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# Do Better Customers Utilize Electronic Distribution Channels? The Case of PC Banking

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# Do Better Customers Utilize Electronic Distribution Channels? The Case of PC Banking

**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 who 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, principally 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.

**Keywords**
online banking, financial services, electronic commerce, customer profitability

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# *Do Better Customers Utilize Electronic Distribution Channels? The Case of PC Banking*

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# Do Better Customers Utilize Electronic Distribution Channels?
# The Case of PC Banking

April, 1999

*Draft - Comments Welcome!*

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# Do Better Customers Utilize Electronic Distribution Channels? The Case of PC Banking


Abstract

Firms are increasingly implementing electronic distribution strategies to augment existing physical infrastructure for product and service delivery. However, to date there has been little systematic study on how these distribution channels affect customer profitability. In this study, we explore the revenue enhancement potential for electronic delivery in retail banking by comparing customers who utilize personal-computer based home banking ("PC Banking") to other bank customers. Our results, based on case studies and detailed customer data from four institutions, suggest that while PC banking customers appear to be more profitable, most of the differences are due to unobservable characteristics of these customers that were present before PC banking was adopted. Demographic characteristics and changes in customer behavior following the adoption of the product account for only a small fraction of the overall differences. We conclude that, at least to date, the primary potential value of the product is in the retention of high value customers rather than cost savings or incremental sales. Our results also suggest that it is important to distinguish behavioral changes from pre-existing customer characteristics when evaluating the impact of added electronic delivery channels.

## 1. Introduction

Firms are increasingly utilizing electronic distribution methods to augment or possibly replace their existing "traditional" product and service delivery processes. For example, Barnes and Noble and Borders both have major initiatives to sell books on the Internet while continuing to invest in new physical stores; catalog retailers such as L.L. Bean, Eddie Bauer and Lands End also have made substantial investments in their on-line presence to augment their existing telephone, mail-order, and outlet stores.[1]

However, nowhere has this trend been more important in business to consumer electronic commerce than the financial services industry, and in particular, retail banking. The first major investment in on-line banking (the Chemical Bank PRONTO system) occurred more than 10 years ago, when the home computer was still a rarity (Kalakota and Frei, 1997). 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. Today, almost all retail banks have on-line inquiry capability for customer account information, and most provide the ability to perform transactions such as balance transfers, withdrawals or bill payments, usually through dedicated software operating on a dial-in network (we term this capability "PC Banking"). In addition, most are planning or in pilot stages in providing transactional capability through the internet.

As these investments become larger and more central to the long-term strategy of financial institutions, it becomes important to understand how (or whether) these investments add value. Most banks recognize the need to have an on-line presence, but there is limited consistency across institutions in their strategy for on-line banking beyond establishing a presence (Hitt, Harker and Frei, 1998). In this study we specifically explore three possible sources of value from electronic distribution: targeting desirable demographic segments, segmenting customers on unobservable but profitable characteristics, and inducing revenue enhancing behavioral changes.[2] To determine the contribution of these value sources we conduct

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[1] See e.g. www.barnesandnoble.com, www.llbean.com, www.landsend.com, www.eddiebauer.com, www.borders.com. Forrester predicts a growth in on-line retail spending from \$7.8Bn in 1998 to \$33 Bn in 2000 (Cooperstein et. al., 1998).

[2] We also consider the potential for cost reduction, but do not believe (contrary to some published reports) that this is a significant contributor to value in the short to medium term. Moreover, these costs savings are predicated on

large sample statistical analyses comparing characteristics and product usage for customers who utilize PC banking to those that do not. Combining these analyses with quantitative and qualitative data from interviews of executives in the firms in our study, we are able to identify and compare most of the relevant sources of value of electronic distribution for retail banks. Moreover, the same general sources of value are likely to be relevant to other types of on-line distribution opportunities by firms with existing "traditional" distribution networks.[3]

Early work on electronic commerce, and the vast majority of the practitioner literature, has emphasized cost savings of on-line distribution. For example, Booz-Allen reports that the marginal cost of an on-line banking transaction is $0.04 while a traditional teller based transaction costs $1.44 (McQuivey et al, 1998). However, even accepting that these figures are reasonable (see Hitt, Frei and Harker, 1998 for a counter argument), cost savings is an unsatisfying primary motivation for many reasons. First, these cost savings are easily replicated by competitors and thus unlikely to create a sustainable competitive advantage. Second, many of these cost reductions are also accompanied by reduced entry barriers (e.g. need for a geographically dense branch network)or increased market transparency further intensifying competition (Benjamin and Wigand, 1995) making it even less likely that banks will benefit from cost savings from on-line distribution. Finally, given that electronic distribution involves substantial and frequent incremental investments in infrastructure as well as incremental service and support, it is not even clear that these types of technologies lead to a net reduction in cost.

Recent work has begun to suggest that a much richer set of strategies is possible in electronic channels that mirror strategies used in traditional commerce. For example, various authors have discussed the role of product differentiation, price discrimination, and the strategic use of search and switching costs in electronic markets (Lee, 1998; Clemons, Hann and Hitt, 1998; Varian and Shapiro, 1998; Bakos, 1997; Clemons and Weber, 1990; Baily, Brynjolfsson and Smith, 1997). However, while these studies are providing the economic footing for a broader view of the value of electronic commerce, these studies have focused primarily on producer behavior and do not directly consider customer variation or behavioral change induced

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other changes in distribution strategy or technological capability which have not yet been made in the institutions in our study.

[3] These lessons may be relevant to markets in which incumbents face new electronic entrants (e.g. book selling and the battles between Barnes and Noble and Amazon.com). However, our analysis of the PC banking market is greatly simplified by the lack of any relevant on-line only players at the time of our study that do not have the existing advantages or disadvantages of a full-fledged retail distribution system.

by the availability of electronic distribution. While market research has examined how the demographics (e.g. age and income) differ between on-line and traditional customers, these studies only provide a superficial view of potentially large differences among customers. In banking, it is well known profit varies substantially across households, even within the same institution and the same demographic segment, and that these differences are critical in understanding retail bank performance and devising profitable strategies (see e.g. Clemons, 1991; Clemons and Thatcher, 1997).

In this study, our objective is twofold. First, we would like to better understand how producer value is created through on-line banking by studying the difference of customer characteristics and customer behavior between PC banking customers and other customers. This is potentially useful to aid existing strategy formulation, to assist in the development of future strategies for similar banking products (e.g. web-based banking), and to inform investments in other types of electronic distribution in non-financial products by banks or other firms. Second, would like to extend the existing empirical work on the strategy and value for electronic commerce by considering the role of differences between on-line and traditional customers. The magnitude and nature of the variation in profitability among customers is critical in financial services where substantial heterogeneity in customer profitability is known to exist, and may be increasingly important as the internet is utilized for "one-to-one" marketing strategies for other products.

Our study is based on interviews of seven large retail banks, four of which also provided extensive customer information file data on all their on-line customers and a larger random sample of regular customers. In total, we have a diverse data set including over 500,000 customers at a single point in time (2$^{nd}$ Quarter, 1998) spanning a range of bank sizes, geographic areas, and customer characteristics. Using these data, we are able to compare the product use, product adoption times, account balances and, in some cases, estimated profitability between on-line customers and a matched sample of regular customers.

Overall, we find that PC banking customers are on average more profitable, use more products and carry greater balances on these products than the traditional customer population. The same results hold when PC banking customers are compared to a matched sample of regular customers. We also find evidence of changes in customer behavior: existing customers who adopt on-line banking have a greater propensity to adopt future bank products than traditional customers do over the same time period. However, the overall contribution of these changes is very small compared to the initial differences in the two customer populations. These differences are remarkably robust across different banking institutions suggesting that this finding is highly general across a range of product variations, geographic locations, customer length of relationship, and other bank-specific factors. Using our interview data, we are able to rule out product differentiation, price discrimination, and cost savings as near- to medium-term benefits. Combining our data analysis and interview findings leads us to conclude that the primary benefit of PC banking is in the possibility for retaining high profit customers. More broadly, these results also suggest that previously unidentified differences in customers can have a large influence on the measured value of electronic distribution investments.

## 2. Value In PC Banking

### *2.1 Economics of Electronic Delivery*

To date, the vast majority of work on the economics of electronic markets has emphasized the potential cost savings through improved communications and coordination (Malone, Yates and Benjamin, 1991), a reduction in Williamsonian transaction costs (Clemons and Row, 1992; Gurbaxani and Whang, 1991), or simply a substitution for relatively fixed cost information technology assets for variable cost human interaction. While the cost benefits are certainly desirable for vendors and heavily emphasized in the trade press on e-commerce, the operational cost savings are often accompanied by increased availability of information about prices and product characteristics. This had led some observers to hypothesize that electronic markets will be characterized by intense price competition and low profitability (Benjamin and Wigand, 1995), a result demonstrated theoretically by Bakos (1997), even for differentiated products. In fact, because the fundamental technologies of electronic distribution are freely available to all market participants, electronic distribution may be particularly likely to become a competitive necessity (Clemons, 1991).

Recent work on electronic commerce has begun to examine ways in which electronic markets can lead to revenue enhancement. One stream of literature focuses on how market imperfections in “real world” markets translate into the electronic domain. Baily, Brynjolfsson and Smith (1997) examined prices for commodity goods (books, CDs) in real and electronic markets and find that in some cases there is more price variability in electronic markets than in traditional markets. They argue that this may be due to the persistence of search costs in electronic markets. Clemons, Hann and Hitt (1998) analyze the market for online travel agents (OTAs) and find OTAs appear to be engaging in both product differentiation and price discrimination. Others have examined how network externalities (Katz and Shapiro, 1986; Varian and Shapiro, 1998) and customer learning can also enable first movers in electronic markets to sustain an initial advantage. The current interest in on-line "communities" tied to e-commerce sites is an example of how network externalities might create incremental value for customers leading to a competitive advantage for early entrants.

Collectively these papers suggest that in addition to generating cost savings, electronic markets may also be utilized for revenue enhancements through more traditional strategies of product differentiation, price discrimination, and the strategic manipulation of switching costs.

### *2.2 Customer Variation in Electronic Markets*

The emphasis of even the recent empirical literature on electronic commerce is heavily skewed toward a detailed characterization of vendor behavior either holding customer characteristics fixed and identical or allowing small variation in aggregate groups. For instance, the consumers in Bakos' (1998) model all face the same search costs and differ only in their preference for non-quality product attributes. Brynjolfsson and Smith (1998) compare whether on-line shopping is less expensive than traditional shopping by examining the costs incurred by a representative consumer (e.g. buys three books on-line with standard shipping compared to driving an average of five miles to a traditional book seller). Even studies which attempt to account for customer heterogeneity are somewhat limited. Clemons, Hann and Hitt (1998) in their study of on-line travel agents emphasize two types of customer preferences -- business travelers who emphasize convenience over price and leisure travelers looking for absolute minimum cost tickets. The essence of Varian and Shapiro's (1998) argument that "versioning" (offering different versions of a product at different price points) is a viable strategy for information goods is that there are a discrete number of well-defined market segments that have different price-quality tradeoffs. The only paper that has addressed the issue of customer heterogeneity is Parasarathy and Bhattacherjee (1998) who utilized survey data to examine how customer characteristics influence the decision to continue or terminate the use of an on-line service.

There are several reasons why customer behavior and profitability might systematically differ in electronic markets. Numerous market research studies (e.g., INTECO, 1998) have shown that the average PC user is slightly younger, more affluent, more likely to be married, and more likely to own a home. A similar set of characteristics has been found in the market research studies of on-line banking users and these differences also appear in our data (see Table 2). To the extent that that demographic characteristics are systematically linked to desirable behavior, such as a greater utilization of high profit products, these could lead to customer differences. However, the magnitude of these linkages have traditionally not been estimated or at least not reported due to the proprietary nature of the required data. It is thus difficult to understand whether this is a substantial effect.

Second, the use of an on-line channel may indicate the presence of other, previously unobserved characteristics. For example, it may be that users of a PC banking product were willing to incur the cost of learning and installing the software because they have a stronger affinity to a particular institution. Customers who adopt PC banking are also likely to have a greater demand for services that are provided inexpensively on-line, such as the need for up-to-date account information. On-line shoppers have also been characterized as highly informed and price sensitive, or as having a high value for their time. In this interpretation, on-line use is a reflection of a previously unidentified, existing behavioral trait which may have an influence on customer profitability.

Third, the use of an on-line channel may encourage consumers, either through design or just as an unintended consequence, to behave in beneficial ways. For example, recommendations on the Amazon.com site may lead to incremental book purchases at a greater rate than they would browsing in a traditional bookstore (Brynjolfsson and Smith, 1998). Stock investors offered the opportunity to trade inexpensively on-line might trade more actively than other that utilize traditional or (non-online) discount brokers, even at the same prices. Interviews with our study participants suggested that consumers who choose on-line banking may be inclined to consolidate their account activity into a single institution to obtain an overall view of their financial status. They may also be more inclined to purchase future products from the same institution when their product needs change due to increased convenience, trust, or familiarity.

Except for some initial studies on the demographic difference (INTECO, 1998) and a few anecdotes on customer purchases,[4] these three sources of customer heterogeneity (demographics, unobserved differences, behavioral changes) have not been extensively studied in the context of electronic distribution. In our analyses we will attempt to investigate all three of these explanations, and in particular, pay close attention to distinguishing existing customer characteristics from behavior changes to the extent it is possible using our data.

*2.3 Overview of the Product*

Most banks, at least by mid-1998, have offered or are planning to offer the ability to access account information and perform simple transactions remotely using a home computer. The majority of existing facilities utilize specialized software and a telephone-dialup connection, usually to a third-party network provider. This software, combined with the server-side technology and network service, is what we refer to as "PC Banking". PC banking comes in two general forms: an interface to a general purpose financial management package such as Quicken, Microsoft Money, or MECA, or a proprietary software system that is unique to a particular bank (e.g. Citibank Direct Access).[5]

While there is substantial variation in technology infrastructure and the involvement of third parties (e.g. network providers, software providers, transaction processors, and fulfillment vendors), the basic functionality provided by PC banking is fairly standardized. At the low end, a customer has the ability to view information about their accounts (balances, recent deposits, last checks processed, etc.) and perform simple transactions such as balance transfers. The next level of functionality includes a bill-payment option ("Bill Pay"), in which customers can establish a list of payees and generate a payment through their home computer. This transaction is either processed through electronic funds transfer or the generation of a paper check by the bank or a third-party processor. Finally, more advanced software might include the ability to perform other types of transactions such as retail stock trades, obtain account information on other bank products (mortgages, credit cards), receive bills ("Bill Presentment"), or apply for other types of financial products such as credit cards, credit lines, insurance, or mortgages.

Most services offer multiple versions of the product; usually a base-level version that has

[4] For example, it is accepted wisdom in the trade press that on-line brokerage customers trade more frequently.
[5] Many of these proprietary products include components designed and produced by third parties such as Visa International. However, these still are considered proprietary because these systems lack the ability to interact with more than one institution.

only information capabilities and an enhanced version that has bill payment. At the moment, bill presentment or other advanced features do exist at some institutions and are in planning stages in most, but are not prevalent (and are not present in any of the institutions for which we have customer data). Our interviews and reviews of the actual product offerings and business plans for the institutions in our study suggest that aside from some cosmetic differences, the fundamental products are very similar across institutions and most institutions have these products available. As such, this market (defined as the market for PC banking services) has been characterized by very little product differentiation to date.[6]

The fee structure for these services varies substantially. Many institutions offer these services essentially for free subject to a minimum balance requirement, while others charge for bill payment and sometimes even basic functionality. The competitive environment generally determines these fees; once one bank in a region begins to offer PC banking for free, most others follows suit. However, even for the products that are free, there are numerous other potential charges (e.g., exceeding a specified number of logons, transactions or payments in a month), making it difficult to compare pricing except for monthly fees.

A comparison of the fee structures for bill payment functionality across the banks in our sample appears as Figure 1. In addition to the substantial variation in initial price, there is a clear trend toward lower monthly fees. Some banks do waive these fees for certain types of high (deposit) balance customers, but this strategy is not prevalent in our sample. Only 1 bank we visited currently had such a program.

It is important to recognize that these fees do not cover the incremental variable costs of the PC product. The banks in our sample report operating costs on the order of $8 to $15 a month per customer; those that have outsourced to a third party provider for bill payment and network services tend to be at the higher end of the cost distribution. These variable costs per customer include network costs, software licensing, ongoing technical and customer support. In addition, these numbers also include ongoing systems support and enhancement, but do not consider the amortization of the initial investment. While some of these costs may decline with greater scale, on a fee revenue versus operational cost basis this product is not profitable, and is not likely to be profitable until a much greater penetration rate is reached. At current levels of

[6] Given the later findings of this paper, that these customers represent an unusually attractive market segment, the fact that price discrimination has not been employed is striking.

penetration (<5% customers), substantial cost reduction in existing delivery channels can be ruled out, although at a greater level in the future, this may be more of a factor. However, this is heavily limited by the nature of the product itself; the high penetration areas for PC banking are also areas where branches are likely to be profitable, making it difficult to achieve substantial cost savings. In addition, the diffusion rate of this product does not appear to be accelerating (unlike, say, the adoption of Internet service over the last several years) suggesting that achieving the required scale may take some time.

Aside from the incremental fees for the use of the product and the two tiered pricing, banks do not report that they are offering different products or treating the customers that utilize the PC banking product any differently than regular customers. Some have attempted e-mail solicitations or some unique promotions, but these were generally not viewed as substantive. As such, we do not believe that price discrimination strategies are currently being employed in conjunction with the product, since all customers are more or less offered the same banking products, whether they are PC customers or not. Again, this suggests that at present, banks are primarily focusing on making the product available rather than linking this product to an overall strategic plan.

These products have been available in the marketplace in various forms for over 10 years (the first well-known product is the Chemical Bank PRONTO system), although the vast majority of these systems were put in place over the last 3 years. In 1998, most banks began planning or actively pursuing the transition from the dedicated PC-banking product (which is relatively high cost) to internet banking which avoids software distribution and network access costs. Of the seven banks we visited, four were planning the transition and three had already released a web site with transactional capability. Most banks are planning on a two-pronged strategy for the future of home banking: a transaction-oriented web site for customers who do not utilize personal financial management (PFM) software, and an internet-based interface to popular PFM products.

Currently, diffusion of PC banking in the United States is estimated at about 2.5% in 1996 and is expected to grow to about 19% by the year 2002 (Matheison, 1998), although these estimates are predicated in Internet-like growth rates. For the banks in our sample, we estimate the rate to be approximately 3% at the time of the study, which is comparable to the aggregate numbers. Of these, 70-85% of the adopters are existing customers; only 15-30% initiated their account with the PC banking account. This relatively low penetration rate combined with the fact that it is not a very good substitute for a teller interaction (only balance transfers and account inquiries are direct substitutes) suggests that the impact on the cost structure of the branch network is going to be very small. The long run outlook for bill payment leading to a reduction in check processing costs is somewhat more promising. However, many PC initiated payment transactions result in the generation of a paper check (banks in our sample estimate this number to be at least 30%) since many payees cannot accept electronic funds transfer payments. This fact, combined with a relatively high error rate (>1%), suggest that improvement in the economics of check processing are not currently being realized. Thus, the current levels of penetration of the PC banking product suggest that cost savings are an unlikely source of value for PC banking, at least in the near term, even before considering the investment costs in providing the service.

Taken together, research in this market and our interview data suggest that, to date, cost savings, new account acquisition, product differentiation and price discrimination have not played a large role in this market. Because the product is fairly uniform and there is standardized customer information available across institutions, we believe this market is an excellent example of a "natural experiment" to study the effects of customer differences in electronic markets. Most of the potential alternative explanations do not appear to be substantive, at least at the time of the study, leading to "apples to apples" comparisons across different banking institutions.

### *2.4 Hypotheses and Research Design*

Our previous discussion suggests an approach to understanding the value of PC banking by comparing the "value" (to be defined in the section on measurement below) of a customer that exists in a traditional banking channel with the value of a customer that utilizes on-line banking. Thus our initial null hypothesis is that:

*H0) Customers who utilize PC banking have the same value as those who do not at a single point in time.*

If we are able to reject this basic null hypothesis, we can then explore what drives the variation in value. As mentioned earlier, these values may differ for three reasons: observable differences (e.g. length of relationship or demographic characteristics), unobserved differences and changes in behavior. The first is straightforward to address:

*H1) There is no difference in value 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 bank).*

Distinguishing between the unobserved heterogeneity and behavioral change is somewhat more difficult. Given the cross sectional nature of our data[7] we are unable to fully characterize how customer behavior changes after they adopt the product and to separate out variation due to the time evolution of a customer account and deviations induced by the adoption of the PC banking product. However, we do have data available on when the customer adopted their various products and thus can compute whether "cross-sell rates"[8] and the value of incremental products differ across populations following the use of PC banking. We would be more likely to believe that the PC banking product led to changes in customer behavior if cross-sell rates increased after the adoption of the PC product as compared to a suitable sample of regular customers (this sample construction will be discussed in the next section). This leads to the following hypothesis, stated in null form:

*H2) There is no difference in the incremental product purchases between customers who utilize PC banking and regular customers following the adoption of the PC banking product.*

Finally, while point-in-time comparisons are useful benchmarks, we could make stronger conclusions if we can demonstrate that the overall present value of accounts is different. Thus, we formulate our final (null) hypothesis that:

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

[7] In fact, even with unlimited time series data it is not obvious that this task can be performed as thoroughly as one would like. Any comparison would have to rest on the assumption that, at some point in the past, customer behavior was representative of their future long-term behavior. In addition, it would require that the data on past customer behavior be consistent and accessible which is likely to be problematic.

*2.5 Methodology*

There are several questions that are raised by the idea of comparing "value" between two customer populations. First, we need a way to compare, in a manner consistent across institutions, customers who purchase a portfolio of products that have different potential profit characteristics. This issue arises in the literature on banking productivity in the attempt to measure banking output. Is it sufficient to add asset balances and liability balances to construct an aggregate "output" or some weighting or priority scheme necessary to estimate the relative value of say a checking account and a mortgage? (see e.g. Berger and Mester, 1997). While we will not be able to resolve this long-standing debate, we can attempt to make our results insensitive to these types of issues by choosing standard metrics and multiple value measures. Second, banking relationships are characterized by a time path of product use and profitability both in terms of the customer's age, but also in the length of the relationship with the institution; new customers generally have relatively low balances and few products and acquire additional products over time. In addition, observable characteristics such as length of relationship, age and income may interact in complex ways thus making it difficult to capture all possibilities in a simple functional form relating observable characteristics to behavior. Finally, we need a way of translating a point in time estimate of observed product use, into a metric of long-term value since customer accounts are best viewed as an asset (they are expensive to acquire and provide a long term revenue stream).[9]

In order to address these issues it is useful to introduce some notation for clarity. Let the characteristics of a customer account be represented by a vector C(·) which 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(·) represent, for example, balances in different products or a collection of binary variables representing whether a customer has an account of a particular type.

Define single-period account value, a scalar, V(C) to be weakly increasing in all

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[8] Cross-sell is a banking industry term for the sale of incremental products to customers with an existing banking relationship. Most banks believe that increasing cross-sell rates is critical to improving profitability given that banking is a mature industry with a relatively slow underlying growth in new accounts.

[9] This particular point is of great significance to those who work on banking customer profitability. On the one hand, customer relationships are costly to acquire and represent a long-lived "asset" suggesting that long-term present value of the relationship is the best metric. On the other hand, given the substantial unobserved heterogeneity known to exist in the customer population and unpredictable macroeconomic and competitive factors, projections of behavior beyond a few years are highly suspect (Richard Spitler, private communication).

components of C, but otherwise unrestricted. This is not a fully general assumption, but appears to be consistent with common characteristic of banking practice.[10] Because C is a function of time, V(·) is also a function of time. The appropriate comparison between two customers (either actual customers or representative customers) A and B is the difference in lifetime account value from an arbitrary time to a time T (possibly unique to A or B) in which the account terminates. We assume that banks are risk neutral and consider all values to be expected values, that they have a constant discount rate (r) across all customers, and do not vary in the types of information (X) that is observable across customers. With these assumptions we can say that customer A has higher value than customer B (subscripts denoting customer, superscripts denoting time points) at point in time $t^1$ (assuming $t^1 > t_A^0, t_B^0$, the time of initiation for both customers) iff:

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

In this form, the comparison of two arbitrary customers is difficult without explicit functional forms for C and V. However, the expression can be greatly simplified if we only compare customers that are identical on all observable variables (X and $t^0$). Assuming T is a function of X and not θ, a sufficient condition but relatively strong condition is that for all $t > t^1$:

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

This can be further simplified since V is monotonic in the components of C, depending on the structure of V. If there is a certain value flow associated with each component of C (an assumption that appears to be fairly reasonable for retail banking -- different products have different margins), e.g.:

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

Then we can derive a somewhat weaker condition that (for all $t > t^1$):

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

However, even with this simplification, we still require information on the full time series

[10] For example, this would be consistent with revenue that is increasing in account balance and cost that is comprised of 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 since it is possible for an incremental account to have negative value in the short run. However, this is less likely to be a problem in a

of $C(\cdot,t)$, yet our data only contains information on $C(\cdot,t\text{-}t^0)$, for a fixed t, although $t^0$ varies across customer pairs. Two possible approaches can be used to resolve this difficulty. First, we can place additional constraints on the form of C. A plausible assumption is that for any given time t*, if $C(\theta_A,t^*\text{-}t^0) > C(\theta_B,t^*\text{-}t^0)$ then this relationship holds for all t>t*. To make this concrete, if a customer has more money on deposit now, we have no reason to believe that this will lead to disproportionately less money on deposit later. Similarly, if a customer has a large mortgage balance now, they are not likely to prepay so much that it would in the future result in a lower mortgage balance later. This is clearly an assumption, but for most banking products does not appear too implausible (and is testable in our data, at least in aggregate). This leads to a test in which we compare sample means at a point in time for the components of C, or a suitable weighted aggregate. These tests are simpler and more closely related to common practice of comparing profitability of customers.

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 our 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. Parametric or non-parametric tests can then be employed to compare the levels over time to determine if one group is systematically higher in value or product use than another.

Our empirical approach will include several different types of tests. First, we will compare various measures of the value drivers © between the PC banking subsample and the overall population, with controls for observable differences (X). Second, we will perform similar comparisons in a matched sample where the values of X for every PC banking customer are matched to the values of X for a corresponding non-PC banking customer. Third, we will calculate and compare the time series evolution of $C(\cdot,t)$ for the matched sample and test whether these values are systematically higher for PC banking or regular customers.

In terms of our original hypotheses, these tests will first be used to compare the populations as a whole without controlling for observable characteristics (H0). We will then compare this to estimates with either matched samples or demographic control variables to determine the influence of demographics focusing first on static cross sectional differences (H1)

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long run comparison since these negative values may be offset by other accounts (if it is a loss leader) or the bank can encourage account termination of the unprofitable accounts through repricing.

and later on long run account value (H3). Next, we will perform similar comparisons limiting our analysis only to products acquired after PC banking was adopted (H2).

## 3. Data

In 1998 we enlisted 7 banks to participate in a comprehensive study of IT-investment practices,[11] which included a general overview of the process as well as an extensive discussion and data-collection effort of PC banking specifically as an example of a recent IT-investment decision. These data include project timelines, initial and ongoing costs, motivation for the investment, and measured outcomes. Some of these data were collected by a formal questionnaire where a specific question could be formulated (e.g., how much did you spend on PC banking prior to release?) while others were obtained in response to open-ended questions (e.g., what did you perceive the value of PC banking to be?).

Each bank was contacted and sent a questionnaire as well as a list of potential open-ended questions. Interviews were then scheduled with the individual or group most knowledgeable about a particular issue. In general, we interviewed the CIO, the head of retail banking, the business leader for the PC banking project, the technical leader for the PC banking project and the marketing person responsible for promoting the product. In some cases, we also met with the head of the call center, branch network or alternative delivery system if they had responsibility for any aspect of PC banking (for example, call center telephone support for the PC banking software). To date, we have conducted interviews with approximately 60 people.

In addition to the interviews, for each bank we attempted to collect a sample of customer records from the banks customer information file (CIF). These data generally include basic demographics (age, income, marital status, and home ownership), and data for each product owned (when initiated, current balance). We also have the date PC banking was initiated. Generally, the data is kept at the household level so we treat the household as the relevant unit of analysis. In some cases, we are also able to obtain estimates of household profitability. Usable data was provided by four of the banks in our sample,[12] although not all banks were able to provide all the fields due to idiosyncrasies in the way they store and retain customer data. To

[11] The banks in our broader sample range from $30Bn in assets to over $200 Bn. While this is clearly not a random sample of banks in the U.S., we do not believe that we have systematically selected “good” PC banking institutions from others. Most of the banks were recruited from relationships with an industry association and personal contacts of the researchers and, thus, we do not believe that they self-selected in a way which would bias the results.

minimize the burden on the banks in our study and ensure comparability across banks, a single "snapshot" of the customer information database was taken in 2nd quarter 1998. This places some strong limitations on the types of analyses we can perform given that we cannot track the behavior of customers over time except to the extent that they adopt new products. However, to our knowledge this is the only multiple-bank dataset of customer data and the only dataset of this magnitude that has been employed in academic research.

For the four banks we analyze in detail, we have a sample of all of the PC-banking households plus ten times as many regular households (these will be used for constructing matched samples for later analysis). Table 1 summarizes the data and observation counts for each of the banks that provided data. For the purposes of this analysis, we aggregate products into several categories as is common in the banking literature on performance measurement: assets (primarily mortgages, home equity loans, consumer loans and credit card receivables), liabilities (interest and non-interest bearing checking deposits, money market deposits, certificates of deposit) and other (investment accounts, mutual funds, safe deposit boxes and trust services). Results are not sensitive to this aggregation; however, it greatly simplifies presentation when we can consider two broad product groups rather than 10+ individual products. Due to its idiosyncratic nature, no analyses are performed on the products classified as "other".

To avoid having outliers influence the results, we exclude all customers with trust accounts, any customer with an aggregate negative balance in assets or liabilities, any customer who is in the highest .05% of any category (profitability, assets, liabilities, number of products) and any customer who is the lowest .05% of profitability.[13] Again, while the results are not sensitive to this outlier removal, interpretation of test and sample statistics is greatly aided by the removal of these households since it is highly unlikely that the PC product is a strong influence of banking behavior in extremely high-wealth households. Different banks use varying definitions of "product" and there is some variation in what types of products they include in their customer information files. This is not a problem for comparing PC banking to regular customers since there is no reason to believe that the use of PC banking is unusually correlated with the types of data the bank keeps on file. However, it does make it difficult to compare

[12] At the current time we have initial data from a fifth bank and negotiations are ongoing for the remaining two.

absolute numbers between institutions. We focus all of our comparisons within the same institutions, and show the variation (or lack of variation) across the different banks as corroboration to limit the impact of cross-bank heterogeneity in data reporting.

For most analyses, we distinguish between the choice to utilize a product (have a non-zero balance) and the utilization of the product conditional on product use. The relationship between use of PC banking and the product adoption decision is modeled using Logit regression, while the resulting balances are modeled by ordinary least squares regression. Due to our large sample size, estimation efficiency is not an issue, and results are robust to a variety of econometric adjustments such as heteroskedasticity corrections and the use of absolute balance levels (including the zeros) as the dependent variable. Because we do not have good predictors of the adoption of PC banking that are not also predictors of product use or profitability, we are unable to perform more complex analyses that address the endogeneity of the PC banking adoption decision. For example, this could be modeled as a Heckman self-selection model (see Maddala, 1977, Chapter 9). In addition, we do not have good measures of account termination that would enable us to estimate switching cost effects due to data unavailability.

Sample statistics are presented in Table 2. Three observations are immediately apparent about the data used in our study. First, customers who utilize PC banking are consistently in wealthier income brackets and between 2 and 6 years younger. They are more likely to be married and own homes. This is consistent with previous market research data on the demographics of PC owners and Internet users. Second, users of PC banking have on average more products, greater asset balances, and greater estimated profitability (where available) on average. All of these described differences are statistically significant. Third, these differences persist across different institutions in our study, although there is some variation on the degree of the difference. While these differences across banks are also statistically significant in many cases, as we will later show, they are not large or systematic in economic difference. In the next section, we will investigate these phenomena in greater detail.

Table 2 also shows some of the limitations in our ability to compare across institutions. The rates of home ownership, marital status, balances and other characteristics across banks vary substantially. Part of this is due to true variation due to geography and other factors while other

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[13] We do not have a similar lower bound exclusion for assets, liabilities or products since the minimum is 0. We do however, exclude any customer with a negative aggregate balance.

variation may be due to varying data-collection methods. We thus make all comparisons relative to the customer type for the bank and do not attempt to draw conclusions about how base rates vary across banks. Where possible, we utilize rank scores rather than absolute levels in an attempt to create greater comparability across institutions.

## 4. Results

In this section, we examine the evidence we have for or against our four hypotheses outlined earlier. These can be loosely summarized as: H0) no difference between PC banking and regular customers, H1) all differences explained by differences in observable characteristics (demographics, duration), H2) no difference between PC banking and regular customers in product use following the adoption of PC banking, and H3) no differences apparent in long run performance, controlling for observable characteristics. The same tests will be performed for each of the institutions in our sample and we will present the results across institutions for comparability.

The results will be presented following the discussion in the "Methodology" section. First we will make static comparisons between PC banking customers and either the pool of regular customers or a suitable matched sample (H1). This provides a reasonable comparison provided that the value metrics (assets, liabilities, products, current profit) are reasonable proxies for current period value, and that current period value is a good indication of long term discounted account value. Second, we will examine product acquisition behavior following the adoption of PC banking using a matched sample analysis (H2). Third, we will examine differences in the value measures over the lifetime of a relationship by plotting and comparing these measures over the length of relationship (H3).

### *4.1 Static Comparisons of PC Banking Customers and Regular Customers*

Our first analyses are based on a regression model in which value drivers (assets, liabilities - Liab, products - Nprod, asset adoption - AssetAdop, liability adoption - LiabAdop, and profitability - $\pi$) are a function of whether the customer utilizes PC banking (PC Banking, a dummy variable), dummy variables for age buckets, income buckets, marital status (married), home ownership (OwnHome), length of the account relationship (LOR) and its square. Thus we estimate:

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

and (where *Assets* and *Liab* are conditional on assets or liabilities being present):

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

Different variants of this regression can be done. Simple comparisons that include only PC banking but none of the control variables can be read off the sample statistics table (Table 2) -- in all cases the differences are highly significant ($p<.001$) and show a positive relationship between PC banking use and asset adoption, asset balance (for those with assets), products and profitability. Liability adoption is significantly higher for PC banking customers at all four of the banks however liability balances are higher for only one of the banks. To examine the importance of the various controls, we report estimates of the baseline regression in Table 3 for a single bank (Bank A). 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). Even with demographic controls, PC customers show consistently higher value in asset adoption, asset balances, liability adoption, liability balances, products and revenue, although again, PC banking only has a positive effect on liabilities for Bank A in this analysis. Results are robust to the use of heteroskedasticity-consistent standard errors (for the OLS regressions) and roughly the same as the OLS standard errors.

In Figures 2 and 3 we show these results using replacing absolute balance levels with a percentage rank for the institution (ranging from 0-1, where 1 is the highest - more discussion of this approach appears below). A comparison of these figures shows that while there is some difference in the value measures of PC customers relative to the population, including demographic controls has little effect. In any event, these controls do not explain the majority of the difference.

*Matched Sample*. To check whether the lack of explanatory power of demographics is due to our functional form for the demographic characteristics being insufficient (especially the relationship duration measures), we repeat the analysis using only a matched sample, comparing PC customers to a matched sample of regular customers. For each customer in our PC banking sample we identify a matching regular 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 the PC 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, row 3 for the percentage of customers we were able to match).

These results are displayed in Figure 4. As before, the differences between PC customers and regular customers are highly significant. In addition, PC banking customers (unlike in the simple statistics analysis) are consistently equal or greater in liability balance. Thus, we can conclude that these differences are robust to using <u>any</u> functional relationship between demographic characteristics and account value as controls in the regression.

*Rank Regression.* Due to differences in reporting and characteristics of banks, it is difficult to compare the statistical results across institutions when value is a continuous measure. Moreover, these analyses are still subject to influence from extreme points since assets in particular, and bank balances more generally tend to have a skewed distribution. While comparisons would still be legitimate using ordinary least squares with balance levels as a dependent variable, it is easier to visualize the results when we reclassify the value measures in rank order since the natural scales of the various value measures no longer affect the coefficient. To perform this analysis we pool the PC and non-PC customers together 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. Since all other variables (except length of relationship squared) are ordinal this is essentially rank regression. The results are shown for the simple comparison in Table 4, the model-based regression in Table 5, and the matched sample in Table 6.

Examining Tables 4-6, across most value measures, PC banking customers are higher in rank order than regular customers. This is consistent across all measures. When the demographic controls are included, the differences change slightly. For asset and liability adoption, demographics explain at most 25% of the difference between PC and regular customers. For the rest of the measures, demographics explain very little as can be seen by comparing Tables 4 and 6 or Figures 2 and 4.

These results suggest that we can reject the null hypotheses for both H0 and H1; there are substantial differences in the value of PC customers and regular customers, even after accounting for observable differences and using multiple approaches (models, matched samples, rank regression, distribution plots) to perform the comparison.

*4.2 Differences in Customer Behavior (Cross-Sell)*

While we are able to establish that PC banking customers are different, we cannot yet distinguish whether these were pre-existing conditions or whether the product changed behavior. Given that most PC banking customers were already customers of the bank, this distinction is crucial for strategy setting. Should banks encourage adoption aggressively in hopes of obtaining beneficial behavioral change or should banks merely make the product available upon request to guard against customer loss? While we cannot address whether customers added to their existing product balances after adopting the products, we can examine new purchase behavior.

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

Detailed data on both the PC bank initiation date is available for banks A and B. Bank D did not provide disaggregated account start data for other accounts. Bank C was unable to provide the initiation date for PC banking so we used a proxy of January 1, 1997 (the inception date of the product). Thus care should be used in interpreting the results from Bank C. In Table 7 and Figure 5 we report the differences in the purchase of products (the fraction that purchase in each subsample) and the balance in the incremental products (conditional on purchase).

Overall, we find that customers who utilize PC banking do tend to acquire assets at a faster rate (in 2 of the 3 banks), and when they acquire assets, they tend to have slightly higher balances. However, just the opposite seems to be true for liabilities: PC customers tend to adopt at a slower rate (in 2 of the 3 banks) and when they adopt, they tend to have lower balances.

Finally, following PC banking adoption, on-line customers tend to adopt products at a slower rate (in 2 of the 3 banks), but when they do adopt, they tend to adopt more products. On balance, the data suggest, at best, a slight increase 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 were good measures of the present value of the entire customer relationship. For reasons discussed in the earlier section, unless we believe that a high value of a customer characteristic today (accounting for the time the customer has been with the bank) will be associated with less profitable activity in the future this assumption is unlikely to change our conclusions. However, it would be useful if the results could more directly evaluate the lifetime value of a customer account, since this is closer to the true objectives of the bank. While our cross sectional data limits the types of analyses that can be performed, we can utilize the fact that our data contains a variety of customers at different stages of their lifecycle. If we are willing to assume that the behavior of customers over time in the past, at least on average, is indicative of future behavior of customers over time then we can compare the various value measures over time. In particular, we can make strong arguments about lifetime value if the value of a PC banking customer (on average) is always higher than the value of a traditional customer at any stage in the lifecycle (see formal treatment in section 2.5).

To make these comparisons we again utilized the matched sample to control for demographic factors that influence profitability. We group each type of customer (PC banking, regular customers) by their account duration -- each group is the portion of customers whose relationship length is within three months of each other (e.g. 0-3 months, 3-6 months...). The three-month guideline was chosen to ensure sufficient samples that the means can be estimated with suitable precision. Narrowing the window increases the noise, while too long a window may mask true customer heterogeneity. However, we experimented with alternative time windows (2 months, 6 months) and found that the results were not substantively changed.

For each type of customer and duration group, we compute the mean and the variance of each of the value measures (products, assets, liabilities) over 15 years. Figures 6-9 plot the time series graphs for one bank, showing the mean level of assets, liabilities, products and profit for

Bank A, comparing PC banking customers and regular customers over different customer relationship lengths. The graphs show that for assets and profitability, PC banking customers are consistently higher across all stages of the customer lifecycle. To quantify these differences, we compute the number of time periods for which the PC banking customers are (on average) higher than the regular customers over a 15 year time span (this period chosen so that we have at least 100 customers in the cell). The results are shown in Table 8. The probability that these two distributions are the same is shown below the percentage figure.[14] Overall, this table shows that PC Banking customers have consistently higher assets, products and profitability, although in two banks, liabilities are actually lower. Thus, this analysis corroborates our earlier assessment that for most value measures, PC Banking customers are consistently more profitable over time, giving us greater confidence that we are capturing both short-run and long-run account differences.

## 5. Discussion

Overall, our results suggests that PC Banking customers are more valuable to the bank than regular customers, even after accounting for demographic differences, account duration and short-run versus long-run profitability. PC Banking customers use more products and carry higher asset and liability balances than regular customers both in a single cross section and over different stages of their account lifetime. They also tend to acquire products at a slighly greater rate then their characteristics would suggest following their adoption of PC Banking, although this primarily relates to existing bank customer who adopt PC Banking rather than newer customers who begin their relationship with the PC product. These results are robust across multiple banks suggesting a general phenomenon rather than a characteristic of a single PC Banking implementation.

In terms of our original hypotheses, we clearly reject the hypotheses that PC Banking customers are the same as regular customers or that demographic differences explain all the difference. We found some evidence to support our second hypothesis, that some of the differences are due to behavioral change -- PC Banking customers acquire additional products at a slightly greater rate even though they start with more products to begin with. These differences

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[14] 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 $p<.05$

hold whether the customer was an existing bank customer or adopted the product when they purchased their first product, although the cross sell behavior and customer difference is substantially smaller.

In order to interpret the results it is useful to broadly categorize the value drivers. Existing customer heterogeneity is a large effect, account for differences in products or balances anywhere from 30% to 200+% for similar customers. Demographics have little effect on the differences between customers. Behavioral change, as measured by cross-sell rates, are statistically significantly higher, but do not contribute substantially to the overall observed differences. Across the three banks, the average PC customer acquires 0.17 more products than the customer population since their adoption of PC Banking. This compares to approximately a 1.5 product per customer between customers in the two channels. Given that the penetration of PC Banking is 3% or less of the customer base and the average customer purchases .8 more products over this time period, this translates into approximately a .6% increase in the cross sell rate across the bank.[15] Thus, while this is potentially important, it does not lead to the large cross-sectional differences in either product levels or cross-sell rates.

*5.1 Strategic Implications*

These comparisons are important in considering the appropriate strategy for PC Banking. If most of the differences are due to existing unobserved customer characteristics and most of the customers that adopt PC Banking are current banking customers, there are really only two substantial sources of (revenue enhancement) value in PC Banking. First, the product could be interpreted as a retention tool for retaining a small, but significant, segment of high value accounts. In essence, the product is a competitive necessity -- there is very little incremental value over the status quo, but potentially large value when compared to the possibility of losing these high profit accounts to other competitors. Second, the adoption of the product is a useful segmentation device that might indicate an opportunity for targeted cross-sell, price discrimination, or other types of strategies.

Interestingly, no bank currently has any program that offers different products, prices or promotions to PC Banking customers, and, thus, the potential segmentation effects are not being

interval. Numbers outside this range suggest significant differences in the distributions.

[15] The calculation is (.17/.8) * 3%= .00638 or .638%

acted upon. Second and more importantly, account retention was only a motivation for the PC banking investment in four of the seven banks we studied. Perhaps more strikingly, even in those institutions, there appeared to be little explicit pursuit of account retention in the product marketing and deployment approach.

In addition, the accounting practices and profitability measurement schemes in place at many of the banks in our sample systematically over-attribute account value to the PC Banking product. This is because the metrics used attribute the underlying differences in customer profitability as indications of behavior changes induced by the PC product rather than a preexisting condition. While in the short run this is merely a transfer of value between different parts of the bank, our results suggest that banks should be cautious about aggressively introducing this product to existing customers. Unless a bank has either sufficient scale (for cost savings in branch distribution) or a well-defined set of target customers that are at risk for defection in the absence of the PC product, incremental customers on the product may generate a loss. They will have neither the unobservable but good characteristics of the earlier adopters, nor will adding the PC channel to their portfolio of interactions save cost. It may, however, be a way of capturing high profit, new customers not otherwise reached by the existing branch network, but there was little evidence that the banks in our sample were able to capitalize on this possible value.

*5.2 Research Implications*

These results suggest that systematic and non-demographic differences in customers can have a substantial effect on the value of electronic distribution. Thus, care should be taken to recognize that those customers present in electronic channels may not be representative of the population of customers as a whole, and this may upwardly skew estimates of projected e-commerce profitability. As such it is important to recognize that unlike many other types of empirical investigation, unobserved heterogeneity between customers in electronic channels may be a very large effect and needs to be specifically addressed in future studies that examine the performance of e-commerce investments. Our study of banking was opportune because we had several years of history and high quality customer data, but the same techniques and approaches can be used by researchers (and practitioners) to understand customer behavior in electronic channels, even if retrospective data is lacking or suspect.

*5.3 Limitations*

There are a number of concerns about the data and analytical approaches used in this study that we raised earlier. The stark differences between the PC customers and the regular customers make us fairly confident that we are capturing true differences, that the measured differences are not influenced measuring value by aggregate account balances, and that we are capturing both short-run and long-run differences. However, we are not able to separately identify balance accumulation in existing products, thus omitting a potential source of value. However, even if this effect is 10x as large as the cross sell effect (which seems unlikely), our basic conclusion -- that preexisting differences drive value -- still holds. However, 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 -- building switching costs. This was entirely due to the difficulty of obtaining the required data, but a useful extension of this work would be to show conclusively whether PC banking customers are indeed less likely to defect to other institutions as would be expected.

In addition, while we have differential value, we do not have differential cost. Since the asset balances are heavily driven by home mortgages, there is not likely to be a large difference in customer cost, since profitability is only slightly influenced by transactional costs compared to balances in this product. The same argument does not necessarily hold for liability products or assets accumulated through credit cards which create teller visits or other types of costly transaction behavior. Preliminary data on one bank in our study suggests that PC customers perform about 30% more transactions of all types. This is small compared to the difference in product utilization. However, even if this were not the case, it is probably not a problem with our current conclusions since the PC product is too small and distributed across the customer base to enable infrastructure changes (e.g. branch staff reduction or closing) and thus the transaction differences have no marginal effect. When PC customers are much more common, their behavior may matter more in the overall cost structure.

*5.4 Conclusions*

Overall, we have shown that customers who utilize electronic channels are much more likely to be profitable than regular customers and that the evidence suggests that most of the differences in profitability existed before electronic channels had influence. While positive behavioral benefits exist, they are relatively small and thus in the short run, not likely to be a substantial profit driver. These results strongly suggest that on-line banking should be adopted defensively by retail banks as a way of retaining high quality accounts. It also suggests that on-line banking is not likely to contribute substantial profit or profit growth by itself, unless substantial changes are made in product design, marketing strategy, scale, and the overall cost structure of the bank.

To the extent that these results carry over to other types of electronic commerce these results have several implications. First, projecting current behavior in electronic channels to future behavior is likely to be problematic since the customers already in electronic channels may be systematically better than the regular population. Second, while non-bank or non-geographically based on-line banking has not been a major factor to date, many types of electronic distribution are not so closely tied to geography or other types of traditional channels. These markets present an opportunity for low cost and targeted entry into electronic distribution; new entrants do not have the baggage of the existing traditional infrastructure and may be able to systematically capture customers that are unusually profitable. Traditional banks are likely to face new and aggressive competition for these high value customers both from on-line "virtual banks" as well as mega-banks (e.g. Citigroup or NationsBank) that have a national brand recognition, but more limited traditional geographic scope.

**Table 1. Observation Counts and Data Availability**

| Data Item | Bank A | Bank B | Bank C | Bank D |
|---|---|---|---|---|
| PC Banking Customers | 24,814 | 11,170 | 16,832 | 14,118 |
| Non PC Banking Customers | 248,758 | 115,147 | 93,250 | 159,925 |
| Percent Matched Sample | 92.5% | 97.3% | 85.3% | 93.5% |
| Age | Exact | None | Exact | Exact |
| Income | Buckets | Buckets | Buckets | Exact |
| Marital Status | Yes | Yes | Yes | Yes |
| Home Ownership | Yes | Yes | Yes | Yes |
| Account Profitability | Profit | 5 Levels | None | Revenue |
| Products Covered^ | All | All | No Credit Cards | All |

^All includes demand Deposit (interest and non-interest), time deposit (savings, CDs), loans (home equity and installment), credit cards, mortgages, IRA accounts, commercial loans, and investments (mutual funds). No bank has complete coverage of all investment accounts. All banks report trust accounts, but all customers with trust assets are excluded from the analysis.

**Table 2. Means of Value, Demographic and Duration Measures by Bank and Customer Type**

| Measure | 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 | 29% | 55% | 30% | 52% | 24.6% | 23.9% | 25% | 42% |
| Assets (for those with assets) | $29,103 | $59,401 | $27,354 | $44,156 | $33,496 | $51,766 | $11,407 | $14,070 |
| Liability Adoption Rate | 99.3% | 99.8% | 99.1% | 99.8% | 81.4% | 97.7% | 99.2% | 99.8% |
| Liabilities (for those with liabilities) | $12,747 | $17,144 | $17,148 | $14,319 | $15,675 | $11,700 | $10,994 | $8,858 |
| Products | 2.8 | 4.3 | 3.5 | 5.2 | 2.9 | 4.1 | 2.0 | 2.5 |
| Profit[b] | $96 | $242 | not available | not available | not available | Not available | $397 | $558 |
| Age | 44 | 40 | not available | not available | 45 | 39 | 44 | 42 |
| Income | $52,500 | $69,900 | $54,100 | $69,600 | $65,500 | $71,500 | $29,500 | $33,600 |
| Own Home | 63% | 75% | 55% | 66% | 30% | 34% | 64% | 63% |
| Married | 33% | 50% | 43% | 54% | 20% | 24% | 48% | 52% |
| Time as Customer (years) | 9.5 | 7.1 | 10.5 | 7.6 | 8.1 | 7.2 | 8.9 | 5.8[a] |
| Time w/ PC Banking (years) | | 1.2 | | 1.0 | | Not available | | 1.7 |
| PC Customers | | 14.7% | | 14.0% | | Not available | | 27.8%[a] |

[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 deduction of cost.

**Table 3. 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 | Revenue |
|---|---|---|---|---|---|---|
| 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 30-40 | 0.297 (0.003022) | -5,455 (1066) | 0.009 (0.00054) | 3,259 (267.3) | 1.709 (0.0177) | 53.6 (4.060) |
| Age 40-50 | 0.277 (0.002993) | -4,753 (1046) | 0.008 (0.00053) | 3,859 (264.5) | 1.530 (0.0175) | 57.7 (4.021) |
| Age 50-65 | 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 ^

**Table 4. 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) |
| Revenue 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 contains an increase in % rank or adoption propensity for PC banking customers, the standard error of this estimate and a sample size. All coefficients significant at p<.01, except as noted by a ^.

**Table 5. 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) |
| Revenue 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 contains an increase in % rank or adoption propensity for PC banking customers, the standard error of this estimate and a sample size. All coefficients significant at p<.01 except as noted by a ^.

**Table 6. 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) |
| Revenue 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 contains an increase in % rank or adoption propensity for PC banking customers, the standard error of this estimate and a sample size. All coefficients significant at p<.01 except as noted by ^.

**Table 7. Cross-Sell Rate Comparison Following PC Banking Introduction (percentage cross sold products)**

| | Bank A | Bank B | Bank C | Bank D |
|---|---|---|---|---|
| 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) | PC: 0.99 times more likely to adopt assets post-PC (0.01848) | not available |
| 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 | PC: +0.069 (0.00997) n=3,310 | not available |
| 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) | PC: 1.44 times more likely to adopt liab post-PC (0.01225) | not available |
| Post-PC Liab Rank Order (for Post-PC Liab>0) | PC: +0^ (0.00544) n=11,276 | PC: +0^ (0.00845) n=4,669 | PC: -0.056 (0.00545) n=11,644 | not available |
| 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) | PC: 1.34 times more likely to adopt products post-PC (0.01194) | not available |
| 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 | PC: +0.067 (0.00436) n=14,633 | not available |
| N | 45,890 | 22,230 | 28,664 | not available |

Each cell contains 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 significant at p<.01, except as noted with a ^

**Table 8. Comparison of PC Banking and Regular Customers over Customer Lifecycle**

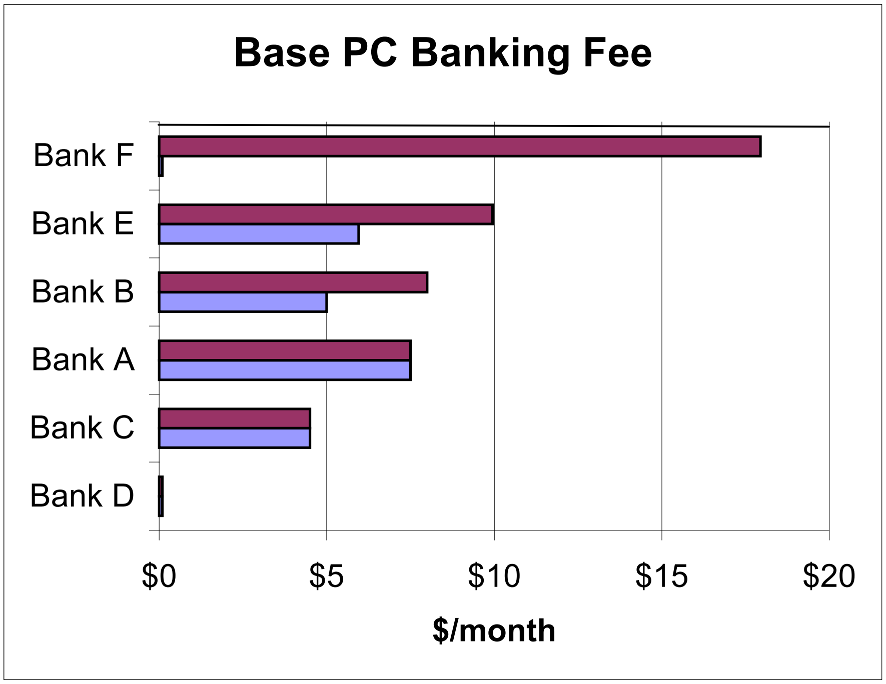
(percentage of quarters where average PC Banking customers is better than the average regular customer over 15 years)

| | 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. PC Banking Monthly Pricing




Top Bar is initial price. Lower bar is price at the time of the study (Summer, 1998).

**Figure 2. Simple Comparison of PC Banking and Non PC Banking Customers**

(if there were not difference between PC banking customers and regular customers, the bar would be 100%)

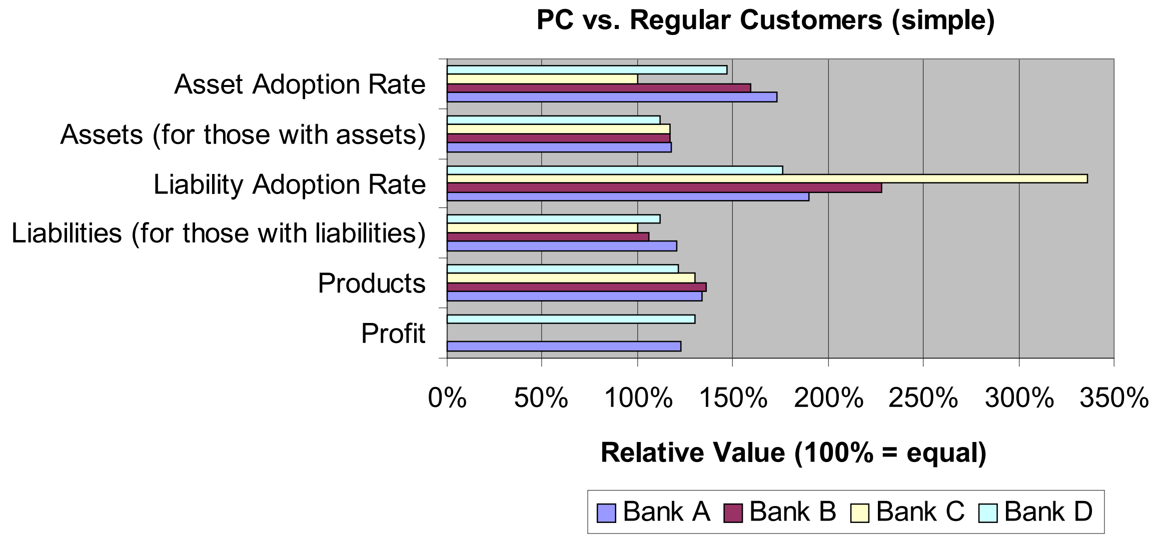



**Figure 3. Comparison of PC Banking and Non PC Banking Customers (Regression Model)**

(if there were not difference between PC banking customers and regular customers, the bar would be 100%)

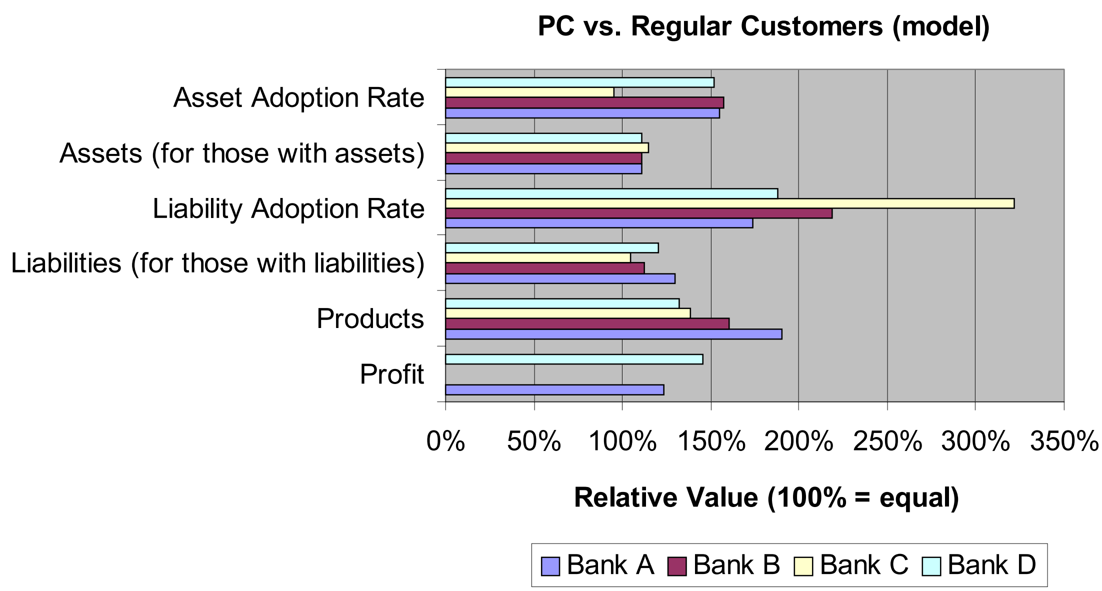


**Figure 4. Comparison of PC Banking and Non PC Banking Customers (Matched Sample)**

(if there were not difference between PC banking customers and regular customers, the bar would be 100%)

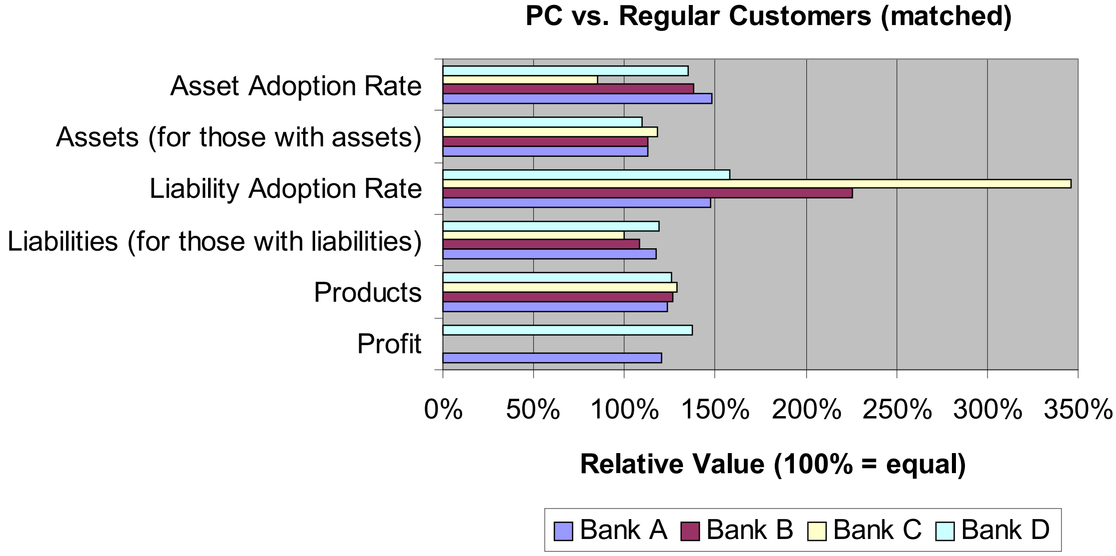



**Figure 5. Relative Cross-Sell for PC Banking and Non PC Banking Customers (Matched Sample)**

(if there were not difference between PC banking customers and regular customers, the bar would be 100%)

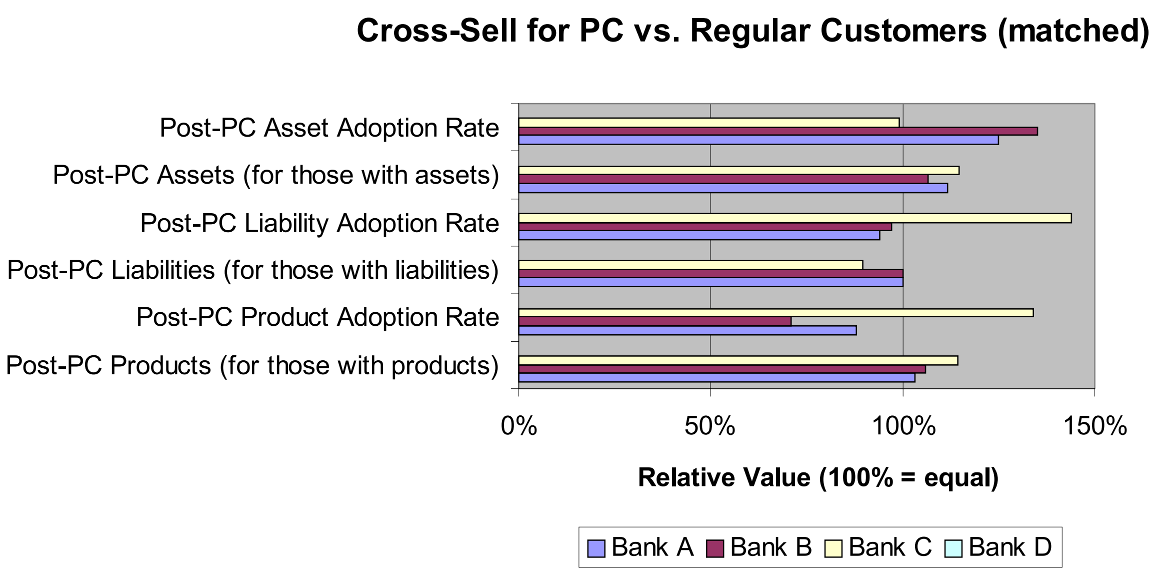


**Figure 6. Account value for different customer relationship lengths: Assets (Bank A)**

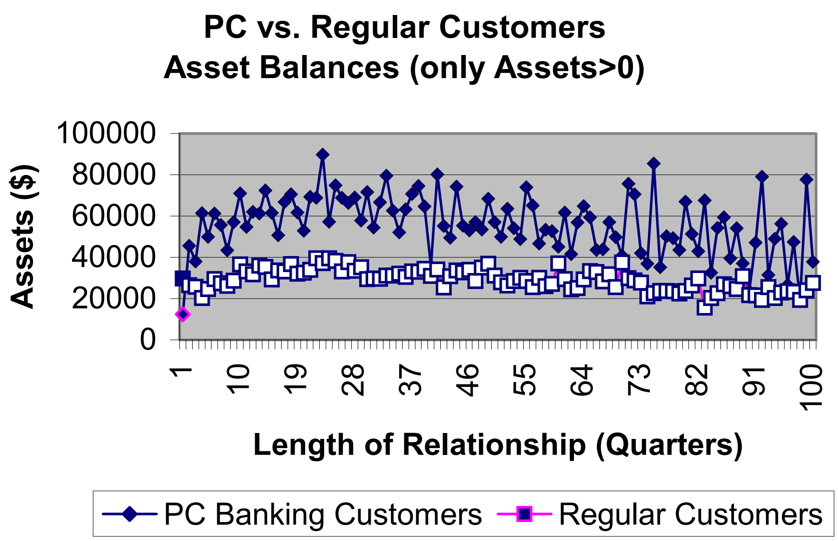



**Figure 7. Account value for different customer relationship lengths: Liabilities (Bank A)**

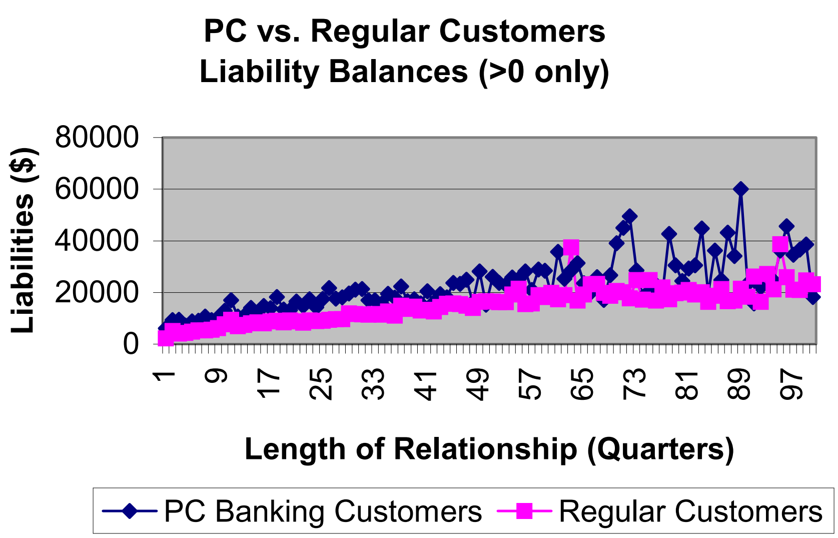


**Figure 8. Account value for different customer relationship lengths: Products (Bank A)**

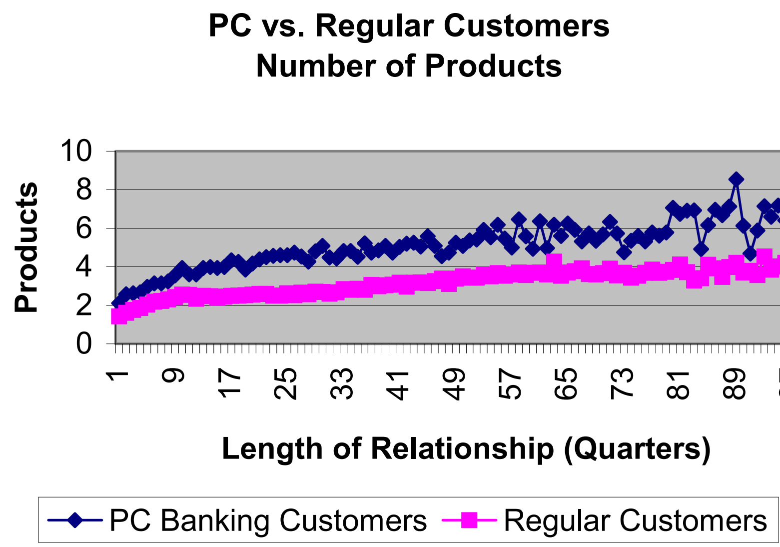
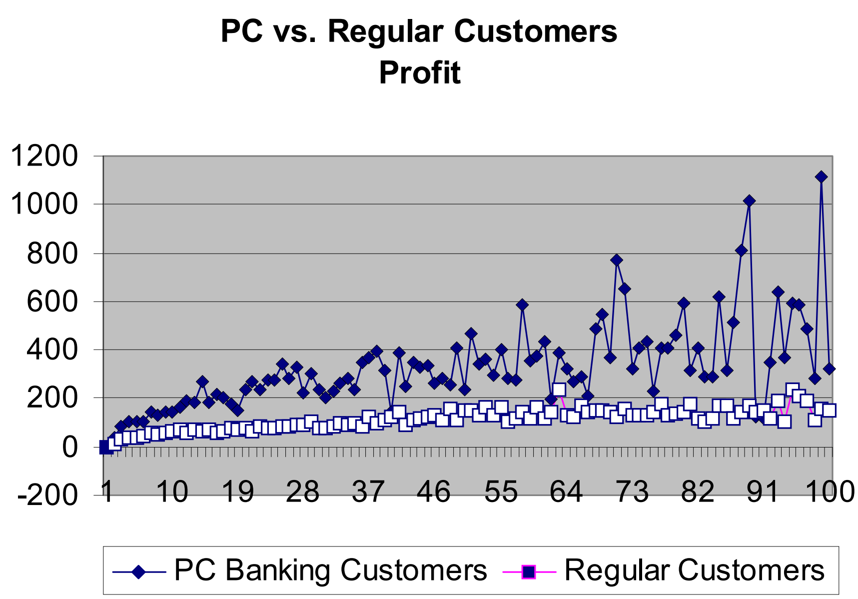



**Figure 9. Account value for different customer relationship lengths: Profit (Bank A)**



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