance metrics. Equation (3) is estimated using two-stage least squares with P_{it-2} as an instrument for ΔP_{it-1} due to the endogeneity of the lagged dependent variable in the first-differenced model (Anderson and Hsiao 1982; Arellano and Bond 1991; Nickell 1981).[10] The sign and significance of λ_2 is the basis for testing (H3)-(H5). In order to avoid a mechanical relationship with profit, I exclude online expense from the cost and profit calculations when estimating (3). Instead, I examine the economic significance of any cost impact of increased online use by using (3) to estimate the post-adoption change in cost and profit conditional on different levels of online use and attach the unit cost for an online transaction to that level of use. The standard errors allow for heteroskedacticity across customers as well as serial correlation within customers. I consider various extensions to equation (3) including instrumenting for change in adoption and change in post-adoption use with exogenous sources of variation defined at the market area level.

[10] The error term in equation (3) 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, with the magnitude of the bias decreasing in the time-series dimension of the panel and not the cross-sectional dimension (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.

4.3 Sample Used for Estimation of Equations (1)-(3)

Tests of H1-H5 require data on the post-adoption cumulative number of online banking transactions performed by each customer. This limits the sample I can use for analysis since I only observe online banking transactions for my sample of customers from September 2001 forward. In particular, I cannot include those customers who were online prior to August 2001. Since my tests exploit within customer variation, I use the following strategy to select the sample for analysis. First, I select the sample of all customers who adopted online banking between August 2001 and December 2001 and for whom I have at least 6-months pre-adoption, and 6-months post-adoption data[11]. This yields 20,649 adopters. Next, I take a random sample of 25,000 customers who are never online during any point in the sample period. These two groups constitute the sample used for estimation of (1)-(3). These 25,000 "offline" customers never "switch" to online and, hence, serve as a control group in the estimation of (1)-(3) in the sense that the coefficient on *USE* will pick up the effects of post-adoption online banking use on transaction behavior and financial performance relative to this group.[12] I discuss alternative research designs, and the robustness of my results to them, in a later section.

4.4 Retention (H6)

I test (H6) by using probit regression to estimate the following model cross-sectionally on the full sample of 525,864 customers:

$$\Pr(RETAIN_i = 1 | .) = \gamma_0 + \gamma_1 ONLINE_i + \gamma_2 TENURE_i + \gamma_3 AGE_i + X_i\beta \quad (4)$$

[11]In the pre-adoption period, I require only that these customers appear in the sample for at least 6 months prior to adoption and have data on the number of transactions in offline channels (branch, ATM, VRU, and call center), COST, REV, PROFIT, and NPROD. Data on number of online transactions is irrelevant in the pre-adoption period, since customers that have not adopted online banking cannot perform transactions in this channel.

[12] I chose a random sample of 25,000 rather than including all offline customers for computational tractability. Inclusion of all offline customers would have resulted in 5,880,583 additional observations (334,124 offline customers x 17.6 observations per customer on average) yielding a total of 6,248,294 observations.

RETAIN is an indicator variable that takes a value of 1 if a customer as of May 31, 2001 remains with the bank as of May 31, 2002. *ONLINE* is an indicator denoting whether or not the customer is an online banking customer as of May 31, 2002. The sign and significance of γ_1 is the basis for testing (H6). All control variables are measured as of May 31, 2002. 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 (Reicheld 1996). *AGE* is included to control for differences among age groups in the propensity to remain with the bank.[13] X_i is a vector of further control variables. I consider several specifications with additional controls for number of accounts held (NPROD), balances in those accounts (BALANCE), and a full set of market area dummies to control for geographic characteristics which may be systematically related to retention such as branch and ATM density within a customer's market area. To address potential self-selection issues, I also estimate a linear version of (4) using two-stage least squares with variables representing high-speed Internet access in a customer's zip code serving as instruments for the online indicator.

5. Results

5.1 Summary Statistics

Panel A of Table 3 contains summary statistics on transactions across channels for online and offline customers. Interestingly, online customers tend to transact more through all offline channels. For example, the median number of total offline transactions per month for online customers is 5 compared to 3 for offline customers.

Panel B of Table 3 shows summary statistics on total revenue, customer profitability, balances, and other customer characteristics. Total revenue and estimated profitability vary

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

widely. Total monthly profit and revenue ranges from well below zero[14] to close to $400,000, reflecting customers with extremely negative or positive balances. Simple comparisons of means and medians between online and offline customers reveals that online customers tend to be younger, have less tenure with the bank, hold more deposit accounts, and most interestingly, tend to have higher mean and median balances, revenue, and profitability than offline customers.

5.2 Substitution Effect (H1)

Before discussing tests of (H1) in detail, I begin with a few observations from Figures 1a and 1b. These figures plot the mean number of transactions by channel for adopters during September 2001 along with the mean number of transactions by channel for customers who were online during the entire sample period, and the mean number for those who were offline for the whole period. In these figures, channels are grouped into offline "self-service" (ATM and VRU) and offline "assisted-service" (branch and call center) channels. I have segmented the sample into four groups: those who adopt and do not use the channel in the subsequent 9 months; those who adopt and use the channel at least once; those who are always offline; and those who are always online. Figure 1a shows that relative to all groups, there appears to be substitution away from other self-service channels upon adoption and use of the online channel by active adopters. When examining Figure 1b, there appear to be no substantial changes in transaction behavior in "assisted service" channels. While there appears to be a "hill" at the adoption 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 1a and 1b also demonstrate

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[14] Negative revenue denotes a customer with an aggregate negative balance in all of his/her accounts. Negative revenue on an overdrawn account reflects the fact that banks are essentially providing customers a loan, with an effective interest rate equal to the banks net-interest spread, while the balance remains below zero and the account remains open.

persistent differences in transaction behavior over time between offline customers and all groups of online customers (adopters and always on).

Table 4 shows results from estimation of equation (1). The only channel that shows a relatively large post adoption substitution effect is the VRU. To benchmark this effect, consider a hypothetical customer who adopts during August 2001. Conditional on using the online channel at least once, the mean number of online banking transactions per month is approximately 10, resulting in average cumulative use of 100 by the end of the sample period 10 months later. The estimates of the substitution effect for the VRU suggest that monthly VRU transactions for this hypothetical customer will be 39% lower on average[15]. There appears to be small rates of substitution from both the call center and the ATM. Interestingly, branch transactions show a net increase rather than substitution. For the same hypothetical customer considered for the VRU example, these estimates suggest a reduction of 7% and 6% for ATM and call center transactions respectively and an *increase* of 1% in branch transactions. The net effect of these results is an approximate 14% reduction in total offline transactions.

To examine the sensitivity of these results to controlling for pre-adoption trends in transaction behavior, results from estimation of a dynamic modification of equation (1) are presented in Table 5. Results are substantively similar to those in Table 4. Considering the hypothetical customer in the previous example, the estimated coefficient on *USE* in Table 5 suggests a decrease in monthly VRU transactions of 33%, an increase in monthly branch transactions of 1%, a decrease in monthly ATM transactions of 4%, a decrease in call center transactions of 6%, altogether resulting in a decrease of about 10% in total offline transactions.

5.3 Volume Effect (H2)

[15] The post-adoption substitution effect conditional on cumulative online banking use of 100 transactions can be computed as $100\text{x}[\exp(\beta_2\text{x}100)-1]$

Figure 1c is similar to Figures 1a and 1b, but plots *total* transaction volume in all channels (including the online channel) for each subsample. Because I only observe online usage for Sep. 2001 forward, the total number of transactions for the "Always On" subsample is only plotted from this point forward. This figure suggests a substantial volume effect from going online for active adopters: the mean number of total transactions almost doubles from approximately 9 to close to 18 for active adopters.

Column 1 of Table 6 shows the results from estimation of equation (2). These estimates suggest that, on average, transaction volumes increase by about 60% after adoption of the online channel. Column 2 of Table 6 estimates a dynamic version of equation (2) and shows a post-adoption increase attributable to adoption of online banking of approximately 39%.

5.4 Cost (H3), Revenue (H4), and Profit (H5)

Table 7 shows results from the estimation of equation (3). Consistent with the substitution effects documented in section 5.2, column 4 of Table 7 shows that total cost excluding the cost of online transactions is decreasing in the use of the online channel as customers substitute some transactions away from channels that are estimated to be relatively more costly (H3). However, column 3 of Table 7 shows that total revenue is also *decreasing* in the use of the online channel (H4). Even without considering the cost of online transactions, column 5 of Table 4 shows that the reduction in revenue more than offsets the reduction in cost leading to a net reduction in customer profitability (H5). Columns 1 and 2 of Table 7 show the results of estimating Equation (3) separately for net-interest and fee revenue. These results suggest that the decline in revenue comes largely from fees rather than net interest revenue.

While endogeneity is a potential issue in estimating equation (3), first differencing controls for many time constant variables that may be correlated with both financial performance and the decision to adopt online banking such as customer demographics and access to technology. However, this methodology does not control for the situation in which current shocks to performance generate future adoption of online banking. For example, unexpected fees from dropping below minimum balance requirements or overdrawing an account may encourage customers to take future actions, such as adopting online banking, to more actively manage their finances. In this situation, endogeneity arises because past shocks in performance are correlated with future adoption and use of online banking. To address these potential endogeneity issues, I estimate equation (3) instrumenting $\Delta ADOPT$ and ΔUSE with the change in online penetration rates in a customer's market area and the interaction of this change with *HSA*, a time constant variable denoting the availability of high-speed internet access in the customer's zip code. Research has shown that banking customers make decisions about adopting online banking based on reports of friends and relatives (Kennickel and Kwast 1997). Prasad and Harker (2000) interpret this source of influence on decisions to adopt online banking as a form of network externality: the larger the size of the network (number of customers adopting online banking), the larger the effects of such a network on the adoption decision. This suggests using online penetration rates in a customer's market area as an instrument for the adoption decision. I include the interaction with *HSA* since these "network" effects may have a larger impact on the customer's decision of how extensively to utilize online banking in areas for which access to the convenience of high speed internet service is more likely.[16] Table 8 shows the results of re-estimating equation (3) using these instruments. The overall estimated impact of online use on profit is similar but slightly more negative. The primary difference is that net interest revenue is no longer significantly related to the use of online banking.

5.5 Economic Significance

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[16] The first differencing methodology precludes the use of time constant variables as instruments. Ideally, if *HSA* were observed monthly, I would simply instrument directly with this variable. However, since *HSA* is time constant,

To illustrate the economic significance of the estimated impact of online adoption and use on cost, revenue, and profit, I consider a typical customer adopting online banking during August 2001. Among customers adopting during this month, those who subsequently used the channel conducted an average of approximately 10 online transactions per month. This results in a cumulative volume of 100 online banking transactions by the end of the sample period 10 months later. Table 9 reports the estimated percentage changes in revenue, cost, and profit for this hypothetical customer. The percentage changes are taken relative to the pre-adoption mean values of revenue, cost, and profit for the sample of customers that adopted during August 2001 and performed at least one online banking transaction over the subsequent 10 months. Under the assumption of a zero unit cost for all online transactions, revenue decreases by 7.5%, cost decreases by 6.6%, and estimated profitability decreases by 7.7%. Assuming National's estimated unit costs for online transactions yields an *increase* in costs of 0.8% and a decrease in profit of 10.3%[17]. At National's estimated unit costs for online transactions, the cost increase from the volume effect (H2) appears to more than offset the small decrease in costs from the substitution effect (H1) yielding a small net increase in estimated customer level costs.

5.6 Retention (H6)

Column 1 of Table 10 shows the results from estimating equation (4). After controlling for tenure and age, online customers are estimated to be approximately 4.2% more likely than offline customers to remain with the bank one year later. Including NPROD and BALANCE as additional controls in Table 10, column 2, lowers the conditional difference in the probability of

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I rely on the interaction of this variable with online penetration rates to serve as an additional instrument.

[17] These estimates take transaction mix into account. For example, for the hypothetical customer considered for this analysis, of the 10 online transactions performed per month, 1 is an electronic bill payment, 4 are balance transfers, and the remaining 5 are simple account inquiries. Each of these transactions has a different estimated unit cost from National's activity based costing system. Due to confidentiality, I cannot disclose the unit costs for each transaction type.

retention to 2.8%. Each additional account is associated with a 6.8% increase in the probability of retention. However, balances held in those accounts are not significantly related to retention. This suggests that the propensity of online banking customers to hold more accounts is partially responsible for differences in retention rates between online and offline customers. While difference χ^2 tests suggest that market area indicators are jointly significant ($p<0.0001$) in column 3 of Table 10, their inclusion does not substantially alter the coefficient on the online indicator. To benchmark the estimated coefficient on the online indicator, the unconditional probability of retention for all customers in the sample is 87.4% representing a customer attrition rate of 12.6%. The estimated coefficient of 2.8% represents a 22% (0.028/0.126) decrease in this attrition rate.

The documented increase in retention associated with the use of online banking 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 dummy in equation (4) is endogenous. I consider a linear version of equation (4)

$$RETAIN_i = \gamma_0 + \gamma_1 ONLINE_i + \gamma_2 TENURE_i + \gamma_3 AGE_i + X_i\beta + \varepsilon_i \quad (5)$$

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

To address this potential endogeneity, I estimate equation (5) using two-stage least squares with variables measuring the availability of high-speed Internet access serving as instruments for *ONLINE*. Specifically, due to the nature of the FCC data, I instrument the online dummy with a dummy indicating between 1 and 4 high speed internet access providers in a customer's zip code, a dummy indicating 4 or more providers, and the number of providers for customers in zip codes with 4 or more high speed internet access providers. These variables are expected to be determinants of the decision to use online banking since 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}). Each of these variables is significant ($p<0.01$) in the first stage regression with the probability of online use increasing in the number of high speed internet access providers. The first-stage R^2 is approximately 0.04, which is relatively large in the context of related consumer level studies in the banking industry (Hitt and Frei 2002; Gross and Souleles 2000).

I estimate (5) with and without NPROD and BALANCE as additional controls since these variables are potentially endogenous in the first-stage regression. I cannot include market area indicators as controls since the variables measuring high-speed Internet access are defined at the zip code level. Many market areas are comprised of a small number of zip codes, and in some cases a single zip code defines a market area. However, the results in column 3 of Table 10 demonstrate that inclusion of a full set of market area indicators has virtually no effect on the estimated *ONLINE* coefficient. The results from estimation of (5) via two-stage least squares are shown in columns 2 and 4 of Table 11. OLS estimates are included in columns 1 and 3 of Table 11 as benchmarks for the two-stage estimates and are largely consistent with the probit estimates in columns 1 and 2 of Table 10. The two-stage estimates of the *ONLINE* coefficient remain positive and significant suggesting that customer retention may be an important value driver for online banking.

5.6 Additional Analyses

The results in Tables 7 and 8 suggest that customer level revenue declines following the adoption and active use of online banking and that this decline is largely the result of a decline in fee-based revenue rather than net-interest revenue on balances. As discussed in the development of hypotheses (H1)-(H3), one possible explanation for these results is that online banking lowers transactions costs from the customer's perspective allowing more active account management. For example, customers may use the increased convenience of online banking to more actively monitor and manage their accounts and avoid fees associated with overdrafts and minimum balance requirements. In order to explore these issues more fully, I construct a subsample of customers with clear economic incentives to manage account balances, and I examine their behavior pre- and post- adoption of online banking. Specifically, starting with the sample of customers used for estimation of equations (1)-(3), I identify all customers who have a specific type of checking account for which I observe the minimum balance requirement.

National offers over 20 different retail checking, savings, and money market accounts. The contracts on some of these accounts specify a minimum balance requirement with a monthly service charge if the balance in the account falls below this minimum requirement at any point in the month. It is difficult to identify the minimum balance required for each account for each customer. Minimum balance requirements are often complex and can be specified in terms of combined balances across numerous account types. In addition, even within a particular account type, minimum balance requirements vary by state. For purposes of my analysis, I construct a subsample of customers with the most common checking account among accounts that specify a minimum balance requirement for avoiding fees. To isolate the effect of online banking on behavior with this account, I exclude customers who hold any other type of account over the entire sample period

Customers with these accounts have a clear incentive to maintain balances in excess of the minimum balance required in order to avoid incurring a relatively high monthly fee. However, this particular account type pays no interest on the customer's deposits providing a disincentive to maintain high balances. Transactions costs associated with monitoring and managing account balances may encourage customers to keep a "cushion" above the minimum requirement that they would not otherwise keep in the absence of such transactions costs. Alternatively, balances may fall below minimum requirements because transactions costs keep customers from more actively monitoring and managing their accounts to ensure that minimum balance requirements are met. To the extent that transactions costs associated with monitoring and managing account balances are important, and to the extent that a technology such as online banking lowers these transactions costs, we should see balances in these accounts moving "closer" to the minimum requirement after the adoption of online banking.

In this section, I use a simple event-study methodology to examine changes in balances held relative to the minimum balance requirement (*RELBAL*) around the adoption of online banking. Specifically, I convert time to event-time by specifying the month of adoption as the event date, and examine changes in *RELBAL* over a period of 6 months prior to adoption and 6 months after adoption of online banking. The subsample constructed for this analysis contains (1) 263 customers who adopted online banking between August 2001 and December 2001 and performed at least one online banking transaction in the subsequent 6 months after adoption (active adopters); (2) 282 customers who adopted online banking between August 2001 and December 2001 and did not perform any online banking transactions in the subsequent 6 months after adoption (inactive adopters); and (3) 549 customers who are never online banking customers at any point in the sample period (offline). The primary group of interest is the active adopter subsample. For comparative purposes, I treat inactive adopters and offline customers as control groups and examine changes in *RELBAL* for these subsamples as well.

Panel A of Table 12 shows descriptive statistics on mean and median *RELBAL* for each of these groups. On average, all groups hold balances in excess of the minimum required. Panel B of Table 12 suggests that there are no significant changes in mean *RELBAL* for any of the subsamples. However, when examining medians, it appears that median *RELBAL* lies just slightly below 1 for all time periods for the offline subsample. For the subsample of inactive adopters, median *RELBAL* lies well below 1 for all months. The pattern of median *RELBAL* for active adopters is particularly interesting. Median *RELBAL* for this subsample is approximately 1 six months prior to adoption, drops just below 0.9 over the next five months, begins to rise just after the month of adoption, and settles just above 1 six months after adoption. These patterns are illustrated in Figure 2. Panel B of Table 12 contains tests for median changes in *RELBAL* for each of these subsamples, where changes are taken both 1.) from 6 months prior to the event date to 1 month prior to the event date, and 2.) from 1 month prior to the event date to 6 months after the event date. The only median change that is significant at conventional levels ($p<0.10$) is the change from 1 month prior to adoption to 6 months after adoption for the subsample of active adopters. The difference in results when examining means and medians is likely the result of extreme high-balance customers.

Balances just below the minimum required will incur a relatively large fee, while balances maintained just above the minimum will not incur such a fee. At National's average net-interest spread for the type of account analyzed in this section, the increase in net-interest revenue associated with the median increase in *RELBAL* is approximately ¼ of the fee associated with falling below the minimum balance requirement. While the evidence is limited, these results provide some insights into at least one source of the decline in revenue documented in Tables 7 and 8. In particular, the results are consistent with the proposition that online banking lowers transactions costs and allows customers to more closely manage balances and avoid fees associated with minimum balance requirements.

5.7 Econometric and Model Specification Issues

In estimation of equations (1)-(3), I include number of accounts (NPROD) as a control variable. However, my specifications only allow for a contemporaneous effect of changes in NPROD. The adoption of new accounts may lead to changes in transaction behavior, cost, revenue, and profit over multiple future periods. To examine the sensitivity of my results to this issue, I excluded all customers who ever had a change in their portfolio of accounts held over the entire sample period and re-estimated these models. Results (not tabulated) are substantively unchanged.

In estimation of equation (3), I use unscaled changes in revenue and profit as dependent variables. There is wide variability among customers in the size of these performance metrics due partially to customers holding extreme balances. Unfortunately, there is no natural scale variable for these metrics. Balances, revenues, and profits can all be negative. While reported standard errors are robust to heteroskedacticity, to the extent that customers with the largest values of these metrics also have the largest changes in these metrics, my coefficient estimates may be biased. To examine the robustness of my results, I excluded lagged performance and re-estimated equation (3) using fixed effects on the changes in performance (not tabulated). This methodology accounts for any customer specific trends in *changes*. In particular, this methodology should control for any customer-specific "size" effect in the changes in performance. While results are similar, the estimated negative effect of online banking use on revenues is slightly larger in magnitude. As an additional robustness check, I also re-estimated equation (3) after dropping customers who ever had changes in profit or revenue in the top 2% in magnitude at any point in the sample period. Again results are very similar.

Finally, endogeneity is an issue in all of my tests. While I have tried to deal with this issue through instrumental variables techniques, my results are subject to assumptions on the validity of the chosen instruments.

6. Discussion and Conclusions

Firms are increasingly implementing technologies, such as the internet, vendor managed inventory, and electronic data interchange with the goals of reducing cost, increasing revenue, and increasing customer retention rates. In this paper, I investigate one technology, online banking, which many firms are deploying with the aim of simultaneously achieving benefits across all three of these performance measures.

I 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 voice response unit) with little or no substitution from more costly service delivery channels (branch and staffed call center); (2) a significant increase in total transaction volume; (3) an increase in estimated cost-to-serve resulting from the combination of (1) and (2); and (4) a reduction in revenues consistent with customers using online banking to more closely manage balances and avoid fees associated with minimum balance requirements. These effects combine to yield a net reduction in estimated short-term customer profitability. However, I find that use of online banking is associated with higher customer retention rates.

These findings have a number of managerial implications. First, the lack of substitution from the most costly service delivery channels suggests that cost reduction through the displacement of traditional channels is not likely to be a major source of value for online banking as has been assumed by much of the banking industry (Christiansen 2001). Moreover, the substantial increase in volume of transactions suggests that banks must carefully consider the cost of providing service in this channel when taking actions to actively encourage customer adoption of online banking. At my research site, increased volume in the online channel more than offsets any reduction in estimated customer level expenses due to substitution of transactions from more costly service delivery channels.

More generally, the finding of a lack of substitution coupled with an increase in the volume of service consumption provides support for the notion that traditional costing methods alone may not be appropriate for decision making in settings where customer interaction is important in determining cost. Estimates of the marginal cost of providing service using a given technology must be considered in conjunction with the likely effects of that technology on overall service consumption. 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 cost across all delivery channels.

Second, while the provision of online banking services may be a competitive necessity, many banks, including my 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 (Hitt et al. 1999). The results in this paper suggest that actions taken to migrate customers to the online banking channel may harm short-term profitability through increased service consumption and more efficient money management by customers. However, online banking may lead to long-term benefits in the form of higher retention rates. Strategies aimed at deploying online banking as a tool to target a smaller set of profitable customers for retention may be more beneficial than strategies which allocate resources towards the active migration of a large segment of marginally profitable to unprofitable customers in the hopes that active use of online banking will make them more profitable (Frei and Hitt 2002).

These findings highlight the potential importance of a “business model” or “balanced-scorecard” approach in the design of performance measurement systems (Kaplan and Norton 1996; Ittner and Larcker 1998) for evaluating investments in service delivery technologies. While customers may capture the gains from new service delivery technologies in the short-term, these gains to the customer may translate into higher customer satisfaction and, in turn, higher customer retention rates leading to potential long term gains in financial performance. Performance measurement systems for evaluating these technologies should explicitly acknowledge these potential tradeoffs.

The costs considered in this paper are unit transactions costs estimated from National’s activity based costing system. As such, all tests performed in this study with respect to cost implicitly assume that resources will be adjusted upward or downward over the medium to long term in response to changes in transaction activity. In ongoing research for my dissertation, I am extending the cost-analysis in this paper to examine the effect of growth in online penetration rates on short, medium, and long-term adjustments to the supply of capacity in the branch and ATM distribution channels.

References

Anderson, S. (1995), “Measuring the Impact of Product Mix Heterogeneity on Manufacturing Overhead Cost,” The Accounting Review, 70(4): 363-388.

Anderson, S. and W. Lanen (2002), “Using Electronic Data Interchange (EDI) to Improve the Efficiency of Accounting Transactions,” The Accounting Review, 77(4): 703-730.

Anderson, T.W. and C. Hsiao (1982), “Formulation and Estimation of Dynamic Models Using Panel Data,” Journal of Econometrics, 18: 47-82.

Arellano, M. and S. Bond (1991), “Some Tests of Specification for Panel Data: Monte Carlo Evidence and an Application to Employment Equations,” Review of Economic Studies, 58: 277-297.

Balakrishnan, R., T. Gruca and D. Nath (1996), “The Effect of Service Capability on Operating Costs: An Empirical Study of Ontario Hospitals,” Contemporary Accounting Research, 13(1): 177-207.

Balakrishnan, R., M. Petersen and N. Soderstrom (1999), “What Drives Staffing in Therapy Clinics,” Working Paper.

Banker, R., G. Potter and R. Schroder (1993), “An Empirical Study of Manufacturing Overhead Cost Drivers,” Journal of Accounting and Economics, 19:115-137.

Becker, R. and V. Henderson (2000), “Effects of Air Quality Regulations on Polluting Industries,” The Journal of Political Economy, 2: 379-421.

Blundell, R., R. Griffith, and F. Windmeijer. (2002) “Individual Effects and Dynamics in Count Data Models,” The Journal of Econometrics 108: 113-131

Campbell, D. and F. Frei (2002), “Explaining Differences in Customer Profitability: Demographics or Endogenous Customer Characteristics,” Harvard Business School Working Paper 02-048.

Chase, R. (1978), “Where does the customer fit in a service operation?” Harvard Business Review, 56(6): 138-139.

Chase, R. (1981), “The customer contact approach to services: Theoretical bases and practical extensions,” Operations Research, 29(4): 698-706.

Chamberlain, G. (1992), “Comment: Sequential Moment Restrictions in Panel Data,” Journal of Business and Economic Statistics, 10: 20-26.

Chen, P. and L. Hitt, (2002), “Measuring switching costs and the determinants of customers retention in Internet-enabled businesses: A study of the online brokerage industry,” Information Systems Research, 13(3): 255-276.

Christiansen. H. (2001). “Electronic Finance: Economic and Institutional Factors,” OECD Financial Affairs Division Occasional Paper, No. 5.

Clemons, E., L. Hitt, B. Gu, M. Thatcher and B. Weber (2002), “Impacts of e-commerce and enhanced information endowments on financial services: A quantitative analysis of transparency, differential pricing, and disintermediation,” Journal of Financial Services Research, 22(1/2): 73-90.

Clemons, E. K. and M. E. Thatcher (1997), "Capital One." In Proceedings of the 30th Hawaii International Conference on Systems Sciences, Maui, Hawaii.

Cohen-Kulp, S. (2002), "The Effect of Information Precision and Information Reliability on Manufacturer-Retailer Relationships," The Accounting Review, 77(3): 653-677.

Cooper, R. (1999). Introduction to Cost Management in "Cost Management for Service Industries," Edited by J.B. Edwards. Boston: Warren, Gorham, & Lamont.

Cooper, R. and R. Kaplan (1999). The Design of Cost Management Systems. New Jersey. Prentice Hall.

Datar, S., S. Kekre, T. Mukopadyay and K. Srinivasan (1993), "The Simultaneous Estimation of Cost Drivers," The Accounting Review, 68: 602-614.

Fitzsimmons, J. and M. Fitzsimmons (2001), Service Management: Operations, Strategy, and Information Technology. New York: McGraw-Hill Inc.

Foster, G. and M. Gupta (1990), "Manufacturing Overhead Cost Driver Analysis," Journal of Accounting and Economics, 12: 309-337.

Foster, G., M. Gupta and L. Sjoblom (1995), "Customer Profitability Analysis: Challenges and New Directions," Journal of Cost Management.

Frei, F. and P. Harker (2000), "Value Creation and Process Management: Evidence from Retail Banking," in Creating Value in Financial Services, edited by E. Melnick, P. Nayyar, M. Pinedo and S. Seshadri. Kluwer Academic Publishers.

Gross, D. and N. Souleles (2000), "Consumer Response to Changes in Credit Supply: Evidence from Credit Card Data," Wharton Financial Institutions Center Working Paper 01-10.

Hausman, J., B.H. Hall, and Z. Griliches. (1984). "Econometric Models for Count Data with an Application to the Patents-R & D Relationship," Econometrica, 52(4): 909-938.

Hitt, L. and F. Frei (2002), "Do Better Customers Utilize Electronic Distribution Channels? Evidence from PC Banking," Management Science, 48(6): 732-748.

Hitt, L., F. Frei and P. Harker (1999), "How Financial Firms Decide on Technology," in Brookings Wharton Papers on Financial Services, 1999, pp. 93-146, edited by Robert E. Litan and Anthony M. Santomero. Washington, D.C.: Brookings Institution.

Hoffman, K. (2002), "Online Banking Aligns Practices: Now that the initial online flurry has subsided, Web-based banks are looking at ROI potential," Bank Technology News, March: 26-29.

Ittner, C. and D. Larcker (1998), "Innovations in Performance Measurement: Trends and Research Implications," Journal of Management Accounting Research, 6: 205-238.

Ittner, C. and D. Larcker (2001), "Assessing Empirical Research in Managerial Accounting: A Value-Based Management Perspective," Journal of Accounting and Economics, 32: 349-410.

Ittner, C. and J.P. MacDuffie (1995), "Explaining plant-level differences in manufacturing overhead: Structural and executional cost drivers in the world auto industry," Production and Operations Management, 4: 312-334.

Kaplan, R.S. and V. G. Narayanan. (2001) "Measuring and Managing Customer Profitability," Journal of Cost Management (September/October): 5-15.

Kaplan, R. and D. Norton (1992), "The balanced scorecard – Measures that drive performance," Harvard Business Review, 70(1): 71-79.

____ and ___ (1996), The Balanced Scorecard: Translating Strategy into Action. Boston, MA: Harvard Business School Press.

____ and ___ (2000), The Strategy Focused Organization. Boston, MA: Harvard Business School Press.

Kennickel, A.B. and M.L. Kwast. (1997). Who Uses Electronic Banking? Results from the 1995 Survey of Consumer Finances," Proceedings of the Annual Conference on Bank Structure and Competition, Federal Reserve Bank of Chicago, May 1997

McQuivey, J., K. Delhagen, K. Levin and M. Kadison (1998), "The Forrester Report: Retail's Growth Spiral," 1(8).

Nickell, S. (1981), "Biases in Dynamic Models with Fixed Effects," Econometrica, 49: 1417-1426.

Online Banking Report. (2000). "Internet Banking by the Numbers: Channel Usage: Online Bankers vs. Offline Bankers."

Parthasarathy, M. and A. Bhattacherjee (1998), "Understanding Post-Adoption Behavior in the Context of Online Services." Information Systems Research (December).

Prasad, B. and P. Harker (2000), "Pricing Online Banking Services Amid Network Externalities," IEEE Proceedings of the 33rd Hawaii International Conference on System Sciences.

Reicheld, F. (1996). The Loyalty Effect: The Hidden Force Behind Growth, Profits, and Lasting Value. Boston, MA: Harvard Business School Press.

Rust, R., V. Zeithaml and K. Lemon (2000). Driving Customer Equity: How Customer Lifetime Value is Reshaping Corporate Strategy. New York, NY: The Free Press.

Shank, J. and V. Govindarajan, (1994). Strategic Cost Management. New York, The Free Press.

Shevlin, R., R. Graeber, J. Sweeney and T. Watson (2002), "The Forrester TechStrategy Report: Online Banking Metrics: Best Practices," April 2002.

Steiner, T. and D. Teixeira (1990). Technology in Banking. New York, Irwin.

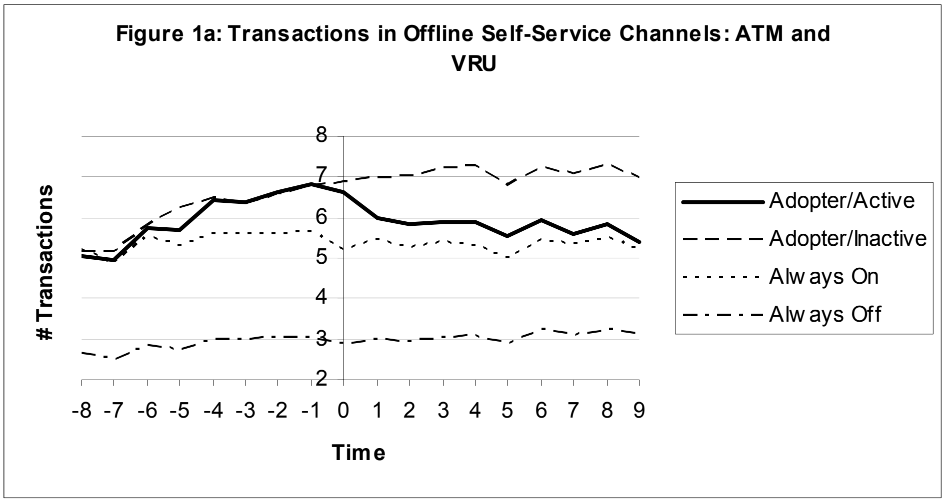
Stoneman, B. (1999), "Mixed Signals," Banking Strategies, 75(6): 32-38.

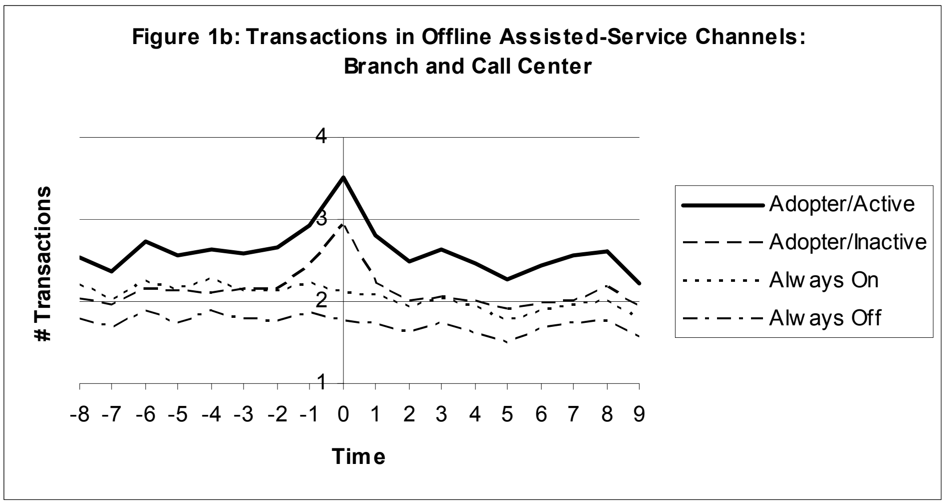
Stoneman, B. (2001), "Rationale for Online Banking Starts to Shift," American Banker, (March 12), p. 6A.

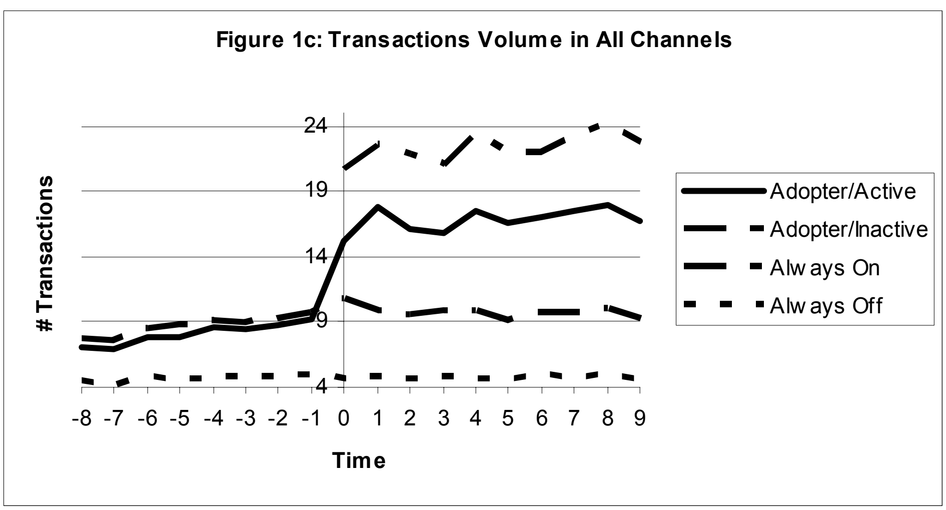
Varian, H. and C. Shapiro (1998). Information Rules. Boston, HBS Press.

Wooldridge, J. (2000), "The Initial Conditions Problem in Dynamic, Nonlinear Panel Data Models With Unobserved Heterogeneity," Michigan State University Working Paper.

Wooldridge, J. (2002). Econometric Analysis of Cross-Section and Panel Data. Cambridge, MA: The MIT Press.







Each figure shows the mean number of transactions through each set of channels for customers that adopted during September 2001 - "0" in each graph corresponds to September 2001. Additionally, each graph shows the mean for customers who were online for the entire sample period (Always On) and customers who were never online during any month in the sample period (Always Off). Total transactions for "Always On" customers are shown only for month "0" onwards since I only observe online transactions for September 2001 and later. The "Adopter/Inactive" sample represents customers who adopted the channel but did not transact through it in the subsequent 9 months. The "Adopter/Active" sample represents customers who adopted the channel and transacted at least once in the subsequent 9 months.

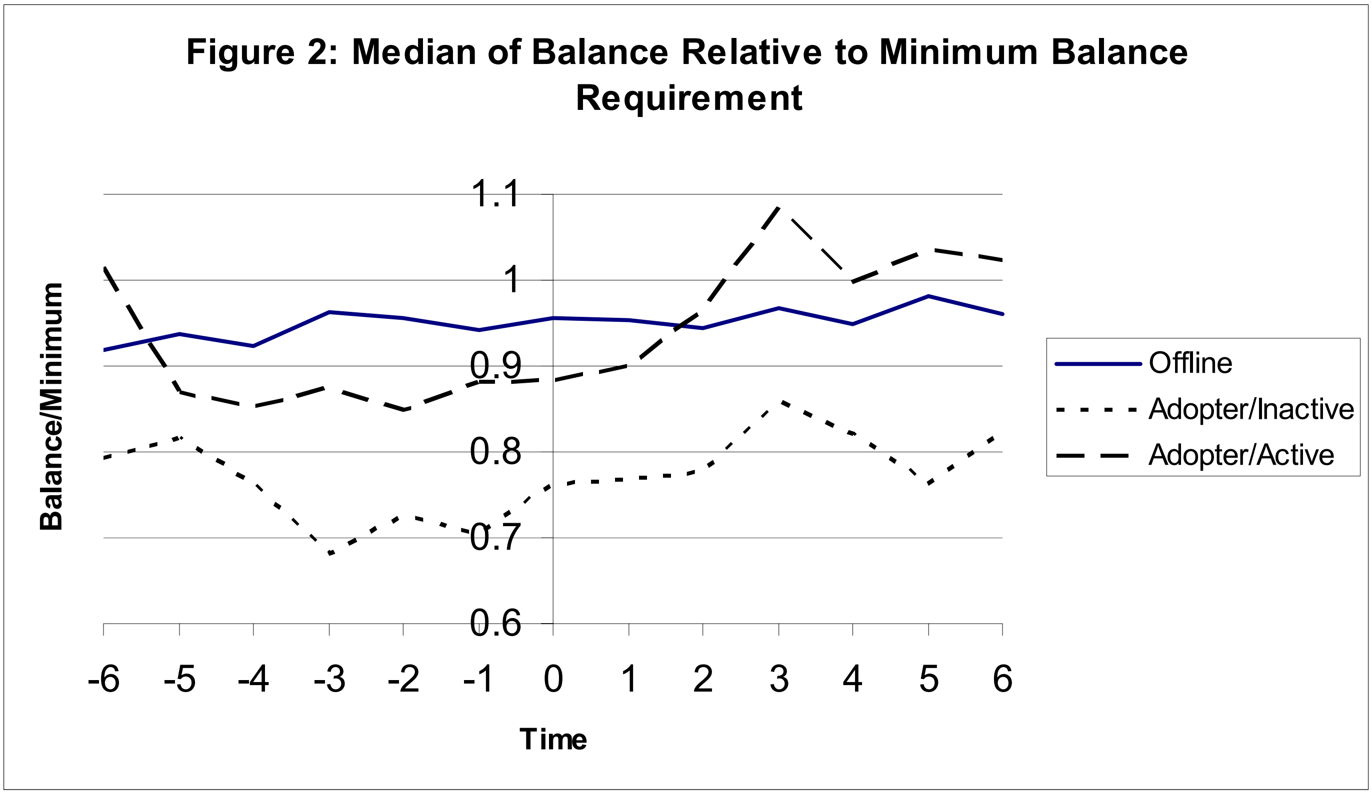


Figure 2 plots the median of average daily balances relative to the minimum balance required to avoid a monthly service fee for 6-months prior to adoption of online banking and 6-months post-adoption. The data in this figure is from a subset of customers with a specific type of checking account for which the minimum balance requirement is known. Time represents event time in months and '0' corresponds to the month of customer adoption of online banking. The figure contains separate plots for (1) customers who adopted online banking and performed at least one online banking transaction in the subsequent 6-months after adoption (Adopter/Active), (2) customers who adopted online banking and did not perform any online banking transactions in the subsequent 6-months (Adopter/Inactive), and (3) customers who were never online banking customers over the entire sample period (Offline).

Table 1: Distribution of Transactions by Channel – May 2001

Branch	% Txn's	Cumulative %
Deposit	59.41%	59.41%
Cash Check	27.20%	86.62%
Withdrawal	8.28%	94.90%
Purchase	3.19%	98.09%
Verify Funds	1.69%	99.78%
Miscellaneous	0.22%	100.00%
ATM		
Withdrawal	56.43%	56.43%
Deposit	18.53%	74.96%
Balance Inquiry	14.62%	89.58%
Incompleted Transaction	4.25%	93.83%
Miscellaneous	4.10%	97.93%
Transfer	2.07%	100.00%
Online		
Query History	49.59%	49.59%
View Basic Account Information	39.71%	89.31%
Payment	6.09%	95.40%
Transfer	4.00%	99.39%
Download Financial Information	0.61%	100.00%

Table 1 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 May 2001. Due to data limitations, I cannot provide a similar breakdown for either of the phone channels (VRU or call center).

Table 2: Estimated Unit Cost for Balance Transfers by Channel – May 2001

Channel	Estimated Per Transaction Cost
Branch*	1
Call Center (Live Agent)	0.94
ATM	0.31
Voice Response Unit (VRU)	0.18
Online	0.09

*Cost of branch transaction normalized to be 1

Each unit cost in Table 1 reflects the estimated unit cost of performing a balance transfer in each channel. This data is provided only to illustrate the magnitude of estimated cost differences across channels. The profitability data used in the paper includes a cost component based on the different unit costs for each type of transaction within each channel.

Table 3: Summary Statistics by Online Status
Sample Size as of May 2001: Total=525,864 (100%), Online=149,689 (28.5%)
Summary Statistics are for Full Sample Pooled Over 18 Months from Jan. 2001-Jun. 2002

Panel A: Transactions by Channel	% Transacting	Mean	Median	Std. Dev.	10%	90%	Min.	Max
Total Offline Transactions								
Offline	70.1	5.84	3	8.15	0	16	0	196
Online	87.1	7.56	5	8.40	0	17	0	262
Branch Transactions								
Offline	48.0	1.69	0	2.73	0	5	0	87
Online	51.0	1.74	1	2.73	0	5	0	94
ATM Transactions								
Offline	41.8	2.57	0	5.04	0	8	0	150
Online	69.4	4.00	2	5.26	0	10	0	136
Call Center Transactions								
Offline	11.8	0.23	0	0.89	0	1	0	65
Online	16.8	0.34	0	1.15	0	1	0	113
VRU Transactions								
Offline	23.3	1.35	0	4.10	0	4	0	151
Online	25.6	1.48	0	4.47	0	4	0	199

Summary statistics are over customer-month observations. Hence, % transacting reflects the proportion of customer-month's with non-zero transactions in a given channel.

Panel B: Revenue, Profit, and other Customer Characteristics	Mean	Median	Std. Dev.	10%	90%	Min.	Max
Revenue							
Offline	34.3	14.1	392.7	0.39	78.5	-1,603	395,556
Online	43.3	23.8	140.4	3.4	95.7	-2,643	59,336
Profit							
Offline	26.9	6.9	392.5	-3.7	114.3	-1,645	395,543
Online	33.5	14	139.8	-4.8	83.2	-2,652	59,334
Number of Accounts							
Offline	1.42	1	0.63	1	2	1	12
Online	1.67	2	0.73	1	2	1	23
Average Daily Balance							
Offline	6,976	1,138	24,785	53	14,787	-47,681	2,591,557
Online	7,134	1,468	30,894	158	14,360	-101,945	4,909,554
Tenure (years)							
Offline	8.5	5.5	8.7	0.7	21.2	0	90.8
Online	6.0	4.0	6.2	0.6	14.1	0	63.8
Age							
Offline	43.3	42.8	21.1	15.5	73.1	0	99.4
Online	37.4	35.5	13.4	21.6	55.4	0	98.4

Revenue: includes net interest revenue on checking and savings account balances as well fee revenue resulting from service charges, minimum balance requirements, overdrafts, etc…
Profit: includes total revenue less unit costs associated with transactions multiplied by transaction volume.
Number of Accounts: includes number of retail deposit accounts including checking, savings, and money market accounts.
Average Daily Balance: Cumulative daily balance divided by the number of days in the month.
Tenure: Length of relationship with National as of May 2001 defined as the number of years since opening the first retail deposit account.
Age: Customer age as of May 2001. Age is recorded as less than 18 for some customers due to parents opening custodial accounts in the name of their children.

Table 4: Substitution Between Offline and Online Service Channels. Fixed Effects Poisson Regression. Sample includes 20,649 online adopters during Aug. 2001 – Dec. 2001 and a random sample of 25,000 customers who remained offline over the entire sample period.
(Standard errors in Parentheses)

	All Offline Channels	Branch	ATM	Call Center	VRU
ADOPT	0.15**	0.16**	0.03**	0.77**	0.16**
	(0.002)	(0.005)	(0.004)	(0.01)	(0.005)
USE	-0.0014**	0.0001**	-0.0007**	-0.0006**	-0.005**
	(0.00002)	(0.00003)	(0.00002)	(0.0001)	(0.00004)
NPROD	0.24**	0.28**	0.20**	0.58**	0.20**
	(0.002)	(0.003)	(0.0025)	(0.0007)	(0.003)
Time Indicators	***	***	***	***	***
Log Likelihood	-1,726,428	-857,605	-1,046,460	-328,841	-748,830
# of Observations	737,700	608,967	520,402	509,415	509,415

*, ** Significant at p<0.05 and p<0.01 respectively
*** Jointly Significant, p<0.001 using Chi-Squared test
Sample sizes for regressions will differ since customers who never use a given channel in any month over the sample period will drop out of estimation for that channel.

Adopt = 1 for month of adoption, 0 otherwise.
Use = Post adoption *cumulative* number of transactions through the online channel, 0 for months prior to adoption, non-adopters, and adopters who do not use the channel.
NPROD = Number of retail deposit products held by customer *i* at time *t*.
Table 4 estimates the following model using the conditional fixed-effects Poisson model due to Hausman, Hall, and Griliches (1984):

$$E(y_{it}) = \exp(\beta_0 + \alpha' time_t + \beta_1 ADOPT_{it} + \beta_2 USE_{it} + \beta_3 NPROD_{it} + \gamma_i)$$

where y_{it} denotes the number of transactions through a given channel for customer i at time t, γ_i is the customer-specific fixed effect, and $time_t$ is a vector of aggregate time dummies.

Table 5: Substitution Between Offline and Online Service Channels Controlling for Lagged Transaction Volume. Random Effects Poisson Regression. Sample includes 20,649 online adopters during Aug. 2001 – Dec. 2001 and a random sample of 25,000 customers who remained offline over the entire sample period.
(Standard errors in Parentheses)

	All Offline Channels	Branch	ATM	Call Center	VRU
ADOPT	0.14**	0.15**	0.03**	0.80**	0.14**
	(0.003)	(0.005)	(0.004)	(0.01)	(0.005)
USE	-0.001**	0.0001*	-0.0004**	-0.0006**	-0.004**
	(0.00002)	(0.00003)	(0.00002)	(0.00007)	(0.00004)
NPROD	0.19**	0.24**	0.15**	0.55**	0.16**
	(0.002)	(0.003)	(0.003)	0.007)	(0.003)
y_{t-1}	0.018**	0.04**	0.026**	0.04**	0.03**
	(0.00006)	(0.0003)	(0.0001)	(0.0007)	(0.0001)
y_0	0.09**	0.31**	0.20**	0.58**	0.22**
	(0.0009)	(0.003)	(0.003)	(0.01)	(0.005)
Time Indicators	***	***	***	***	***
Log Likelihood	-1,805,428	-971,063	-1,136,207	-413,078	-809,367
# of Observations	760,325	760,325	760,325	760,325	760,325

*, ** Significant at p<0.05 and p<0.01 respectively
*** Jointly Significant, p<0.001 using Chi-Squared test

Adopt = 1 for month of adoption, 0 otherwise.
Use = Post adoption *cumulative* number of transactions through the online channel, 0 for months prior to adoption, non-adopters, and adopters who do not use the channel
NPROD = Number of retail deposit products held.
$\mathbf{y_{t-1}}$ **=** One month lag of the Number of transactions in a given channel.
$\mathbf{y_0}$ **=** Number of transactions in a given channel for the initial month the customer appears in the sample.

Table 5 estimates the following model using the conditional maximum likelihood approach of Wooldridge (2002, pp. 677-678):

$$E(y_{it}) = \exp(\beta_0 + \rho_0 y_{i0} + \rho_1 y_{it-1} + \alpha' time_t + \beta_1 ADOPT_{it} + \beta_2 USE_{it} + \beta_3 NPROD + \gamma_i)$$

where y_{it} denotes the number of transactions through a given channel for customer i at time t, y_{i0} denotes the first observation on y_{it} for each customer, γ_i is the customer-specific fixed effect, and $time_t$ is a vector of aggregate time dummies.

Table 6: Volume Effect of Online Channel. Dependent Variable is Total Transaction Volume through All Channels (Including Online). Sample includes 20,649 online adopters during Aug. 2001 – Dec. 2001 and a random sample of 25,000 customers who remained offline over the entire sample period.

	(1)	(2)
ADOPT	0.39**	0.38**
	(0.002)	(0.002)
POST	0.47**	0.33**
	(0.002)	(0.002)
NPROD	0.24**	0.20**
	0.001)	(0.0016)
y_{t-1}		0.014**
		(0.00003)
y_0		0.084**
		(0.0009)
Time Indicators	***	***
Log Likelihood	-2,040,722	-2,071,153
# of Observations	740,828	760,325

*, ** Significant at p<0.05 and p<0.01 respectively
*** Jointly Significant, p<0.001 using Chi-Squared test

Adopt = 1 for month of adoption, 0 otherwise.
Post = 1 for all months after the initial month of adoption, 0 otherwise.
NPROD = Number of retail deposit products held.
$\mathbf{y_{t-1}}$ **=** One month lag of the Total number of transactions across all channels.
$\mathbf{y_0}$ **=** Total number of transactions across all channels for the initial month the customer appears in the sample.

Column 1 of Table 6 estimates the following model using the conditional fixed-effects Poisson model due to Hausman, Hall, and Griliches (1984):

$$E(y_{it}) = \exp(\alpha_0 + \delta' time_t + \alpha_1 ADOPT_{it} + \alpha_2 POST_{it} + \alpha_3 NPROD_{it} + \eta_i)$$

where y_{it} denotes the number of transactions through a given channel for customer i at time t, η_i is the customer-specific fixed effect, and $time_t$ is a vector of aggregate time dummies.

Column2 of Table 5 estimates the following model using the conditional maximum likelihood approach of Wooldridge (2002, pp. 677-678):

$$E(y_{it}) = \exp(\alpha_0 + \rho_0 y_{i0} + \rho_1 y_{it-1} + \delta' time_t + \alpha_1 ADOPT_{it} + \alpha_2 POST_{it} + \alpha_3 NPROD_{it} + \eta_i)$$

where y_{it} denotes the total number of transactions through all channels for customer i at time t, y_{i0} denotes the first observation on y_{it} for each customer, η_i is the customer-specific fixed effect, and $time_t$ is a vector of aggregate time dummies.

Table 7: Effects of Adoption and Use on Components of Customer Profitability. Sample includes 20,649 online adopters during Aug. 2001 – Dec. 2001 and a random sample of 25,000 customers who remained offline over the entire sample period.

	Net Interest Revenue	Fee Revenue	Total Revenue	Cost	Profit
Performance$_{t-1}$	0.59***	0.01**	0.03**	0.04***	0.03**
	(0.08)	(0.003)	(0.014)	(0.01)	(0.01)
ADOPT	-0.04	2.98***	2.99***	0.64***	2.42*
	(0.22)	(0.71)	(0.74)	(0.04)	(1.2)
USE	-0.005*	-0.027***	-0.028***	-0.007***	-0.022**
	(0.003)	(0.01)	(0.01)	(0.001)	(0.01)
NPROD	3.02***	4.97**	8.55***	3.87***	4.68*
	(0.44)	(2.4)	(2.50)	(0.05)	(2.50)
Time Indicators	+++	+++	+++	+++	+++
# of Observations	714,540	714,540	714,540	714,540	714,540

Standard errors in parentheses; *, **,*** Significant at p<0.10, p<0.05, and p<0.01 respectively
+++ Jointly Significant, p<0.001 using Chi-Squared test

Adopt = 1 for month of adoption, 0 otherwise.
Use = Post adoption *cumulative* number of transactions through the online channel, 0 for months prior to adoption, non-adopters, and adopters who do not use the channel.
NPROD = Number of retail deposit products held.
Performance$_{t-1}$ = One month lag of financial performance.
Table 7 estimates the following model:

$$\Delta P_{it} = \gamma'\Delta time_t + \rho\Delta P_{it-1} + \lambda_1 \Delta ADOPT_{it} + \lambda_2 \Delta USE_{it} + \lambda_3 \Delta NPROD_{it} + \varepsilon_{it}$$

time$_t$ denotes a full set of time dummies. ΔP_{it-1} is instrumented with the twice lagged level, P_{it-2}, in all specifications.

Table 8: Effects of Adoption and Use on Components of Customer Profitability. Instrumented with Market Area Variables. Sample includes 20,649 online adopters during Aug. 2001 – Dec. 2001 and a random sample of 25,000 customers who remained offline over the entire sample period.

	Net Interest Revenue	Fee Revenue	Total Revenue	Cost	Profit
Performance$_{t-1}$	0.53***	0.01***	0.03***	0.05***	0.03***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
ADOPT	0.22	1.91*	2.05*	0.28***	1.94
	(0.25)	(1.15)	(1.19)	(0.03)	(1.2)
USE	0.003	-0.048***	-0.041**	-0.011***	-0.028*
	(.003)	(0.02)	(0.02)	(0.001)	(0.016)
NPROD	2.82***	6.10***	9.85***	4.19***	5.38***
	(0.24)	(1.14)	(1.17)	(0.03)	(1.17)
Time Indicators	+++	+++	+++	+++	+++
	710,872	710,872	710,872	710,872	710,872

Standard errors in parentheses; *, **,*** Significant at $p<0.10$, $p<0.05$, and $p<0.01$ respectively
+++ Jointly Significant, $p<0.001$ using Chi-Squared test

Adopt = 1 for month of adoption, 0 otherwise.
Use = Post adoption *cumulative* number of transactions through the online channel, 0 for months prior to adoption, non-adopters, and adopters who do not use the channel.
NPROD = Number of retail deposit products held.
Performance$_{t-1}$ = One month lag of financial performance

Table 8 estimates the following model:

$$\Delta P_{it} = \gamma' \Delta time_t + \rho \Delta P_{it-1} + \lambda_1 \Delta ADOPT_{it} + \lambda_2 \Delta USE_{it} + \lambda_3 \Delta NPROD_{it} + \varepsilon_{it}$$

time$_t$ denotes a full set of time dummies. ΔP_{it-1} is instrumented with the twice lagged level, P_{it-2}, in all specifications. $\Delta ADOPT$ and ΔUSE are instrumented using the change in online penetration rates in a customer's market area and the interaction of this variable with *HSA*, a time constant variable denoting the availability of high-speed internet access in the customer's zip code. *HSA* is derived from FCC form 477 data, and is measured as of June 2001.

Table 9: Economic Significance of the Estimated Impact of Adoption and Use of Online Banking on Components of Customer Profitability.

	At zero online transaction cost		At estimated online transaction cost	
	$ Change	% Change	$ Change	% Change
Revenue	-2.89	-7.5%	-2.89	-7.5%
Cost	-0.65	-6.6%	0.08	0.8%
Profit	-2.24	-7.7%	-2.96	-10.3%

Table 9 shows the estimated change in customer profitability for a hypothetical customer adopting online banking during August 2001. Among customers adopting during this month, those who subsequently used the channel conducted an average of approximately 10 online transactions per month. This results in a cumulative volume of 100 online banking transactions by the end of the sample period 10 months later. Columns 2 and 4 report the estimated percentage changes in revenue, cost, and profit for this hypothetical customer. The percentage changes are taken relative to the pre-adoption mean values of revenue, cost, and profit for the sample of customers that adopted during August 2001 and performed at least one online banking transaction over the subsequent 10 months.

Table 10: Probit Estimates of Retention on Online Status
Cross-Sectional Sample of 525,864 Customers Observed in May 2001 and June 2002

Variable	(1)	(2)	(3)
ONLINE	0.042*	0.028*	0.026*
	(0.003)	(0.003)	(0.003)
TENURE	0.013*	0.01*	0.01*
	(0.0004)	(0.0004)	(0.0004)
AGE	0.006*	0.006*	0.006*
	(0.0003)	(0.0003)	(0.0003)
NPROD		0.068*	0.062*
		(0.002)	(0.002)
BALANCE		0.00002	0.00002
		(0.00002)	(0.00003)
Market Area Indicators			+++
N	525,864	525,864	523,942
Likelihood Ratio χ^2 (df)	2,377 (3)	3,033 (5),	3,885 (395),
	ρ<0.0001	ρ<0.0001	ρ<0.0001
R^2	4.5%	6.6%	8.5%

Standard errors in parentheses; * p<0.01
Estimated coefficients reported as marginal effects at the mean value of all variables.
+++ Jointly Significant, p<0.001 using Chi-Squared test

ONLINE = 1 for online banking customers as of May 31, 2001 and 0 otherwise.
TENURE= Length of time (in years) since customer established first account relationship with the bank. Measured as of May 31, 2001.
AGE = age of customer (in years) as of May 31, 2001.
NPROD = Number of retail deposit products held as of May 31, 2001.
BALANCE = Average daily balance in retail deposit accounts as of May 31, 2001
Market Area Indicators = Dummy variables for each of 400 market areas served by the bank.

Table 11: OLS and Two-Stage Least Squares Regressions of Retention on Online Status. Cross-Sectional Sample of 525,864 Customers Observed in May 2001 and June 2002

Variable	OLS 1	TSLS 1	OLS 2	TSLS 2
Constant	0.63*	0.58*	0.57*	0.55*
	(0.009)	(0.016)	(0.009)	(0.014)
ONLINE	0.047*	0.16*	0.032*	0.086*
	(0.003)	(0.02)	(0.003)	(0.03)
TENURE	0.013*	0.013*	0.011*	0.012
	(0.0004)	(0.0004)	(0.0004)	(0.0004)
AGE	0.006*	0.007*	0.007*	0.007
	(0.0003)	(0.0003)	(0.0004)	(0.0004
NPROD			0.055*	0.048*
			(0.002)	(0.004)
BALANCE			0.00001	0.00001
			(0.00001)	(0.00001)
N	525,864	525,864	525,864	525,864
R^2	3.3%	1.1%	4.4%	3.9%

Standard errors in parentheses; * $p<0.01$
TSLS estimates instrument the online dummy with a dummy indicating between 1 and 4 high speed internet access providers in a customer's zip code, a dummy indicating 4 or more providers, and the number of providers for customers in zip codes with more than 4 high speed internet access providers. This somewhat ad hoc categorization is necessary due to the way Form 477 data is collected and reported by the FCC.

ONLINE = 1 for online banking customers as of May 31, 2001 and 0 otherwise.
TENURE= Length of time (in years) since customer established first account relationship with the bank. Measured as of May 31, 2001.
AGE = age of customer (in years) as of May 31, 2001.
NPROD = Number of retail deposit products held as of May 31, 2001.
BALANCE = Average daily balance in retail deposit accounts as of May 31, 2001.

Table 12: Analysis of Changes in Average Daily Balance Relative to Minimum Balance Requirements around the Adoption of Online Banking for a Subsample of Customers Facing Minimum Balance Requirements.

Panel A: Descriptive Information on Balances Relative to Minimum Required

	Offline		Adopter/Inactive		Adopter/Active	
Month	Median	Mean	Median	Mean	Median	Mean
-6	0.92	1.48	0.69	1.43	1.01	1.50
-5	0.94	1.58	0.72	1.45	0.87	1.52
-4	0.92	1.52	0.66	1.42	0.85	1.45
-3	0.96	1.53	0.58	1.35	0.88	1.44
-2	0.96	1.54	0.66	1.37	0.85	1.39
-1	0.94	1.53	0.62	1.42	0.88	1.38
0	0.96	1.53	0.68	1.48	0.88	1.49
1	0.95	1.51	0.67	1.39	0.90	1.48
2	0.94	1.49	0.71	1.44	0.97	1.48
3	0.97	1.53	0.76	1.59	1.08	1.57
4	0.95	1.52	0.74	1.51	1.00	1.53
5	0.98	1.55	0.65	1.45	1.04	1.58
6	0.96	1.58	0.73	1.63	1.02	1.46

Panel B: Tests of Pre-Post Adoption Changes in Balance Relative to Minimum

	Offline		Adopter/Inactive		Adopter/Active	
	-6 to -1	-1 to 6	-6 to -1	-1 to 6	-6 to -1	-1 to 6
Mean Difference in Balance Relative to Minimum	0.05	0.05	-0.01	0.20	-0.13	0.18
p-value	0.49	0.50	0.92	0.11	0.20	0.34
Median Difference in Balance Relative to Minimum	0.01	0.01	-0.02	0.03	-0.02	0.05
Number that Increase	283	287	134	155	126	146
Number that Decrease	264	259	148	127	137	117
Number with No Change	2	3	0	0	0	0
p-value for Wilcoxon sign-test	0.44	0.25	0.44	0.11	0.54	0.08

Columns 1, 3, and 5 of Panel B respectively show the mean and median changes in *RELBAL* (defined as BALANCE/MINIMUM where BALANCE is the customer's average daily balance and MINIMUM is the minimum required balance to avoid a fee) from 6 months prior to adoption to 1 month prior to adoption for a sample of offline customers (never online during the sample period), a sample of customers who adopted online banking but did not use it to perform any transactions in the 6-months after adoption, and a sample of customers who adopted online banking and used it to perform at least one transaction in the subsequent 6 post-adoption months. Columns 2, 4, and 6 show the corresponding changes from 1 month prior to adoption of online banking to 6 months after adoption.