Do Better Customers Utilize Electronic Distribution Channels?

The Case of PC Banking

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Abstract

Many service firms are pursuing electronic distribution strategies to augment existing physical infrastructure for product and service delivery. But little systematic study has been made for whether and how characteristics or behaviors might differ between customers who use electronic delivery systems and those that use traditional channels. We explore these differences by comparing customers who utilize personal computer based home banking (PC banking) to other bank customers. Case studies and detailed customer data from four institutions suggest that PC banking customers are apparently more profitable, apparently due to unobservable characteristics extant before the adoption of PC banking. Demographic characteristics and changes in customer behavior following adoption of PC banking account for only a small fraction of overall differences. It also appears that retention is marginally higher for customers of the online channel.

1. Introduction

From booksellers to mass merchandisers, firms are increasingly utilizing electronic distribution methods to augment or possibly supplant "traditional" product and service delivery processes. Barnes and Noble and Wal-Mart among others, have already transitioned to a hybrid model of physical stores and online delivery, and catalog retailers such as L.L. Bean, Eddie Bauer, and Lands End have augmented their existing telephone, mail-order, and outlet stores with substantial investments in their online presence.

Nowhere has this trend been more important in business-to-consumer electronic commerce than in the financial services industry, especially in retail banking. Major investments in online banking date back to the early 1980's when the home computer was still a rarity (Steiner and Teixeira, 1990). Moreover, this introduction followed several decades of innovation in electronically-enabled bank service delivery that included automatic teller machines, touch tone telephone banking, voice response units, and centralized, technology-intensive telephone call centers. In 2000, online banking was utilized by approximately 10% of all retail banking customers in the United States; for "leading edge" banks such as Wells Fargo the number might be as high as 25% (Wells Fargo company reports).

As these investments in online delivery become larger and more central to the long-term strategy of financial institutions, it becomes important to understand whether and how they add value to the banks that invest in them. We explore three possible sources of value from electronic distribution that we believe to be important to this industry and likely generalizable to other online distribution environments: segmenting customers on unobservable, but profitable characteristics; targeting desirable demographic segments; and inducing revenue enhancing behavioral changes.[1] Data limitations dictate less than a thorough analysis of the related issue of customer retention.

Our principal objective of the study is to understand the potential sources of value of online for the institutions that adopt it, by examining customer characteristics and behaviors in both online and offline channels. Secondarily, we hope that this research will inform electronic commerce strategy by identifying and measuring how customer characteristics and behaviors differ between "traditional" and "online" channels in an industry where this is known to be important (Clemons and Thatcher, 1997). Previous work on the value of electronic commerce has emphasized cost savings potential and strategic behavior (e.g., price discrimination, differentiation), but not examined extensively issues associated with differences between customers who use online and traditional channels. In addition, previous work has not compared the direction or magnitude of the multiple potential sources of value simultaneously.

We conducted interviews at seven large retail banks, four of which also provided extensive customer information file (CIF) data on all online customers and a larger random sample of other customers. We subsequently obtained account retention data from an additional bank. Our diverse data set encompassed more than 500,000 customers at one point in time (2nd Quarter, 1998), spanning a range of bank sizes, geographic areas, and customer characteristics. We used these data to compare product use, product adoption times, account balances, and (where available) account profitability between online customers and other customers.

Overall, we find PC banking customers, on average, to be more profitable, use more products, and maintain higher balances than the traditional customer population. We also find evidence that customers who adopt online banking have a greater propensity than traditional customers to adopt future bank products over the same time period, but differences in product adoption is quite small compared to the initial differences in the two customer populations.

These differences are remarkably robust across different banking institutions and customer segments, suggesting that these findings may generalize across different banks and geographic regions. Our results also suggest that previously unidentified differences in customers can have a significant influence on the measured value of electronic distribution investments and that retention of high profit customers is thus likely to be an important value driver for investments in online distribution and service.

2. How Does PC Banking Create Value for Banks

2.1 Economics of Electronic Delivery

Most work to date on the profitability of electronic markets or electronic delivery investments has emphasized potential cost savings through improved communications and coordination (Malone, Yates, and Benjamin, 1987), a reduction in Williamsonian transaction costs (Clemons and Row, 1992; Gurbaxani and Whang, 1991), or simply substitution of relatively fixed cost information technology assets for variable cost human interaction. Other work has considered how revenues might be enhanced in electronic markets through price discrimination, product differentiation, or competitive advantages created by network effects (Baily, Brynjolfsson, and Smith, 1997; Clemons, Hann and Hitt, 1998; Varian and Shapiro, 1998).

Few studies, however, have focused on the issue of customer heterogeneity. At the forefront of many models of search (Bakos, 1991, 1997), customer characteristics have been used to explain observed price dispersion in online markets (Brynjolfsson and Smith, 1998; Clemons, Hann, and Hitt, 1998; Lee, 1998; Varian and Shapiro, 1998). However, even in these studies customer characteristics are either fixed or not hypothesized to vary between online and traditional markets. One exception, Parasarathy and Bhattacherjee (1998), utilized survey data to examine how customer characteristics are correlated with the decision to continue or terminate the use of an online service.

Customer characteristics and profitability might differ systematically in electronic markets for a number of reasons. Numerous market research studies (e.g., INTECO, 1998) have shown the average PC user to be slightly younger, more affluent, more likely to be married, and more likely to own a home. Market research studies of online banking users reveal similar sets of characteristics, which are reflected in our data (see Table 1). Demographic characteristics, to the extent that they are systematically linked to desirable behaviors such as a greater utilization of high profit products, could generate customer differences.

There may also be customer characteristics that translate into differences in customer behaviors and ultimately, profitability. A strong affinity to a particular institution might, for example, account for the willingness of users of a PC banking product to incur the cost of learning and installing software. Customers who adopt PC banking are also more likely to exploit services provided inexpensively online (e.g., up-to-date account information). Therefore, online use might reflect a previously unidentified, existing customer trait that might influence customer profitability.

Finally, there may be direct effects of an online channel on customer behavior that leads to greater customer profitability. Convenience or additional customer information may encourage incremental product purchase (e.g., recommendations at Amazon.com) or more frequent transaction activity (e.g., online brokerage, see Barber and Odeon, 1999). Our interview data suggests that consumers might tend to consolidate accounts when adopting online banking for increased convenience or because they tend to adopt online banking at their most trusted institutions.

These three sources of customer heterogeneity (demographics, unobserved differences, and behavioral changes) have neither been extensively studied nor compared in the context of electronic distribution. Our analyses, to the extent possible with the data available to us, attempt to distinguish existing customer characteristics from behavior changes.

2.2 Overview of the Product

Our study focuses on “PC Banking” products which enable customers to access their accounts from their home computer using proprietary software (either custom or standard personal financial management software such as Quicken). Although technology infrastructure and involvement of third parties (e.g., network and software providers, transaction processors, and fulfillment vendors) exhibits substantial variation across institutions, the basic functionality provided by PC banking is fairly standardized. Most banks offer a free or low cost inquiry-only service, a “billpay” service that initiates electronically payments via paper check or electronic funds transfer, and some ability to apply for new products and services online. Our interviews, reviews of actual product offerings and business plans of our study institutions, and subsequent review of current market practices (including web-based banking)[2] reveal little product differentiation in online banking. This reduces potential biases in our study from heterogeneity across institutions, but limits our ability to link product features to customer behavior.

The approximately 6.5 million customers using PC and online banking in 2000 is expected to grow to about 32 million by the year 2003 (IDC Report). The penetration rate of approximately 3% in our data compares to the market average of 2.5% at the time of our study (Matheison, 1998). Seventy to eighty-five percent of adopters are existing customers; only 15%-30% initiated their banking with a PC account – existing product use will thus be an important determinant of overall profitability of online customers.

2.3 Measuring "Value" in Banking Services

To compare "value" to the institution between two customer populations we need to be able to translate a diverse set of product choices into a single value metric, a known difficulty in banking performance measurement (see, e.g., Berger and Mester, 1997). We attempt not to resolve this long-standing debate, but rather to make our results insensitive to this concern by choosing standard metrics and multiple value measures.

In addition, banking relationships tend to be characterized by a time path of product use and profitability; new customers generally have relatively low balances and few products and acquire additional products over time (perhaps with a decline later in life as people enter retirement). Moreover, observable characteristics such as length of relationship, age, and income might interact in complex ways that make it difficult to capture all possibilities in a simple functional form that relates observable characteristics to behavior. We address this problem through matched sample comparisons that augment regression modeling.

Finally, because customer accounts are best viewed as assets (i.e., they are expensive to acquire and provide a long term revenue stream), we need a way to translate an estimate of observed product use at a given time into a metric of long-term value. We address this concern by conducting tests that, even if they cannot measure value directly, can make directional comparisons of long-term value between two populations.

To formalize these arguments let the characteristics of a customer account be represented by a vector $C(\cdot)$ that takes as arguments a vector of observable characteristics unrelated to product choice such as age and income (X), a vector of unobserved characteristics (θ), and time since the initiation of the account (t). The components of $C(\cdot)$ represent, for example, balances in different products or a collection of binary variables that represent customer accounts of particular types.

Define single-period account value V(C), a scalar, to be weakly increasing in all components of C, but otherwise unrestricted. This is not a fully general assumption, but appears to be consistent with a common characteristic of banking practice.[3] Because C is a function of time, V(·) is also a function of time. The appropriate comparison between two customers (either actual or representative) A and B is the difference in lifetime account value from an arbitrary time to a time T (possibly unique to A or B) at which the account terminates. We assume that banks (1) are risk neutral and consider all values to be expected values, (2) have a constant discount rate (r) across all customers, and (3) do not vary in the types of information (X) that is observable across customers. These assumptions enable us to state that customer A has higher value than customer B (subscripts denoting customer, superscripts denoting time) at time t^1 (assuming $t^1 > t_A^0, t_B^0$, the time of initiation for both customers) iff:

$$\sum_{t=t^1}^{T_A} \frac{V(C(X_A,\theta_A,t-t_A^0))}{(1+r)^{t-t^1}} > \sum_{t=t^1}^{T_B} \frac{V(C(X_B,\theta_B,t-t_B^0))}{(1+r)^{t-t^1}}$$

Note that in this model, all components are observable except θ. Our analysis will proceed by making comparisons of two customer populations, defined by observable criteria like PC banking use, that can be performed without knowing the explicit functional forms for C and V or the values of θ for each group. The expression above can be greatly simplified if we compare only customers that are identical on all observable variables (X and t^0). Assuming T to be a function of X and not θ, a sufficient but relatively strong condition is that for all $t>t^1$:

$$V(C(\theta_A, t-t^0)) > V(C(\theta_B, t-t^0))$$

V being monotonic in the components of C, depending on the structure of V, this can be further simplified. There is a certain value flow associated with each component of C that aggregates to total value (an assumption that appears to be fairly reasonable for retail banking since the two principal drivers of profits are product type and product usage). Thus:

$$V = \sum_{i=1}^{I} w_i C^i \qquad \text{where } w_i > 0 \; \forall \; i \in [1..I]$$

We can then derive the somewhat weaker condition that (for all $t>t^1$):

$$\sum_{i=1}^{I} w_i [C^i(\theta_A, t-t^0) - C^i(\theta_B, t-t^0)] > 0$$

Even with this simplification we still require information on the full time series of $C(\cdot,t)$. Yet our data contain only information on $C(\cdot,t-t^0)$ for a fixed t (although t^0 varies across customers). There are two possible approaches to resolving this difficulty. One, we can place additional constraints on the form of C. A plausible assumption is that for any given time t*, if $C(\theta_A,t^*-t^0)> C(\theta_B,t^*-t^0)$ we can assume that this relationship holds for all t>t*. This implies that higher value customers now will be higher value in the future. Although clearly an assumption, for most banking products this does not appear too implausible and is testable in aggregate. This suggests a test that compares sample means for the components of C or a suitable weighted aggregate at a point in time.

Alternatively, we dispense with these strong assumptions about time evolution by assuming that, in expectation, $C(\theta_g)$ is representative of all customers in group g (in the preceding discussion $g \in [A, B]$). We can then use the data variation in our sample to sketch out the time component of C for each subgroup of customers and compare value measures over time.

Our empirical approach includes several types of tests. To control for observable differences (X), we compare various measures of the value drivers (C), such as asset (loan) and liability (deposit) balances between the PC banking customers and other customers using both regression (conditional on X) and matched sample comparisons where PC customers and non-PC customers are matched based on values of X. We also will calculate and compare the time series evolution of C(·,t) for the matched sample and test whether these values are systematically higher for PC banking or regular bank customers.

2.4 Hypotheses and Research Design

Our previous discussion suggests an approach to understanding the value of PC banking by comparing the "value" of a customer (Mulhern, 1999) that exists in a traditional banking channel with the value of a customer that utilizes online banking. Thus our initial null hypothesis is that:

H0) Customers who utilize PC banking have the same value for the bank as those who do not.

If we are able to reject the null hypothesis, we can explore what drives the variation in value. We earlier suggested that these values might vary for reasons of observable differences (e.g., length of relationship or demographic characteristics), unobserved differences, and changes in behavior. The first is addressed straightforwardly:

H1) There is no difference in value for the bank between PC banking customers and regular customers after accounting for observable characteristics (e.g., age, income, marital status, home ownership, and length of relationship with the institution).

Distinguishing between unobserved heterogeneity and behavioral change is somewhat more difficult. One way in which we can examine behavior change is to consider whether customers adopt additional products at a greater rate. An increase in cross-sell rates[4] following adoption of the PC product relative to a suitable "control group" would suggest behavioral change. This suggests the following hypothesis, stated in null form:

H2) There is no difference in incremental product purchases between regular customers and customers who adopt the PC banking product.

Tests of this hypothesis may suggest the presence or absence of a casual link between PC banking adoption and new product use, but may also represent a more elaborate version of our earlier story – that the unobserved characteristic is a propensity to adopt more products than other, similar customers in the population. Although point-in-time comparisons are useful benchmarks, our conclusions would be strengthened by a demonstration that the overall present value of accounts is different. Consequently we test that:

H3) There is, after accounting for observable characteristics, no difference in the present value of accounts between customers who use PC banking and those who do not.

Finally, account retention may be an important driver of value not captured by product balances. One additional bank provided a limited account data for two time periods that enabled us to investigate whether online banking plays a role in customer retention:

H4) The proportion of customers who leave the bank does not differ between customers who use online banking and those who do not.

3. Data

In 1998 we enlisted seven banks to participate in a comprehensive study of IT-investment practices that included a general overview of the process as well as extensive collection of objective and subjective data on PC banking.[5] These data include project timelines, initial and ongoing costs, investment motivation, market research reports, and measured outcomes. The data collection included interviews with more than 60 individuals in a variety of functions related to PC banking and a data extract of customer account records from each bank's customer information file (CIF) as of 2nd quarter 1998. Our analysis is focused on these CIF data, which include household-level data on customer demographics (e.g., age, income, marital status, and home ownership), product ownership (e.g., acquisition date, current balance), the use of PC banking and, in some cases, account profitability. Following common practice in bank profitability measures we aggregate products into assets (loans), liabilities (deposits) and other products (e.g., trust, brokerage). Further detail and summary statistics on our key measures are shown in Table 1. To limit the potential influence of data errors and inconsistencies, we exclude all customers with trust accounts, with aggregate negative balances in assets or liabilities, in the highest .05% of any category (profitability, assets, liabilities, number of products), and in the lowest .05% of profitability. Results are not sensitive to this adjustment.

The relationship between the use of PC banking and the product adoption decision is modeled using Logistic regression, the resulting balances by ordinary least squares regression. Estimation efficiency is not an issue given our large sample size and our results are robust to econometric adjustments such as heteroskedasticity corrections and the use of absolute balance levels (including the zeros) as the dependent variable. Because all our customer characteristic variables are potentially correlated with both PC product adoption and profitability, we are unable to perform more complex analyses that address the simultaneity between adoption of PC banking and profitability, and thus cannot draw strong conclusions about causality.

Three initial observations are suggested by the sample statistics presented in Table 1: 1) Customers who utilize PC banking are consistently in wealthier income brackets, between two and six years younger, and more likely to be married and own homes, consistent with previous observations about Internet users; 2) PC banking customers have higher product usage and asset balances; and 3) These differences persist across the institutions in our study. We investigate these phenomena in greater detail in the next section.

Table 1 also indicates significant heterogeneity in customer populations across banks. This is partly due to geographic differences and partly due to differences in CIF data capture across institutes. We therefore perform all comparisons across customer groups within institutions and utilize within-bank ranks of the various measures for comparisons.

4. Results

4.1 Static Comparisons of Regular and PC Banking Customers

Our first analyses are based on a regression model in which multiple value drivers – assets (Assets), liabilities (Liab), number of products (Nprod), asset adoption (AssetAdop), liability adoption (LiabAdop), and profitability (π) -- are modeled as a function of whether the customer utilizes PC banking (PCBanking), a dummy variable. Dummy variables are also provided for age buckets, income buckets, marital status (Married), and home ownership (OwnHome). We also include length of the account relationship (LOR) and its square (LOR^2) to capture the observed concave relationship between relationship length and account value (see Figure 3). Thus, we estimate (using logistic regression):

$$\Pr(AssetAdop) = \alpha_0 + \alpha_{PC} PCBanking + \gamma_{LOR} LOR + \gamma_{LOR2} LOR^2 + \\ \sum_{\text{i=age groups}} \gamma_{i,age} A_i + \sum_{\text{j=inc. groups}} \gamma_{j,income} I_j + \gamma_{oh} OwnHome + \gamma_{Mar} Married + \varepsilon$$

and separately,

$$\Pr(LiabAdop) = \alpha_0 + \alpha_{PC} PCBanking + \gamma_{LOR} LOR + \gamma_{LOR2} LOR^2 + \\ \sum_{\text{i=age groups}} \gamma_{i,age} A_i + \sum_{\text{j=inc. groups}} \gamma_{j,income} I_j + \gamma_{oh} OwnHome + \gamma_{Mar} Married + \varepsilon$$

For continuous variables such as the number of products we estimate equations of the form (using ordinary least squares):

$$Nprod = \alpha_0 + \alpha_{PC} PCBanking + \gamma_{LOR} LOR + \gamma_{LOR2} LOR^2 + \\ \sum_{\text{i=age groups}} \gamma_{i,age} A_i + \sum_{\text{j=inc. groups}} \gamma_{j,income} I_j + \gamma_{oh} OwnHome + \gamma_{Mar} Married + \varepsilon$$

We also separately estimate similar equations for profitability (π), assets (*Asset*) and liabilities (*Liab*). For the assets and liabilities measures, we only include customers who have non-zero assets and liabilities respectively to prevent confounding the adoption decision from the quantity decision by the customer.

To test H0, we estimate this equation without control variables. A significant coefficient on α_{PC} suggests that PC banking customers contribute more value to the bank than regular customers. These statistics can be can be read off the sample statistics table (Table 1); in all cases the differences are highly significant (p<.001) and suggest a positive relationship between PC banking use and asset adoption, asset balance (for those with assets), number of products and profitability. For PC banking customers, liability adoption is significantly higher at all four of the banks, liability balances higher at only one of the banks. For testing H1, we also examine the coefficient α_{PC} in a regression with controls for customer characteristics included. The results of this analysis for one bank (Bank A) are presented in full detail in Table 2. The results suggest that the demographic controls explain a substantial portion of account value (with few exceptions all variables are significant at p<.01 or better), but not the difference in value between PC banking customers and other customers. However, there is still considerable variation in account value due to factors outside of our model as shown by the moderate R^2 values (typically 5-20%). This is because (as is known in the banking literature) there are large variations of customer profitability *within* demographic segments and is consistent with our earlier discussion that unobserved customer characteristics may be significant contributors to profitability. However, due to our large sample sizes, all regressions and the almost all the individual coefficients are highly significant (coefficients jointly significant at p<.0001 in all cases). Even with demographic controls, PC customers have consistently higher value across all value measures. Similar results across the other banks are discussed below.

Matched Sample. To check whether demographics' lack of explanatory power is a consequence of our functional form for demographic characteristics being insufficient, we repeat the analysis using only a matched sample of regular and PC banking customers. For each customer in our PC banking sample we identify a matching regular banking customer with the same age (nearest 10 years), marital status, income bucket, home ownership, and relationship duration. This approach finds a match for 80% of PC banking customers. We then relax the relationship time constraint to +/-3 months to obtain an incremental 10% of matches and all remaining unmatched customers are dropped (see Table 1 for the percentage of customers we were able to match).

A comparison of PC banking customer to regular customers is displayed in Figure 1 – a significant difference between these groups would lead us to reject H1. As before, the differences between regular and PC banking customers are highly significant and persist across institutions. We conclude that these differences are robust to *any* systematic functional relationship between demographic characteristics and account value used as controls in the regression.

Rank Regression. Because of some incomparability of value measures across institutions and the potential for extreme points influencing the analysis, it is easier to interpret the results across institutions if we reclassify the value measures in rank order so that the natural scales of the measures no longer affect the results. To perform this analysis we pool the PC and non-PC customers and compute rank scores for each value measure (i.e., 0-1, where higher numbers represent the percentage of customers below a particular customer). We then use this as the dependent variable. All other variables (except length of relationship squared) being ordinal, this is essentially rank regression. For results of the simple comparison see Table 3 (testing H0), the model-based regression Table 4 (testing H1), and the matched sample Table 5 (an alternative test of H1).

Examining Tables 3-5, across most value measures PC banking customers are rank ordered higher than regular banking customers. Including the demographic controls changes the differences slightly. For asset and liability adoption, demographics explain at most 25% of the difference between regular and PC banking customers. For the rest of the measures demographics explain very little, as can be seen by comparing Tables 3 and 5.

These results suggest that we can reject the null hypotheses for both H0 and H1; there are substantial differences in the value of regular and PC banking customers, even after accounting for observable differences and using multiple approaches to perform the comparison.

4.2 Differences in Customer Behavior (Cross-Sell)

Although we are able to establish that PC banking customers are different, we cannot yet attribute the difference to pre-existing conditions or product induced behavior change, a distinction crucial to strategy setting, given that most PC banking customers are already bank customers. Should banks encourage adoption aggressively in hopes of benefiting from behavioral change or merely make the product available upon request to discourage defection? Although we cannot determine whether customers augmented their balances after adopting PC banking, we can examine new purchase behavior.

To make this comparison properly, we must account for the general tendency of customers to purchase additional products over time. For this analysis, we take all PC banking customers, labeled for exposition, A_1, A_2...A_n (where we have n matched customers), and their corresponding matched regular banking customers, labeled B_1, B_2...B_n. We determine for each PC banking customer, the date of adoption, labeled D_1, D_2...D_n. For each customer (i) we then compare the products acquired by customer A_i at time > D_i against the products acquired by customer B_i at the same time. Thus we control for the natural growth rate of an account over time; a difference is only captured when product adoption over time exceeds the product adoption of the matched customer measured from the same date.

Detailed data on the PC banking initiation date was available from banks A and B. We report in Table 7 and Figure 2 differences in the purchase of products (the fraction that purchase in each subsample) and balances in the incremental products they purchase. A significant difference between the control group and the group that adopted PC banking for any of the value measures would lead us to reject H2.

Overall, we find that customers who utilize PC banking tend to acquire assets at a faster rate and, when they do acquire assets, to maintain slightly higher balances. The opposite seems to be true for liabilities: PC customers tend to adopt at a slower rate and, when they do adopt, to maintain lower balances. Possible reasons might be that PC banking enables more efficient management of liabilities so that less money is held in non-interest bearing accounts; online banking may also be correlated with the use of online brokerage which would also imply lower liabilities at banks. Finally, following adoption of PC banking, online customers tend to adopt products at a slower rate. On balance, the data suggest a slight increase, at best, in product cross-sell following the adoption of PC banking.

4.3 Long Run Customer Comparison

The previous analyses relied heavily on the assumption that current customer characteristics are good measures of the present value of an entire customer relationship. We can also get some sense of the evolution of customer value over time by using our cross-sectional data that includes different customers at different lifecycle (length of relationship) if we assume that past behavior is at least on average indicative of their future behavior. If the value of a PC banking customer is (on average) always higher than that of a traditional banking customer at any stage in the lifecycle (this is discussed formally in Section 2.4), then we can make stronger arguments about lifetime value.

In making these comparisons, we again use the matched sample to control for demographic factors that influence profitability. We group each type of customer (PC banking, regular banking) by account duration; each group is the portion of customers whose length of relationship is within three months (e.g. 0-3 months, 3-6 months, and so forth). The three-month guideline was chosen to ensure sufficient samples to enable the means to be estimated with suitable precision – alternative ranges (two months, six months) yielded similar results.

For each type of customer and duration group, we compute the mean and variance of each of the value measures (products, assets, liabilities) over 15 years. The analysis for profits for Bank A, shown in Figure 3 (other graphs for products, liabilities and assets, omitted for space, are similar), suggests that PC banking customers have substantially higher customer value across all stages of the customer lifecycle. To formalize this observation, we compute the number of time periods for which the value of PC banking customers is (on average) higher than that for regular banking customers over a period of 15 years (the time span chosen to ensure at least 100 customers in each period). The results for all banks and value measures are presented in Table 7 – if we find that PC banking customers are higher on their value measures over time, this would lead us to reject H3. This hypothesis test of the probability that these two distributions are the same is shown below the percentage figure.[6] Overall, Table 7 shows PC banking customers to consistently have higher assets, products, and profitability, although in two banks liabilities are lower. This analysis thus corroborates our earlier assessment that, for most value measures, PC banking customers are consistently more profitable over time, boosting our confidence that we are capturing both short- and long-run account differences.

4.4 Customer Attrition

Although our data do not permit an extensive study of the relationship between channel usage and attrition, we were able to collect a limited data set from an organizational peer of the institutions we studied. We examined at this firm the effect of online banking (the successor to PC banking) on customer retention. In 1999, 12.4% of the approximately 650,000 customers in our study region used online banking. One year later, the retention rate of customers that used online banking was 3.6% higher (significant at $p<.001$) than that for customers who did not – this leads us to reject H4. As we were unable to control for demographics in this analysis and have no ability to distinguish causality, it remains an open question whether the higher retention rate is attributable to online use. However, the data do support our conjecture that customer retention might be a significant value driver and when combined with the observation that PC banking adopters tend to be higher value customers.

5. Discussion

Overall, our results suggest that PC banking customers are more valuable than regular banking customers, even after accounting for demographic differences, account duration, and short- versus long-run profitability. Both in a single cross section and over different stages of their account lifetime, PC banking customers use more products and maintain higher asset and liability balances than regular banking customers. They also tend, following adoption of PC banking, to acquire products at a slightly faster rate than their observable characteristics would suggest. The latter finding, however, relates to existing bank customers who adopt PC banking rather than to new customers who begin their relationship with the PC product. The consistency of the results across institutions suggest that these findings may be generalizable.

In terms of our original hypotheses, we clearly reject the hypotheses that PC banking customers are the same as regular banking customers and that demographics explain all differences (H0 and H1). We found some evidence to support our hypothesis that some differences reflect behavioral change: PC banking customers appear to acquire products at a slightly faster rate, although this is more pronounced for customers who were existing bank customers at the time of PC banking adoption.

Broadly categorizing the effect size of the value drivers aids interpretation of the results. Overall customer heterogeneity between online customers and regular customers is a large effect, accounting for differences in products and balances anywhere from 30% to 200+%. Differences in demographics between these two populations accounts for very little of these differences. Behavioral change, as measured by cross-sell rates, is statistically significantly higher for online customers, but again is not large enough to contribute substantially to overall observed differences. Across the two banks the average PC banking customer, following adoption, acquires 0.17 more products than the customer population. This compares to an approximately 1.5 product per customer difference between customers in the two channels overall. Therefore, our results suggest that most of the differences are due to preexisting but unobserved characteristics of customers that adopt online banking. While the nature of these characteristics is unknown, our interviews suggest that two leading possibilities are perceived opportunity cost of time and trust or affinity for a particular institution – both would be correlated with profitability as well as PC banking adoption.

5.1 Strategic Implications

The foregoing comparisons are important to consider in formulating the appropriate strategy for PC and online banking. Given that most online banking users are existing customers, and there is limited behavioral change, PC banking may be important in two ways: 1) as a retention mechanism for high value accounts, and 2) as segmentation device for targeting unusually profitable customers.

At the time of the study no bank had in place a program that offered PC banking customers different products, prices, or promotions. Thus, potential segmentation effects were not being exploited. Second, and more important, account retention was mentioned as a motivation for investing in PC banking in only four of the seven banks we studied. Perhaps most striking is that even in those institutions there appeared to be little explicit pursuit of account retention in the product marketing and deployment approach. This suggests that at least at the time of our study, banks were not exploiting potentially important the potential incremental benefits of online banking, while overemphasizing differences in the customer populations which is not affected by PC banking use which also leads them to overstate the incremental value of online banking. In the short run this merely transfers value between different parts of the bank, but our results suggest that banks should be cautious about aggressively introducing this product to existing customers on the basis of these “value” differences.

5.2 Research Implications

Our results suggest that systematic and non-demographic differences in customers can have a substantial effect on the value of electronic distribution. To treat customers presently in electronic channels as representative of the population of customers as a whole, might upwardly skew estimates of projected e-commerce profitability. Because it might prove to be a very large effect, unobserved heterogeneity between customers in electronic channels needs to be specifically addressed in future studies that examine the performance of e-commerce investments. While banking is unique in that customer profitability measurement is already common practice, similar techniques can be extended to essentially any online business.

5.3 Limitations

We raised earlier a number of concerns about the data and analytical approaches used in this study. We are nevertheless fairly confident that we are capturing true differences between the regular and PC banking customers and that we are capturing both short- and long-run differences. We are not, however, able to separately identify balance accumulation in existing products, thus omitting a potential source of value. But even if this effect is ten times as large as the cross-sell effect (which seems unlikely), our basic conclusion, that preexisting differences drive value differences, still holds. A useful extension would be to examine models that can address time series variation in behavior in a more detailed manner. We also cannot directly estimate an important part of the value of PC banking, namely, building switching costs, although our results on retention would be consistent with a switching cost story. This is entirely due to the difficulty of obtaining the required data. A useful extension of our work would be to show conclusively whether PC banking customers are, indeed, less likely to defect to other institutions. Our preliminary results suggest that this is true, but the analysis is incomplete, as we were unable to control for demographics. Similarly, our ability to make causal inferences about whether PC adoption causes differences in behavior or is a signal of different characteristics is also limited. However, given that we find a small relationship between PC banking and new product adoption, the importance of that causal link (in either direction) is likely to be small. However, this does not rule out that profitability and PC banking adoption have a common antecedent without a causal link.

Moreover, although we have differential value, we do not have differential cost. Asset balances being heavily driven by home mortgages, there is not likely to be a large difference in customer cost since profitability in this product is influenced only slightly by transactional costs compared to balances. The same argument does not necessarily hold for liability products or assets accumulated through credit cards, which generate teller visits or other types of costly transaction behavior. Industry estimates suggest that PC banking customers perform more transactions across all channels, but this has not yet been systematically analyzed. However, this cost difference seems to be small compared to the difference in revenue due to increased product utilization (Online Banking Report, 2000).

Finally, it is difficult to make precise predictions about the behavior of future adopters. On the one hand, because existing adopters are substantially more profitable than non-online customers, at high levels of adoption, the relative profitability of this segment must decline. However, the profit effects of intermediate levels of adoption are not clear – it may be that online banking users are biased toward being more profitable which may sustain these differences for some time. However, in the end, we have no evidence that the product induces change in the profitability of customers in a significant way, which again points to retention as a significant source of long-term value. Should these customers prove unprofitable to retain, banks have other instruments such as pricing to address this issue.

5.4 Conclusions

Our analysis advances the notion that customers in electronic channels, even if they do not significantly change behavior, might differ systematically from other customers. Second, our analysis emphasizes the difficulty faced by established firms that might face online-only entrants; to the extent that online customers are more valuable, new entrants may be able to "cream skim" better accounts, the profitability of which will, of course, depend on the associated cost structure. Finally, our results suggest that the use of online channels as a retention tool holds promise, but further analysis is required to judge the extent of its impact and the direction of causality.

Table 1. Means of Value, Demographic, and Duration Measures by Bank and Customer Type

(each cell contains the mean; standard deviations in parentheses)

Measure	Variable Symbol	Bank A Regular	Bank A PC Banking	Bank B Regular	Bank B PC Banking	Bank C Regular	Bank C PC Banking	Bank D Regular	Bank D PC Banking
Asset Adoption Rate	AssetAdop	29%	55%	30%	52%	24.6%	23.9%	25%	42%
Assets (for those with assets)	Assets	$29,103 ($65,911)	$59,401 ($107,274)	$27,354 ($44,988)	$44,156 ($62,644)	$33,496 ($52,555)	$51,766 ($73,355)	$11,407 ($14,709)	$14,070 ($16,192)
Liability Adoption Rate	LiabAdop	99.3%	99.8%	99.1%	99.8%	81.4%	97.7%	99.2%	99.8%
Liabilities (for those with liabilities)	Liab	$12,747 ($38,745)	$17,144 ($48,234)	$17,148 ($39,540)	$14,319 ($339,64)	$15,675 ($32,498)	$11,700 ($27,740)	$10,994 ($23,149)	$8,858 ($17,364)
Products	Nprod	2.8 (2.7)	4.3 (3.7)	3.5 (2.7)	5.2 (3.5)	2.8 (3.2)	4.1 (4.0)	2.0 (1.1)	2.5 (1.2)
Profit[b]	Profit	$96 ($546)	$242 ($944)	not available	not available	not available	not available	$397 ($532)	$558 ($596)
Age	{A}[c]	44 (16)	40 (13)	not available	not available	51 (14)	42 (11)	44 (9)	42 (8)
Income	{I}[c]	$52,500 ($32,100)	$69,900 ($35,900)	$54,100 ($34,100)	$69,600 ($35,900)	$65,500 ($33,600)	$71,500 ($32,660)	$29,500 ($13,800)	$33,600 ($15,100)
Own Home	OwnHome	63%	75%	55%	66%	30%	34%	64%	63%
Married	Married	33%	50%	43%	54%	20%	24%	48%	52%
Time as Customer (months)	LOR	114 (109)	85 (88)	126 (122)	91 (94)	97 (89)	86 (80)	107 (116)	70[a] (81)
Time w/ PC Banking (years)			1.2 (0.8)		1.0 (0.7)		not available		1.7 (2.2)
PC Customers	PCBanking		14.7%		14.0%		not available		27.8%
Observations		248,758	24,814	115,147	11,170	93,250	16,832	159,925	14,118
Percent Matched Sample			92.5%		97.3%		85.3%		93.5%

[a] - Time as customer defined by checking account open date rather than first account open date.
[b]- For Bank A, profitability is actual customer revenue per product less standard costs per product. For Bank D, this figure represents revenue without deducting costs.
[c] – Brackets represent a set of dummy variables representing levels of these measures. Means and standard deviations are calculated using the midpoint of the range covered by the dummy variables.
[d] – Percent matched sample is the number of households that could be matched in the PC banking sample.
Liabilities include demand deposit (interest and non-interest) and time deposit (savings, CDs). Assets include home equity and installment loans, credit cards (except for Bank C), and mortgages.

Table 2. Regression of Value Measures on Demographics, Duration and PC Banking Use (Bank A only, OLS regression unless otherwise noted)

	Logit: Asset Adoption Rate	Assets (for those with assets)	Logit: Liability Adoption Rate	Liabilities (for those with liabilities)	Products	Profit
Intercept	-0.140 (0.002997)	37,715 (1167)	0.977 (0.00053)	-879 (265.6)	-0.083 (0.0176)	-19.7 (4.026)
PC Customer	0.196 (0.002997)	22,569 (699.4)	0.004 (0.00053)	5,041 (264.1)	1.179 (0.0176)	129.5 (4.026)
Time as Customer	5.59E-05 (7.31E-07)	-1.220 (0.2094)	3.10E-06 (1.30E-07)	2.174 (.06458)	0.000042 (4.29E-06)	0.02 (9.83E-04)
Time as Customer^2	-2.48E-09 (5.98E-11)	2.64E-05^ (1.69E-05)	-1.61E-10 (1.06E-11)	0^ (5.27E-06)	-1.33E-08 (0.00E+00)	2.50E-07 (8.00E-08)
Age 18-22	0.310 (0.004486)	-2,774 (1405)	0.004 (0.00080)	5,267 (397.1)	2.537 (0.0263)	81.0 (6.027)
Age 23-30	0.325 (0.003463)	-13,645 (1172)	0.008 (0.00062)	3,287 (306.3)	1.939 (0.0203)	48.1 (4.653)
Age 31-40	0.297 (0.003022)	-5,455 (1066)	0.009 (0.00054)	3,259 (267.3)	1.709 (0.0177)	53.6 (4.060)
Age 41-50	0.277 (0.002993)	-4,753 (1046)	0.008 (0.00053)	3,859 (264.5)	1.530 (0.0175)	57.7 (4.021)
Age 51-65	0.248 (0.002992)	-9,840 (1044)	0.007 (0.00053)	5,768 (264.3)	1.332 (0.0175)	38.1 (4.020)
Age > 65	0.121 (0.003283)	-19,682 (1205)	0.005 (0.00058)	17,335 (290)	1.130 (0.0192)	38.0 (4.411)
Income 15-20	0.026 (0.004774)	-9,967 (1532)	0.005 (0.00085)	-1,769 (421.1)	-0.036^ (0.0280)	-25.6 (6.415)
Income 20-30	0.034 (0.003673)	-6,951 (1182)	0.003 (0.00065)	-786 (324.2)	0.028^ (0.0215)	-7.9^ (4.935)
Income 30-40	0.054 (0.003125)	-8,536 (1001)	0.003 (0.00056)	-1,094 (275.9)	0.104 (0.0183)	-10.9 (4.198)
Income 40-50	0.062 (0.003499)	-6,256 (1085)	0.004 (0.00062)	-889 (308.8)	0.144 (0.0205)	0.8^ (4.701)
Income 50-75	0.078 (0.003258)	757.5^ (1007)	0.004 (0.00058)	1,664 (287.5)	0.374 (0.0191)	27.9 (4.377)
Income 75-100	0.110 (0.004014)	13,748 (1153)	0.003 (0.00071)	7,259 (354.2)	0.831 (0.0235)	107.7 (5.393)
Income 100-125	0.115 (0.004784)	17,191 (1314)	0.003 (0.00085)	7,352 (422.1)	0.880 (0.0280)	126.2 (6.428)
Income >125	0.145 (0.005076)	39,205 (1353)	0.002 (0.00090)	10,558 (447.8)	1.147 (0.0298)	220.2 (6.819)
Own Home	0.034 (0.002589)	3,495 (801.7)	0.001 (0.00046)	164^ (228.5)	0.211 (0.0152)	-15.3 (3.479)
Married	0.041 (0.002051)	-965^ (566.3)	0.0001^ (0.00036)	224^ (180.8)	0.343 (0.0120)	-21.9 (2.755)
N	273,565	86,700	273,565	271,891	273,565	273,565
R^2	11.8%	5.6%	0.6%	6.3%	17.5%	2.5%

Standard errors in parenthesis; All coefficients significant at $p<.01$ or better, except as noted with a ^. Cox and Snell R^2s reported for logistic regression analyses.

Table 3. Comparison of PC and Regular Customer Account Value: Rank Order Regression of Percentiles (no demographic controls)

	Bank A	Bank B	Bank C	Bank D
Assets Adoption Rate	PC: 1.73 times more likely to have assets (0.00676)	PC: 1.59 times more likely to have assets (0.00988)	PC: 0.98 times more likely to have assets (0.00979)	PC: 1.47 times more likely to have assets (0.00899)
Assets Rank Order (for Assets>0)	PC: +0.086 (0.00267) n=86,700	PC: +0.082 (0.00403) n=40,439	PC: +0.081 (0.00491) n=26,942	PC: +0.058 (0.00401) n=46,207
Liability Adoption Rate	PC: 1.90 times more likely to have liab (0.07563)	PC: 2.28 times more likely to have liab (0.1159)	PC: 3.10 times more likely to have liab (0.02589)	PC: 1.76 times more likely to have liab (0.08583)
Liability Rank Order (for Liability>0)	PC: +0.100 (0.00191) n=271,898	PC: +0.028 (0.00282) n=125,617	PC: +0^ (0.00248) n=92,329	PC: +0.057 (0.00253) n=172,783
Products Rank Order	PC: +0.164 (0.00184)	PC: +0.174 (0.00274)	PC: +0.134 (0.00229)	PC: +0.106 (0.00240)
Profitability Rank Order	PC: +0.113 (0.00191)	not available	not available	PC: +0.146 (0.00251)
N	273,572	126,624	113,044	174,043

Each cell posts an increase in % rank or adoption propensity for PC banking customers, the standard error of this estimate, and a sample size. All coefficients are significant at p<.01, except as noted by a ^.

Table 4. Comparison of PC and Regular Customer Account Value: Rank Order Regression with Controls for Demographics

	Bank A	Bank B	Bank C	Bank D
Asset Adoption Rate	PC: 1.55 times more likely to have assets (0.00727)	PC: 1.57 times more likely to have assets (0.01059)	PC: 1.03 times more likely to have assets (0.01511)	PC: 1.51 times more likely to have assets (0.00947)
Assets Rank Order (for Assets>0)	PC: +0.054 (0.00270) n=86,700	PC: +0.052 (0.00398) n=40,439	PC: +0.071 (0.00482) n=26,942	PC: +0.054 (0.00403) n=46,207
Liability Adoption Rate	PC: 1.74 times more likely to have liab (0.07658)	PC: 2.19 times more likely to have liab (0.1164)	PC: 3.31 times more likely to have liab (0.04645)	PC: 1.88 times more likely to have liab (0.08862)
Liability Rank Order (for Liability>0)	PC: +0.088 (0.00179) n=271,891	PC: +0.043 (0.00269) n=125,617	PC: +0.017 (0.00238) n=92,329	PC: +0.081 (0.00233) n=172,783
Products Rank Order	PC: +0.114 (0.00169)	PC: +0.161 (0.00246)	PC: +0.142 (0.00216)	PC: +0.126 (0.00225)
Profit Rank Order	PC: +0.096 (0.00193)	not available	not available	PC: +0.168 (0.00233)
N	273,565	126,600	110,082	174,043

Each cell posts an increase in % rank or adoption propensity for PC banking customers, the standard error of this estimate, and a sample size. All coefficients are significant at p<.01, except as noted by a ^.

Table 5. Comparison of PC and Regular Customer Account Value: Rank Order Regression, Matched Sample

	Bank A	Bank B	Bank C	Bank D
Asset Adoption Rate	PC: 1.48 times more likely to have assets (0.00956)	PC: 1.38 times more likely to have assets (0.01369)	PC: 0.84 times more likely to have assets (0.01339)	PC: 1.35 times more likely to have assets (0.01309)
Assets Rank Order (for Assets>0)	PC: +0.059 (0.00406) n=20,930	PC: +0.058 (0.00590) n=9,814	PC: +0.085 (0.00655) n=7,691	PC: +0.045 (0.00611) n=9,213
Liability Adoption Rate	PC: 1.47 times more likely to have liab (0.09449)	PC: 2.26 times more likely to have liab (0.1292)	PC: 3.42 times more likely to have liab (0.02936)	PC: 1.58 times more likely to have liab (0.1003)
Liability Rank Order (for Liability>0)	PC: +0.081 (0.00267) n=45,680	PC: +0.041 (0.00387) n=22,121	PC: +0^ (0.00366) n=25,194	PC: +0.087 (0.00352) n=26,296
Products Rank Order	PC: +0.104 (0.00261)	PC: +0.140 (0.00357)	PC: +0.126 (0.00324)	PC: +0.114 (0.00334)
Profitability Rank Order	PC: +0.092 (0.00266)	not available	not available	PC: +0.157 (0.00342)
n	45,890	22,230	28,664	26,418

Each cell posts an increase in % rank or adoption propensity for PC banking customers, the standard error of this estimate, and a sample size. All coefficients are significant at p<.01, except as noted by ^.

Table 6. Cross-Sell Rate Comparison Following PC Banking Introduction (percentage cross sold products)

	Bank A	Bank B
Post-PC Asset Adoption Rate	PC: 1.25 times more likely to adopt assets post-PC (0.01275)	PC: 1.35 times more likely to adopt assets post-PC (0.02158)
Post-PC Assets Rank Order (for Post-PC Assets>0)	PC: +0.055 (0.00671) n=7,599	PC: +0.032 (0.01175) n=2,585
Post-PC Liability Adoption Rate	PC: 1.06 times less likely to adopt liab post-PC (0.01085)	PC: 1.03 times less likely to adopt liab post-PC (0.01647)
Post-PC Liab Rank Order (for Post-PC Liab>0)	PC: +0^ (0.00544) n=11,276	PC: +0^ (0.00845) n=4,669
Post-PC Product Adoption Rate	PC: 1.12 times less likely to adopt products post-PC (0.1161)	PC: 1.29 times less likely to adopt products post-PC (0.01354)
Post-PC Products Rank Order (for Post-PC Products>0)	PC: +0.015 (0.00396) n=17,653	PC: +0.029 (0.00531) n=10,569
N	45,890	22,230

Each cell posts an increase in % rank or adoption propensity for PC banking customers, the standard error of this estimate, and, in some cases, a sample size. All coefficients are significant at p<.01, except as noted with a ^.

Table 7. Comparison of Regular and PC Banking Customers over Customer Lifecycle

(Percentage of quarters in which average PC banking customer is better than the average regular customer over 15 years)

	Bank A	Bank B	Bank C	Bank D
Assets	100% p<.0001	100% p<.0001	63.3% p<.05	95.0% p<.0001
Liabilities	96.7% p<.0001	35.0% p<.05	38.3% p<.05	96.7% p<.0001
Products	100% p<.0001	100% p<.0001	100% p<.0001	100% p<.0001

P-values represent the probability that the samples are the same.

Figures

Figure 1. Comparison of PC Banking and Non PC Banking Customers (Matched Sample)

(Absent differences between regular and PC banking customers, the bar would be 100%.)

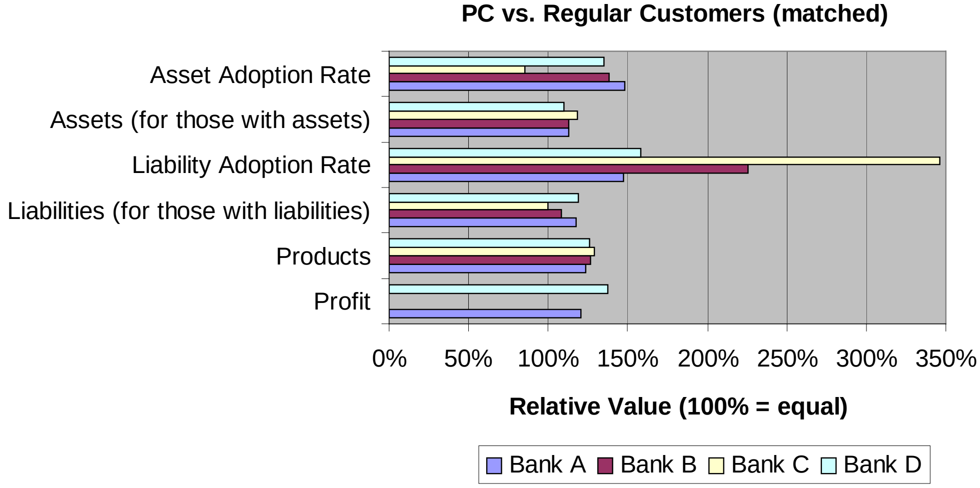


Figure 2. Relative Cross-Sell for PC Banking and Non PC Banking Customers (Matched Sample)

(Absent differences between regular and PC banking customers, the bar would be 100%.)

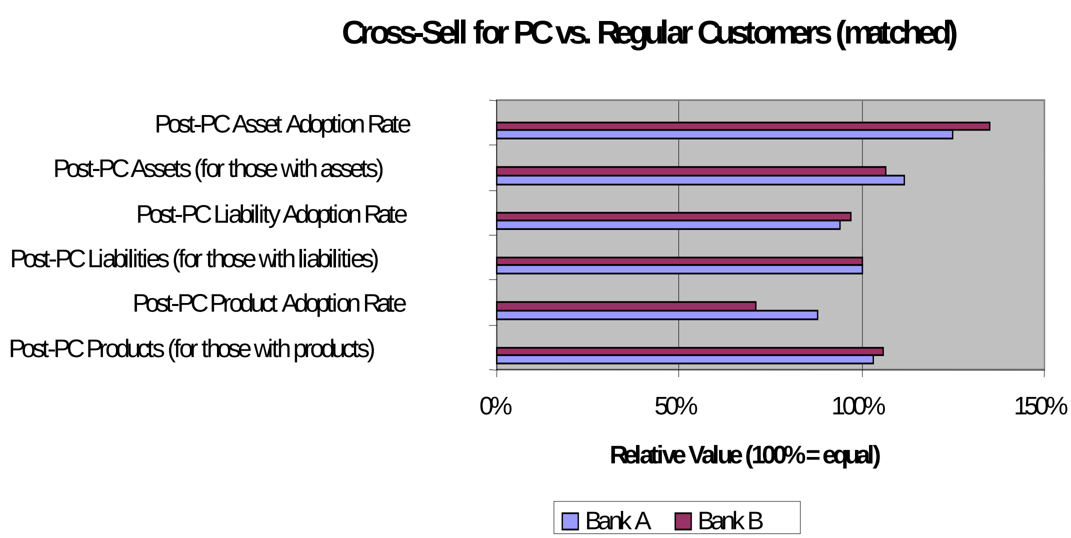
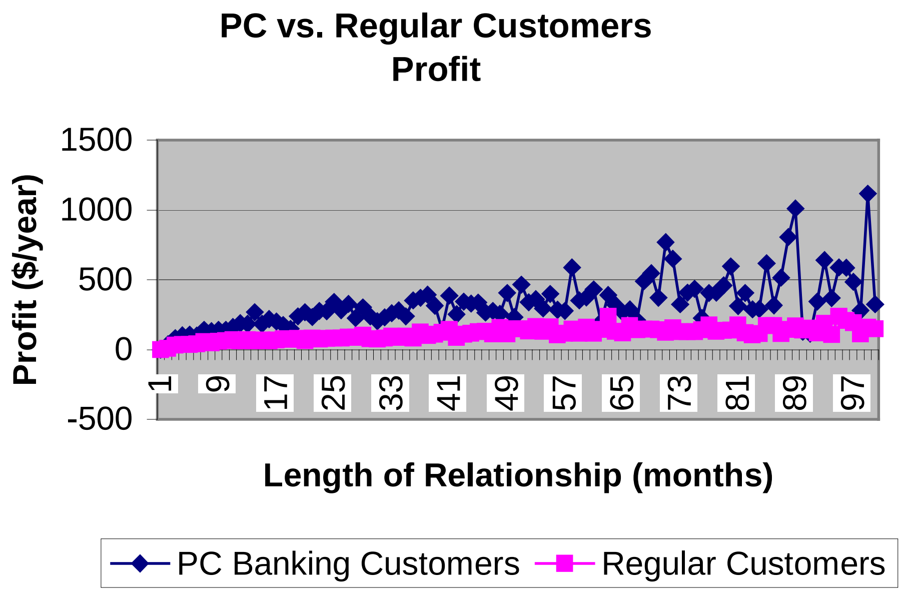


Figure 3. Account Value for Different Customer Relationship Lengths: Assets (Bank A)



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[1] We conjecture that the potential for cost reduction considered in our earlier work is not likely to be large due to the relatively small penetration of online banking, limited substitution between online and off-line transactions, and the incremental infrastructure and support costs (Hitt, Frei, and Harker, 1999), but lack the data to draw strong conclusion one way or another on this issue. Recent reports in the banking trade press do support this view (Stoneman, 2001).

[2] For instance, the narrative descriptions of Gomez.com, which tracks the characteristics of the top online banking web sites, suggest that the principal differentiation between products is breadth (how many services are offered), the integration of different services, and the degree of customer (telephone) support.

[3] This would, for example, be consistent with revenue increasing in account balance and cost that comprises a fixed account startup cost plus some ongoing cost that is either fixed or proportional to balance. This formulation is more problematic if the components of C represent the use or non-use of accounts, it being possible for an incremental account to have negative value in the short run. This is less likely to be a problem in a long run comparison since negative values might be offset by other accounts (if a loss leader) or the bank can encourage termination of unprofitable accounts through repricing.

[4] “Cross-sell rate” is an industry term for how many incremental products a customer purchases after initiating a relationship with the bank. Increasing cross-sell rates is one of the primary approaches in modern banking strategy for improving profitability.

[5] The banks in our broader sample range from $30 billion to more than $200 billion in assets. Although clearly not a random sample of U.S. banks, we do believe that we have not systematically selected “good” PC banking institutions. The banks (with the exception of the one examined for retention analysis) that provided data are typically “technology followers,” so our results may not extend to leaders or laggards. Most banks having been recruited from relationships with an industry association and personal contacts, we do not believe that they self-selected in a way that might bias the results.

[6] These are computed assuming that if the distributions are the same, each time period represents a Bernoulli trial (probability = .5) that one distribution will be higher than another. The numbers 40% and 60% represent the $p<.05$ interval. Numbers outside this range suggest significant differences in the distributions.