Working Paper #06-27

October 2006

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Abstract

The availability and variety of online services has increased dramatically in recent years. Many questions remain, however, regarding patterns of online service use, consumer preferences when using online services, and how consumers substitute between equivalent online and offline services. Using an extensive data set of consumer adoption and usage of the online banking service of a major German bank, this paper analyzes consumers' adoption and usage of online banking over the period August 2001 to July 2003, including the effect of demographics and branch banking on usage of online banking. We also examine the relationship between Internet availability and channel choice as well as usage. Finally, we analyze the effect of channel usage on customer level and product-specific revenues earned by the bank and derive revenue implications of online banking.

✧ We are grateful to several data providers for access to their data: Acxiom Deutschland GmbH, Neu-Isenburg for the zip-code level demographic data; Deutsche Bundesbank / Bearbeitung Acxiom Deutschland and Hoppenstedt Firmeninformationen GmbH for local banking directories; and Lutum + Tappert DV-Beratung GmbH Bonn for zip-code boundaries. This research was supported by the NET Institute www.NETinst.org.

1 Introduction

The increasing availability of online services has the potential to increase consumer welfare in a number of ways. Consumers who use the Internet can save time when ordering groceries online and having them delivered to their home; they can access information such as financial, political, or local news more easily and frequently cheaper than offline; or they can manage their personal finances by closely monitoring their checking and credit card accounts online and instantaneously transferring funds, ultimately saving money due to a more efficient allocation of financial resources.

A large body of literature studies consumers' and firms' adoption of the Internet. Work by authors such as Fairlie (2004), Aron and Burnstein (2003), Goolsbee and Klenow (2005), and Forman, Goldfarb, and Greenstein (2004, 2005) finds significant differences in adoption between demographic groups, pointing to lower penetration among minorities, low-income, lesser educated and rural households. This is particularly true for the early years of Internet adoption. This effect is attenuated by lower rates of computer ownership and a lower likelihood of residing in areas with several, competing Internet access providers. Research that studies the adoption of specific Internet services such as online grocery retailing (Bell and Song (2004)), Internet car retailing (Morton, Zettelmeyer, and Silva-Risso (2001)), or online banking (Hitt and Frei (2002)) comes to similar conclusions.

While some work studies differences between firms' decisions to adopt and subsequently use a new service or product (Battisti and Stoneman (2003), Astebro (2004), and Zhu and Kramer (2005)), most research on the penetration of new technologies among consumers has focused on the initial decision to adopt a new service, as opposed to the subsequent decision to actively use the service. This focus on the adoption decision may, however, lead to biased assessments of the welfare gains of the new service. Goettler and Clay (2006) find, for example, that approximately 40% of customers of an online grocer never place an order with the service. Thus, by looking only at adoption one might overestimate the welfare gains of the services' introduction. A focus on the initial adoption decision only may also result in a skewed picture of the distribution of welfare gains across demographic groups. Work by Goldfarb and Prince (2006) points to significant differences between the profile of consumers who initially adopt the Internet and those who subsequently use it intensively. Their results suggest that the likelihood of adoption of the Internet increases in income and education, but that usage conditional on adoption declines in income and education, even when correcting for the selection problem that low-income adopters likely have higher tastes for usage than the average low-income household. Since actual usage of the Internet reflects opportunity costs of time in addition to monetary considerations, benefits among actual adopters may hence no longer be distributed disproportionately across demographic groups. A more detailed analysis of factors that drive actual usage of new services adds an important element to the debate over public policies to overcome disparities in access to new technologies.

Firms introduce online platforms for a variety of reasons. Offering an online channel may allow the firm to lower costs by allowing it to reduce its physical network of outlets, as in banking; to reach new customers, such as those in areas where the local demand itself is insufficient to sustain a standalone outlet; or to respond to the entry of pure online players, such as in book retailing. Measuring determinants of customers' sustained usage, as opposed to only their adoption, of new channels is important to inform the cost and revenue implications of online services. This is particularly true since service providers frequently use different promotion strategies for initial adoption and sustained use of the online channel. Banks, for example, initially promoted the trial of online banking heavily, but provided few incentives to encourage continued use of the service. Their customers' decisions to sign-up for the service thus at least partly reflect these promotional efforts while their usage decisions more accurately mirror underlying banking needs and potential switching and learning costs of using a new channel.

In this paper, we study consumer adoption and actual usage of new services using the example of online banking in Germany. The German setting is of advantage since in contrast to the US, German banks from the inception of their online banking service enabled customers to conduct a wide range of services online, ranging from pure account monitoring to sales and purchases of securities. As a result, online banking had the potential to fully substitute for branch banking.

Our study is based on a confidential data set of 55, 602 customers of a German retail bank. The data set allows us to measure both adoption and usage. We distinguish between usage for informational purposes, such as to monitor checking or brokerage accounts or access information about the bank's policies, and usage for transactional purposes. Banking customers benefit from online information and transactions in multiple ways. By more frequently monitoring their accounts, consumers are better able to adjust their spending behavior to reflect their current assets. Consumers who use online banking for both informational and transactional purposes can, in addition, shift funds between different accounts more rapidly and thus, avoid overdraft charges. Moreover, consumers save time on their transactions if they conduct them online instead of in the branch. The fact that in practice, not all customers in our data set use the online banking service, even though they sign up for it, suggests that such benefits are offset at least in part by (perceived) costs to online banking in the form of security risks, learning costs, and switching costs. By separately analyzing the adoption and usage decisions, we shed light on which customer groups are likely to incur such costs.

This paper contributes to the recent literature on adoption and usage of online services in two ways: (1) We analyze both consumers' initial adoption and sustained usage of an online service accounting for heterogeneity in geographic markets and consumer demographics. (2) We investigate in detail which types of consumers benefit from the introduction of online banking. To do so, we account for two different types of actual usage, usage for informational and usage for transactional purposes. Our results show important differences in the profile of adopters and users, in particular with respect to the effect of age and income on adoption and usage. They suggest that the adoption decision reflects the customer's ease of using new technologies, while the usage decision reflects the customer's actual banking needs. Our results suggest that promoting adoption among customers with more complex banking demands could significantly enhance overall welfare, and from the bank's perspective, facilitate the migration of its customers to the online channel.

The remainder of the paper is organized as follows: We first introduce our data and provide a set of descriptive analyses that allow a first understanding of consumers' decisions to adopt and use the online channel. We then introduce our empirical approach and our empirical results. We differentiate between adoption of the online service, first trial of the service and usage for informational and transactional purposes. We also provide first results on the revenue implications of online banking. We conclude with a summary of our results and their implications for consumer behavior in related environments.

2 Data and Descriptive Statistics

2.1 Data

The primary data source for the project is a confidential, customer-level data set made available to us by a major German retail bank on the banking activities of 55,602 individual account holders over a 24-month period from August 2001 to July 2003. The data contain information on when the customer set up his account with the bank, the type of banking products used by the customer (brokerage account, checking account), basic demographic information (gender, age), his branch location at the zip-code level, which we use to proxy for the customer's residence, and the customer's authorization to use different types of banking services. The data also provide detailed information on the customer's actual usage of the online interface, in particular the monthly number of logins into his online account, the monthly number of transactions conducted online, and the bank's revenues derived from the customer's checking and brokerage accounts.

Both telephone and online banking are forms of non-branch banking, for which the customer needs to sign up separately. The data records whether a consumer activated telephone banking and the exact date of activation of online banking. Across customers, 21.7% have access to telephone banking by the end of the data set in July 2003. Such low levels of penetration of telephone banking mirror trends in the German banking sector nationwide. Forrester (2005) finds, for example, that in 2004, less than 10% of account holders use telephone banking at least once a month. The bank introduced online banking in November 1997. By July 2003, 21.6% of customers activate their access to the service. The unique aspect of the data set is that it allows us to distinguish the initial decision to adopt the service from the subsequent decision to actively use it.

While early online banking in the US was limited to pure account monitoring, the typical online banking service offered by German banks consistently allowed customers to monitor both checking and credit card accounts, to initiate domestic and foreign wire transfers, to purchase or sell brokerage account holdings if applicable, or to set up recurring payments. Customers do not incur additional charges for signing up for the online channel, nor are they offered a different fee schedule, at least in the early years of online banking. The data contain information on the monthly number of each of these types of online transactions, as well as the total number of logins into the online banking platform. These usage details allow us to construct measures of intensity and purpose of use of the online channel. Of the 12,006 customers with online banking access, only 51.4% logged into their account at least once in a given month. In addition, only 38.6% used the online channel to complete at least one transaction in a given month, suggesting that a significant fraction of customers use online banking primarily for account monitoring.

We complement this primary data set with two secondary data sets. First, we include aggregate data on consumer demographics at the ZIP code level obtained from the market research company Acxiom Deutschland GmbH. The data contain annual information on population density, education, per-capita income, movement into a zip code and the average number of automobiles per capita. This data set comprises data on Internet availability and average Internet usage in the ZIP code, which allows us to account for consumers' ease of access to the Internet as one measure of the opportunity cost of using online banking. We have four measures of Internet usage: usage of online news, of financial information services, of home-banking and of travel services.

Second, we obtain information on the number of retail bank branches per ZIP code in each year operated by the bank and its competitors from Acxiom Deutschland GmbH and from

Hoppenstedt Firmeninformationen GmbH. We use the information on the banking network to construct several measures of competitive branch density. We compute the number of own and competitor branches per square kilometer in a customer's ZIP code, in all ZIP codes that are within 3 miles of a customer's ZIP code and in all ZIP codes that are within 15 miles of a customer's ZIP code. These measures allow us to account for the local density of retail banking as a measure of the attractiveness of online banking relative to branch banking due to differences in travel time to reach a branch. The average zip-code has two of our banks' branches within a three mile radius (standard deviation of 2.44) and another 12.8 branches within a 15 mile radius (standard deviation of 15.09 branches). There is thus significant variation in the density of the bank's network even at a local level within a small radius around the customer's zip code. Similar patterns arise in the density of competitor branches.

2.2 Descriptive analyses

In this section we present first results on differences between customers that signed up for online banking and customers that did not sign up for online banking. An analysis of the customer-level data points to the following patterns in online banking adoption and usage. By the end of the data set 22.69% of customers have activated the online banking service. Figure 1 shows the cumulative share of these customers that adopted Internet banking during a given quarter, going back to the first quarter of 1999, the earliest adoption date of a customer in our sample. The share of adopters grows nearly linearly over time, with adoption speeding up slightly in the initial quarters after 1999. The fact that the adoption pattern does not mirror the common S-shape pattern documented in the literature (for example, Griliches (1957) and Mansfield (1962)) may reflect that online adoption is conditional on (high-speed) Internet penetration, which we do not control for in the chart.

Table 1 contrasts the demographic characteristics of online and offline customers, denoting as an online customer a customer with online banking authorization. These customers are less likely to be male relative to their offline counterparts. We find a nonlinear effect of age: While very young customers (<20 years) and customers above the age of 40 are more likely to be offline customers, customers in the intermediate intervals are more likely to sign-up for online banking. Online banking customers also live in low migration areas with more highly educated and urban residents. The analysis of consumers' per-capita income shows a nonlinear pattern. While consumers with a very low income (< 14,000 Euro) and a very high income (> 21,000 Euro) are more likely to use online banking, consumers with an intermediate income are more likely to use the traditional banking channel. Online banking customers further live in areas with wide spread Internet access and usage.

In addition, online customers use the full spectrum of alternative channels offered by the bank more extensively than other customers: among online banking customers, 29.6% also activated telephone banking while only 19.7% of other customers did so. This suggests that online banking customers have in general a greater affinity for using alternative channels for management of their financial assets. Using the online banking service requires that a customer has at least either a checking account or a brokerage account with the bank, as opposed to only a savings account, which manifests itself in the higher frequency of checking and/or brokerage account holders among the bank's online banking customers. These patterns point to a higher preference for alternative banking channels by online banking customers and to their banking needs lending themselves more easily to the capabilities of an online banking interface.

The analysis of the density of our bank's and its competitors' branch network shows significant differences only for very high branch densities: A very high density of our bank's branch network (> 6 branches/km²) reduces a customer's likelihood of adopting online banking, possibly due to lower costs of branch banking, while a high competitive branch density (> 20 branches/km²) increases the likelihood.

We next provide descriptive results on the usage behavior of online banking customers summarized in Table 2. The average active customer with at least one login has 7.8 logins per month, which translates into an average of 4.4 monthly transactions that are initiated through the online system. The bottom panel of Table 2 summarizes correlations between different types of transactions by online banking users. There are strong positive correlations between a customer's number of logins and transactions. The fact that they are not perfectly correlated reflects that online banking is not only used for initiating transactions but also for other purposes such as account monitoring.

The majority of online transactions are domestic wire transfers (on average 3.8 transfers per month) compared to only 0.2 recurring payments and 0.1 securities transactions. Online transactions represent approximately 17.0% of all transactions for active online customer. Their total number of transactions averages to 25.0, relative to 6.8 transactions by offline customers. We thus find that consumers are heterogeneous in their underlying demand for the type and number of banking services they use and in particular that active online customers use banking services more intensively than the remaining customers.

In summary, we find significant differences between online and offline customers. Consumer heterogeneity is thus likely to drive valuation of online banking, both in terms of adoption and usage. While we observe many factors that correlate with a customer's inherent demand for banking services, unobserved heterogeneity likely remains. We now outline an econometric framework that allows us to separate the effects of the various determinants of the adoption decision and to exploit the panel nature of our data set in controlling for unobserved differences in customers' propensities to adopt and use online banking.

3 Econometric Framework

In adopting and using an online channel a consumer makes two separate decisions. The consumer first decides to sign up for the service. Once a consumer has adopted the service, she then decides whether to actually use the service and determines her usage intensity in each usage period. As in Goldfarb and Prince (2006), we model her initial adoption decision as a function of her optimal amount of transactions. A consumer who has adopted online banking chooses an optimal number of online transactions and logins to maximize

$$\begin{aligned}&\max_{L,T} \sum\nolimits_{t=1,\dots T} U(L_{it}, T_{it}, B_{it}, Z_{it}) \\ &\text{s.t. } P_{it} + p_{it}^{on} T_{it} + p_{it}^{off} B_{it} + Z_{it} \leq Y_{it} \text{ and } t_{it}^{on}\left(L_{it} + T_{it}\right) + t_{it}^{off} B_{it} \leq H_{it}\end{aligned} \qquad \textbf{(1)}$$

where L_{it} denotes the number of logins in period t, T_{it} and B_{it} the number of online and offline transactions, respectively, and Z_{it} the outside good. Usage choices are subject to budget and time constraints. We denote as Y_{it} the customer's income and as H_{it} the number of hours she spends in total on banking activities in period t. The consumer pays a fixed quarterly maintenance fee of P_{it} for her bank account and a price of p_{it}^{on} and p_{it}^{off} – which is potentially zero – for each online and offline transaction. Similarly, she spends t_{it}^{on} in time for each login or online transaction and t_{it}^{off} in traveling to the branch to conduct an offline transaction.

The consumer's utility maximization problem yields optimal numbers of logins and online transactions L_{it}^* and T_{it}^* that depend on the monetary and non-monetary costs of completing the activity online relative to offline at the bank's branch. Thus L_{it}^* and T_{it}^* are functions of p_{it}^{on}, p_{it}^{off}, t_{it}^{on}, and t_{it}^{off}, as well as other, non-price shifters of demand.

Given the consumer's optimal usage of online banking for transactional and informational purposes were she to adopt, her initial adoption decision is based on a comparison of the indirect utility from adopting to that of continuing to use branch banking only. Consumer *i* then chooses to adopt online banking provided

$$\sum_{t=1,\dots T} U(L^*_{it}, T^*_{it}, B_{it}, Z_{it}) \geq \sum_{t=1,\dots T} U(0,0,B_{it}, Z_{it}) \tag{2}$$

We parameterize the stream of future utility differences as a function of consumer observables. Specifically, we estimate

$$\begin{aligned}\Pr(Adopt) &= \Pr\left(\sum_{t=1,\dots T} U(L^*_{it}, T^*_{it}, B_{it}, Z_{it}) - \sum_{t=1,\dots T} U(0,0,B_{it}, Z_{it}) \geq 0\right) \\ &= \Pr\left(\alpha_1 f_1(DENS_i, TRANS_i) + \alpha_2 f_2(INTACT_i) + X_i^A \alpha_3 + \varepsilon_i^A \geq 0\right)\end{aligned}$$

Since we do not observe each consumer's total amount of time spent on banking activities, we include contemporaneous demographic characteristics, X_i^A, that correlate with a consumer's financial needs, such as her age or educational attainment. We include functions of the bank's branch density within a 3-mile radius around the consumer's location, $DENS_i$, and the extent of car ownership in the consumer's zip code, $TRANS_i$, as proxies for time spent to conduct banking activities offline. Similarly, we include measures of the extent of Internet usage in the zip code relative to the national average, $INTACT_i$, to capture time spent for online transactions. ε_i^A represents unobserved determinants of the customer's usage decision, such as her Internet sophistication. We assume that ε_i^A is a normally distributed idiosyncratic error term, giving rise to a probit model of the adoption decision.

We observe usage for customers who chose to adopt online banking. We parameterize their demand for online transactions and usage as

$$L_{it}^{*} = \beta_1 f_1(DENS_{it}, TRANS_{it}) + \beta_2 f_2(INTACT_{it}) + X_{it}^{L}\beta_3 + \beta_4 \frac{\phi_i}{\Phi_i} + \varepsilon_{it}^{L}$$

$$T_{it}^{*} = \gamma_1 g_1(DENS_{it}, TRANS_{it}) + \gamma_2 g_2(INTACT_{it}) + X_{it}^{T}\gamma_3 + \gamma_4 \frac{\phi_i}{\Phi_i} + \varepsilon_{it}^{T} \qquad \textbf{(3)}$$

The vectors X_{it}^{L} and X_{it}^{T} are subsets of the characteristics X_i^{A} included in the adoption decision, varying over time where available. ε_{it}^{L} and ε_{it}^{T} are individual-specific idiosyncratic error terms that capture unobserved determinants of usage. To allow for individual specific heterogeneity in the usage of online services, we decompose ε_{it} into a time-invariant individual specific taste for banking ν_i and a random, normally distributed error term μ_{it} that captures random fluctuations over time in a consumer's need for banking services.

We account for possible selection in consumers who chose to adopt and then use the service by including a Heckman selection term, ϕ_i / Φ_i, in the models. This is allows us to correct for the fact that customers may choose to adopt and to subsequently use the service intensively for common unobserved reasons. For example, studies on Internet adoption suggest that the average low-income household is less likely to adopt than the average high-income household. Those low-income households that choose to adopt are thus likely households who place an above-average value on using online banking and using the service intensively. We instrument for the potential endogeneity of the consumers' observed usage choices by including variables in the adoption equation that drive adoption, but are independent of a consumer's usage intensity. We use three instruments. The density of competitor branches within a three mile radius from the consumer's zip code captures competitive pressures that may induce our bank to promote the availability of online banking more intensely in some areas than in others. The index of Internet availability in the consumer's zip code, which reflects differences in Internet access as opposed to usage, measures differences in cost to adoption across geographic areas. Last, an indicator of whether the consumer uses telephone banking or not is included as a proxy for the consumer's openness to using new technologies.

As Table 2 illustrates, the number of online transactions and logins among customers that decide to use the service is relatively low, with a mean number of transactions of 4.36 and a mean number of logins of 7.79, conditional on usage. To account for the discrete nature of our data, we employ panel count data techniques. Since a large number of our independent variables do not vary over time, estimating fixed effects models removes a large amount of interesting variation from our analysis. Instead, we estimate a negative binomial fixed effects model accounting for consumer heterogeneity in the distribution's dispersion parameter, and a Poisson random effects model. As a benchmark, we also estimate a negative binomial cross-sectional model based on the last monthly observation for each household.

The above model considers the adoption decision as a discrete, one-time decision. It abstracts from the timing dimension of the consumer's decision. To investigate the extent to which customers differ in their propensity to adopt at a given point in time, we consider two extensions to the base model. First, we separately estimate the probit adoption model defining as adopters those who signed up for the service in the initial months of its availability. Second, we explicitly model the consumer's time until adoption from the bank's initial introduction of the online banking service. We estimate a current offline customer's likelihood to sign up for the online service on a given day after the introduction of online banking as a duration model (Sinha and Chandrashekaran (1992), Dekimpe, Parker and Sarvary (2000)), using both a Cox proportional hazard and a parametric Weibull specification.

4 Results and Implications

4.1 Adoption

We first analyze a consumer's decision to adopt online banking in a probit model. We include demographic and bank-specific explanatory variables. *MALE* is an indicator variable for the account holder's, or in the case of joint accounts, primary account holder's gender and *AGE* denotes the primary account holder's age in years. *DURATION CUSTOMER REL.* measures the days since the opening of the customer's first account with the bank. We include various zip code level characteristics that vary annually. *BANK DENSITY, 3 MILES* and *COMPETITOR DENSITY, 3 MILES* measure the number of branches and competitor branches in zip codes within a three mile radius around the customer's zip code as a share of the zip codes' area in thousands of square kilometers. The secondary school attainment variables measure the share of zip code residents with vocational, 10 years, and 13 years of secondary schooling representing the customer's likelihood of achieving each of the educational levels, with the left out category being 9 years of schooling. *INCOME* is average annual per capita income in the zip code, measured annually in thousands of Euro. *CAR OWNERSHIP* represents the average number of cars per household in the zip code as of January 2004. *INTERNET AVAILABILITY* is an index of the availability of ISDN lines in the zip code relative to the national average in 12/2002. Lastly, *INTERNET USAGE* is an average index of the intensity of use of the Internet for general news, economic, business, and financial news, and travel planning relative to the nationwide average as of 12/2002.

The first three columns in Table 3 show the results of the probit adoption model. We find that men are more likely to adopt online banking than women and that on average, the likelihood of adoption decreases with age. While the marginal effect of age is negative for a customer of average age, the first panel in Figure 2 more fully illustrates the nonlinear effect of age on a consumer's decision to sign-up for online banking. An additional year in age increases the likelihood of adoption for very young and relatively old consumers, while it decreases the likelihood of adoption for medium-aged customers. This indicates that the traditional linear assumption of the effect of age on usage of online services may be oversimplified.

The results also show that the length of a customer's relationship with the bank and ownership of a checking and a brokerage account are positively correlated with the decision to sign up for online banking. Consequently, the adoption decision likely reflects differences in customers' banking needs.

The likelihood of adoption increases in the customer's educational attainment. While this finding is consistent with prior studies on the adoption of the Internet and online services, the marginal effects indicate that education only slightly affects the adoption probability and is far less important than gender or account ownership.

In line with our descriptive results in section 2.2 we find that the lower the branch density of our bank, the more likely a customer is to adopt online banking. In contrast, a higher competitive branch density increases the likelihood of adoption. One possible explanation for these patterns relies on the bank's efforts to actively migrate customers online. In areas with highly concentrated branch networks, competition between banks is likely stronger, possibly inducing the bank to promote its online banking service more heavily. A second, complementary, interpretation is that customers in areas with low branch densities incur high transportation costs in visiting a branch, increasing the benefits to the online interface, as outlined in the framework in section 3. Such benefits should manifest themselves in the usage decision as well, which we investigate further below.

Our results further indicate a nonlinear effect of income on adopting online banking. While the marginal effect indicates that the likelihood of adoption decreases in income for the average customer, the bottom panels in Figure 2 provides a more detailed analysis illustrating that this effect is strongest for consumers whose income exceeds Euro 24,000.

Urbanization and mobility measures, such as population density, migration into the zip-code, and car ownership, do not affect the decision to sign-up for the online banking service. Consistent with previous results, we find that the availability of Internet access increases a consumer's likelihood to sign up for online banking. Yet, the intensity of Internet activity does not affect the sign-up decision.

We now explore the extent to which the adoption decision differs for early adopters. We define early adopters to be customers within the 20th percentile of adoption time, corresponding approximately to customers who adopt by January 2000 (panel 2 of Table 3). Interestingly, the marginal effects show that gender is far less important in the decisions of early adopters than at later stages. We still find an overall negative effect of age. Figure 2 shows, however, that the negative marginal effect increases almost linearly with age, confirming the results of prior studies that young consumers benefit more from new technologies than older consumers. We also find that income is not a good predictor of adoption by early adopters. This effect may arise because our earliest income data are from December 2001 and may not reflect income at the time of the early adopters' adoption decision from 1997 to early 2001.

To more specifically account for the length of time that has elapsed since the introduction of the service, we estimate duration models of a customer's decision when to sign-up for online banking. Table 5 includes results from two alternative specifications, a Weibull and a Cox proportional hazard model. The models' results are very similar and confirm the probit results.

They illustrate that adoption is strongly driven by gender, with men being 36% more likely to adopt than women at any point in time, and by the extent of a customer's banking activities. Owners of a checking (brokerage) account are 115% (96%) more likely to adopt than other customers. A more detailed analysis of the effect of age and income on the time to adoption (Figure 3) again shows nonlinear effects. The predicted time to adoption remains relatively constant for customers below the age of 40, but increases exponentially for older age groups. At the same time, customers with intermediate income levels between 18,000 and 21,000 Euro have the longest predicted time to adoption.

4.2 Trial

Table 2 illustrates that only 51.36% of online banking customers logged into the service at least once and, thus, actively used online banking. We therefore consider an alternative definition of adoption of online banking and define a customer to have adopted if she logs into the online banking platform at least once during our data set (Panels 1 and 2 in Table 4). While we find similar effects in terms of statistical and practical significance for gender, age, education and income, there are also important differences to the earlier results. In particular, neither the density of the bank's branch network nor the density of the competitors' branch network have a statistically significant impact on the consumer's decision to try online banking. This would be consistent with the fact that the consumer's decision to sign-up for online banking is at least partly driven by a bank's efforts to promote the online channel to specific consumer groups: The bank likely targets consumers in geographic areas with a high competitive density in order to improve its competitive position and retain customers. Those customers might, however, not have a particularly high propensity to log into the platform as a consumer's decision to use the service may be more driven by consumers' needs for banking services and the relative cost of alternative channels. Consistent with this interpretation is the fact that a consumer's trial of the service conditional on signing-up (Panel 3 in Table 4) is correlated with mobility: the lower the average number of cars in a customer's zip-code, the more likely is the consumer to sign-up for online banking. This indicates that consumers with high transportation costs, proxied by car ownership, and thus high costs of branch banking are more likely to actively use online banking.

4.3 Sustained usage intensity

Just as the determinants of a consumer's trial of online banking may differ from those of her initial adoption, so could drivers of her sustained usage intensity. While signing up for online banking and even logging into the platform once may be relatively simple and costless in terms of time spent, the customer may expend more effort on learning to use the new technology to complete transactions. As a consequence, we would expect consumers to be heterogeneous with respect to the – perceived or real – cost of switching to the online channel for transaction purposes. This heterogeneity in usage transaction costs may differ from consumer heterogeneity in the initial adoption decision, in particular if the initial adoption (and less so actual usage) is driven by a bank's targeted marketing activities. The bank only weakly promoted actual usage of the channel by granting customers a small discount on a capped number of transactions. Understanding customers' usage behavior has, however, important consequences from the bank's perspective: any cost savings to the branch network from the introduction of the online channel can only be realized if consumers use the online channel for their basic information and transaction needs.

Table 6 presents the results of count models of the number of logins into online banking. Panel 1 shows the estimated coefficients for a negative binomial model that accounts for fixed effects in the distribution's dispersion parameter, panel 2 presents the results of a Poisson regression with consumer-specific random effects, and panel 3 presents the results of a negative binomial cross-sectional model. As outlined in section 3, all models control for potential selection effects in the usage equation.

The results are largely consistent across specifications and confirm some of the above results for the adoption decision. Across models, we find, however, that the number of logins increases in age. The detailed analysis of the marginal effect of age in Figure 4 shows a near linear relationship between the number of logins and age. This result contrasts with the U-shaped relationship between age and likelihood of adoption shown in Figure 3, which resulted in a negative marginal effect for the customer of average age. While younger customers may be more open to adopting new technologies, older customers thus have a higher propensity to actually use the service, possibly due to lower opportunity costs of time or a more complex financial profile. We also find that the number of logins increases with the density of the retail network, possibly because the density of the branch network is correlated with unobserved tastes for banking services not captured by customers' income and age. These effects suggest that the bank's strategy of promoting primarily the service, but not usage of the service, might not target intensive users of online banking well.

In addition, we find evidence that a consumer learns how to use online banking over time: consumers who signed up for online banking less than 6 months ago have, on average, fewer logins than more experienced online banking customers. While both ownership of a checking account and ownership of a brokerage account increase a consumer's usage intensity, ownership of a checking account drives login behavior more than the ownership of a brokerage account. This points to the importance of the informational aspects of online banking that enhance a consumer's ability to balance her checking account, while information relevant to the brokerage account, such as stock quotes, is accessible from a wide variety of other sources. The results provide mixed support for the basic trade-offs that govern the attractiveness of online banking relative to branch banking. Across specifications, consumers in areas with lower car ownership have a higher number of logins. At the same time, however, login activities are higher for customers in areas with high branch densities, even though this effect is not statistically significant across specifications. This suggests that the extent of a consumer's online activity may be weakly driven by the consumer's cost of using the alternative channel.

We next turn to the analysis of online transactions. The results in Table 7 confirm to a large degree the results from the login analysis; however, some of the effects lose their statistical significance. Similar to the login analysis, long-term customers of the bank use the platform more intensively for transactional purposes, but customers use it less so during the first six month of online banking activity. In addition to having a higher number of logins, customers with checking accounts also have a higher number of transactions than those with brokerage accounts.

In summary, our findings indicate that adoption likely reflects the technological sophistication of the user and thus lower opportunity costs of time in adopting a new service. Young and male customers are both more likely to sign-up for online banking. The adoption behavior of customers also likely reflects the bank's promotional activities. Long-term customers or customers with a brokerage or a checking account are more likely adopters, as are customers in areas with a high competitive branch density. In contrast, the usage decisions more closely reflect the customer's actual banking needs. Lower income customers log into their account more often, indicating a higher propensity to monitor their account balance, potentially to avoid paying overdraft fees. Similarly, older customers are more intense users, possibly due to their more complex financial situation. Actual transactions increase with a consumer's income indicating a greater inherent need for banking services by high-income consumers. We now turn to an analysis of the extent to which such usage intensity translates into higher revenue for the bank, as a first indication of the profit implications of heterogeneity in usage behavior.

4.4 Effect of Online Banking on Revenues

Currently, most managers assume that online customers are more profitable than offline customers. The Bank of America states, for example, that the company's 12.6 million online customers are 27 percent more profitable than their offline counterparts (Europress Publications 2005). As the above results show, however, there is significant heterogeneity in customer usage of the online channel. In this section, we assess to what extent such usage heterogeneity correlates with heterogeneity in revenues generated by online banking customers. The profitability of online banking customers may stem in part from decreases in maintaining an extensive branch network and in part in higher revenue generated by online customers. Since our data does not include information on costs associated with maintaining a particular customer's account, we focus on the revenue side of profitability. The data contains information on the customer-specific revenue the bank earns in a given quarter per product (checking, savings, and/or brokerage accounts). Our central analysis focuses on the relationship between online checking account usage and checking account revenues. We then turn to additional analyses of brokerage account revenue and overall revenue.

The revenues a bank earns from a customer's checking account are composed of (1) a monthly account maintenance fee of Euro 10 – 15, in our bank's case. The bank did not charge fees for completing a transaction but granted a small discount per online transaction. (2) A bank earns revenues from interest on balances customers hold in their accounts that the bank invests at market interest rates. Other sources of revenue that are not captured by our data include interest charged to customers for overdrawing their accounts. Online banking has the potential to decrease revenues from checking accounts both through the discount provided by the bank and due to transactions customers conduct to reduce the daily balance held in their account for safekeeping and instead invest it in alternative, higher interest bearing accounts.

The first part of Table 8 reports the results of a random effects regression of the quarterly checking account revenue in Euro on the number of online domestic transactions, controlling for demographic characteristics and correcting for selection in customers with non-zero transactions. We use the transactions data in logarithmic form to adjust for outliers in the usage data. We find that revenues decrease in the number of online transactions by 0.18 Euro for an additional transaction above the mean of 2.7 transactions. At this average, the direct effect of transactions on revenue is similar to the bank's reimbursement per online transaction. In addition, revenue decreases with the extent of Internet activity. This effect of Internet activity provides some support for the hypothesized effect of monitoring on revenues since intensive Internet users are likely to balance their account more frequently leading to lower revenues for the bank. We also find that customers who both a brokerage and a checking account generate an additional Euro 3.60 in checking account revenue. Such multi-product customers likely hold a higher share of their wealth with the bank increasing the bank's product-specific revenues from that customer.

The results with respect to revenues from brokerage accounts are a direct effect of the bank's pricing structure for brokerage account: Customers were not charged a monthly fee but paid a fee of 0.5–1% of the value of their order with a minimum amount of Euro 20–35 per order. Fees did not differ for online and offline transactions. In line with that we find a strong positive effect of brokerage transactions on brokerage revenues. Lastly, we analyze the effect of all online transactions on the bank's total revenues with a customer including revenues from other sources such as credit and investment funds and find that overall revenues increase with the total number of online transactions. This result supports prior findings that attributed revenue increases to on the effect of online banking on revenues.

Our results indicate, however, that to fully understand the impact of online banking on a bank's revenue and ultimately profitability, a more detailed analysis is required than can be found in previous studies: (1) The effect of online banking on revenues may largely differ between products, both due to pricing structures and due to the benefits different types of product-specific transactions provide to consumers. (2) While prior analyses focus on the effect of customer's initial adoption, our results show that online banking customers' revenues are strongly affected by the actual number of transactions completed by the customer. The work motivates a more detailed analysis of the revenue implications of online banking relative to branch-banking that more explicitly accounts for self selection among customers into the two channels and temporal changes in revenue across customers. In the absence of a clean, controlled introduction of online banking to randomly selected customers, a more structural model of customer's choice of channel based on expected utility gains from using alternative channels and the resulting implications for the bank's profitability could provide further insights into the profitability of online banking and allow an assessment of alternative strategies to migrate certain customer groups to the online platform.

5 Conclusion

In this paper we analyzed consumer's adoption and usage of an online service and its revenue implications in the context of online banking. We find heterogeneity in consumers' adoption patterns in online banking, both with respect to whether consumers adopt online banking and when consumers adopt online banking. Our results only partly confirm earlier results by Hitt and Frei (2002) and Campbell (2003) that adoption rates of the Internet and online services are more pronounced for highly educated, high-income, or male consumers. We instead find evidence of nonlinearities in the relationship between age and income and the likelihood of adoption. In addition, factors that proxy for the customer's actual need for online banking services are of larger practical significance than the customer's demographic profile. In contrast, we find that older and wealthier customers who adopt are more intense users in terms of logins or transactions, possibly due to their more complex financial situation and greater demand for banking services. Our revenue analysis highlights important differences between the revenues generated by online banking customers across different products used by the customer.

Our findings have several important implications. First, they highlight the importance of assessing welfare effects of new technology introductions based on customer usage, as opposed to adoption behavior only. Our results indicate for example, that even after controlling for the possible self-selection of older customers into online banking based on their expected net benefit from the service, they use online banking intensively, but have low overall adoption rates. Second, the relative under-representation of usage-intensive adopters suggests that there is room for the bank to increase the penetration of its online banking service by targeting customers with high benefits from online banking, but potentially high costs of adoption, instead of sophisticated technology users with low costs of adoption and limited banking needs.

One means to do so would be to provide stronger incentives for customers to move to the new channel, for example through channel-specific pricing. While our bank offered very limited discounts for the use of the online channel, charging more extensively reduced prices for usage of the online channel may increase high-usage customers' propensities of adoption.

Tables and Figures

Table 1
Demographic Attributes of Online Banking and Other Customers (%, n=55,602)

		Online Banking customers[1]	Other customers	Difference stat. sig. at 99% level
Gender	Male	53.01	61.56	x
	Missing value	9.43	8.35	x
Age	below 20	1.68	3.92	x
	20-30	23.80	13.85	x
	30-40	35.97	23.54	x
	40-50	19.96	20.16	x
	50-60	9.71	15.51	x
	60-70	4.87	14.34	x
	>70	3.66	7.98	x
	Missing value	2.60	1.38	x
Telephone Banking[1]		29.59	19.72	x
Type of account owned	Checking	94.90	81.52	x
	Brokerage	94.40	80.94	x
Secondary educational attainment (zip code)	Vocational school	37.15	37.18	
	13 yrs of schooling	17.07	16.38	x
	10 yrs of schooling	17.48	17.04	x
	≤ 9 years of schooling	29.29	29.38	x
Income (zip code, Euro)	<13,000	2.51	2.47	
	13,000-14,000	8.94	8.09	x
	14,000-15,000	5.58	3.91	x
	15,000-16,000	5.46	6.28	x
	16,000-17,000	14.20	14.77	
	17,000-18,000	20.68	21.16	
	18,000-19,000	16.51	18.84	x
	19,000-20,000	11.56	10.84	
	20,000-21,000	4.94	5.25	
	>21,000	9.60	8.38	x
Population density (zip code, pop per km²)	<250	7.28	7.63	
	250-500	9.56	10.82	x
	500-1,000	9.66	11.27	x
	1,000-5,000	38.76	38.32	
	5,000-10,000	23.70	22.18	x
	>10,000	11.04	9.78	x
Density of bank's branch network (branches per km² in zip code)	<2	95.44	95.08	
	2-4	3.73	3.76	
	4-6	0.34	0.38	
	>6	0.34	0.58	x
Density of competitors' branch network (branches per km² in zip code)	<5	37.51	38.71	
	5-10	31.21	32.37	
	10-20	12.96	12.80	
	>20	18.32	16.12	x
Mobility (percent of pop in zip code)	Migration into zip code	4.33	4.50	x
	Migration out of zip code	4.16	4.34	x
	Car ownership	49.34	48.82	
Internet index (zip code)	Activity	109.57	108.07	x
	Availability	106.41	105.29	x

[1] Online and telephone banking customers denote those who signed up for the services by the end of the sample.

Table 2
Monthly Usage by Online and Offline Customers

Usage of different types of online and offline services

		Mean	Minimum	Maximum
Online Banking Customers (187,915 month-customer obs)				
Logins	% obs. with non-zero logins	51.36		
	Number of logins[1]	7.79	1.00	301.00
Online Transactions	% obs. with non-zero transactions	38.67		
	Number of transactions[1]	4.36	1.00	130.00
	Recurring payment	0.15	0.00	32.00
	Domestic wire transfer	3.78	0.00	130.00
	Securities transaction	0.11	0.00	47.00
	Other	0.33	0.00	66.00
Offline transactions[1]		20.6	0.00	2,040.00
Other Customers (826,696 month-customer obs)				
Offline transactions		6.8	0.00	27,099.00

Correlation between monthly number of transactions of different types

Transaction type 1	Transaction type 2	Correlation
Online Banking Customers (187,915 month-customer obs)		
Login	Offline transaction	0.17
Login	Online transaction	0.51
Login	Online wire transfer (domestic)	0.47
Offline transaction	Online transaction	0.19
Offline transaction	Online wire transfer (domestic)	0.17
Online transaction	Online wire transfer (domestic)	0.95

Notes:

[1] Logins and transactions are conditional on at least one login or transaction, respectively, in a given month.

[2] Other types of transactions include foreign wire transfers, direct debit payments, and reversal and group wire transfers.

Table 3
Probit Model of Decision to Adopt Service

	Dep. Variable = Sign Up Y/N					
	All Adopters			Early Adopters[2]		
	Coef.	Std. Err.	Marg. Eff.	Coef.	Std. Err.	Marg. Eff.
Male	0.2009	0.0167 ***	0.0564	0.2287	0.0239 ***	0.0199
Age						
Age	0.0224	0.0041	-0.0048	0.0436	0.0075	-0.0010
Age*Age	-0.0005	0.0000 ***		-0.0007	0.0001 ***	
Banking						
Duration customer rel.	0.0022	0.0003 ***	0.0006	0.0054	0.0003 ***	0.0005
Telephone banking	0.2897	0.0204	0.0868	-0.1590	0.0325	-0.0132
Brokerage account	0.4383	0.0398 ***	0.1037	0.0164	0.0528	0.0014
Checking account	0.4822	0.0721 ***	0.1104	0.1583	0.0901 *	0.0123
Bank density, 3 miles	-0.0504	0.0237 **	-0.0143	-0.0741	0.0289 **	-0.0066
Competitor density, 3 miles	0.0021	0.0012 *	0.0006	0.0026	0.0013 **	0.0002
Secondary educational attainment						
Vocational school	0.0174	0.0076 **	0.0049	-0.0067	0.0107	-0.0006
13 yrs of schooling	0.0123	0.0032 ***	0.0035	0.0068	0.0049	0.0006
10 yrs of schooling	0.0008	0.0032	0.0002	0.0118	0.0051	0.0010
Income						
Income	-0.1268	0.0368 ***	-0.0023	0.0052	0.0434	0.0011
Income*Income	0.0033	0.0009 ***		0.0002	0.0010	
ZIP-code population density	-0.0016	0.0031 `		-0.0073	0.0038 *	-0.0007
Migration into ZIP-code	-0.0150	0.0066	-0.0042	-0.0093	0.0061	-0.0008
Car ownership	0.0137	0.0203	0.0039	-0.0012	0.0108	-0.0001
Internet availability	0.0023	0.0008 ***	0.0007	0.0041	0.0011 ***	0.0004
Internet usage	0.0008	0.0010	0.0002	0.0010	0.0011	0.0001
Constant	-1.8486	0.5516 ***		-3.3230	0.7214 ***	
Log Likelihood		-16,024.29			-6,399.30	
Number of observations		32,269			32,269	
Pseudo-R^2		0.0765			0.0663	

[1] Standard errors allow for clustering at the zip code level.

[2] Early adopters are defined as having signed up in the first three years of the availability of online banking

Table 4
Probit Model of Decision to Adopt Service, Alternative Definition of Adoption

	Dep. Variable = Login at least once Y/N								
	All Adopters			Early Adopters[2]			All Adopters[3]		
	Coef.	Std. Err.	Marg. Eff.	Coef.	Std. Err.	Marg. Eff.	Coef.	Std. Err.	Marg. Eff.
Male	0.1736	0.0184 ***	0.0355	0.0199	0.0157	0.0072	0.0108	0.0311	0.0040
Age									
Age	0.0208	0.0047	-0.0035	0.0103	0.0028 ***	0.0009	-0.0061	0.0070	-0.0027
Age*Age	-0.0005	0.0001 ***		-0.0001	0.0000 ***		0.0000	0.0001	
Banking									
Duration customer rel.	0.0024	0.0003 ***	0.0005	0.0058	0.0004 ***	0.0021	0.0018	0.0006 ***	0.0007
Telephone banking	0.3015	0.0209	0.0678	-0.1106	0.0201 ***	-0.0405	0.1555	0.0335	0.0560
Brokerage account	0.7477	0.0555 ***	0.1024	-0.2969	0.0340 ***	-0.1001	0.8487	0.0891 ***	0.3286
Checking account	0.6060	0.0908 ***	0.0880	-0.1659	0.1272	-0.0577	0.4982	0.1428 ***	0.1936
Bank density, 3 miles	-0.0289	0.0215	-0.0060	0.0130	0.0211	0.0047	0.0409	0.0325	0.0149
Competitor density, 3 miles	0.0017	0.0011	0.0004	0.0004	0.0011	0.0001	-0.0007	0.0014	-0.0002
Secondary educational attainment									
Vocational school	0.0233	0.0086 ***	0.0048	-0.0158	0.0085 *	-0.0057	0.0238	0.0138 *	0.0087
13 yrs of schooling	0.0144	0.0033 ***	0.0030	-0.0008	0.0035	-0.0003	0.0119	0.0055 **	0.0044
10 yrs of schooling	0.0066	0.0036	0.0014	0.0128	0.0035 ***	0.0046	0.0137	0.0059	0.0050
Income									
Income	-0.0884	0.0352 **	-0.0008	0.0913	0.0361 **	0.0061	0.0470	0.0423	0.0037
Income*Income	0.0024	0.0009 ***		-0.0021	0.0008 **		-0.0010	0.0010	
ZIP-code population density	-0.0029	0.0029	-0.0006	-0.0001	0.0029	0.0000	-0.0020	0.0043	-0.0007
Migration into ZIP-code	-0.0209	0.0081	-0.0043	-0.0116	0.0039 ***	-0.0042	-0.0135	0.0070	-0.0049
Car ownership	-0.0120	0.0181	-0.0025	-0.0123	0.0249	-0.0044	-0.0415	0.0091 ***	-0.0151
Internet availability	0.0025	0.0009 ***	0.0005	0.0006	0.0007	0.0002			
Internet usage	0.0008	0.0010	0.0002	-0.0004	0.0010	-0.0001	0.0007	0.0012	0.0003
Constant	-3.2678	0.5741 ***		-0.1551	0.6378		-2.6050	0.8106 ***	
Log Likelihood		-12,601.42			-20,099.14			-4,602.36	
Number of observations		32,269		32,269				7,380	
Pseudo-R^2		0.0804		0.0203				0.0263	

[1] Standard errors allow for clustering at the zip code level.

[2] Early adopters are defined as having at least one login in the first three months of the sample period.

[3] Sample restricted to customers who have signed up for online banking.

Table 5
Duration Model of Days Until Sign-up for Online Banking

	Weibull Model				Cox Prop. Hazard Model		
	Coef.	**Std. Err.[1]**	**Marg. Eff.**	**Haz. Ratio**	**Coef.**	**Std. Err.**	**Haz. Ratio**
Male	0.3111	0.0248 ***	-751.6781	1.3649	0.3074	0.0240 ***	1.3598
Age							
Age	0.0661	0.0060	162.2958	1.0683	0.0660	0.0054	1.0682
Age*Age	-0.0012	0.0001 ***		0.9988	-0.0012	0.0001 ***	0.9988
Banking							
Duration customer rel.	0.0035	0.0004 ***	-8.4128	1.0035	0.0036	0.0004 ***	1.0036
Telephone banking	0.3972	0.0289	-904.3513	1.4876	0.3778	0.0252	1.4591
Brokerage account	0.6715	0.0676 ***	-1886.1340	1.9571	0.6547	0.0665 ***	1.9245
Checking account	0.7673	0.1315 ***	-2229.6930	2.1540	0.7519	0.1006 ***	2.1211
Bank density, 3 miles	-0.0814	0.0383 **	194.8250	0.9218	-0.0807	0.0272 ***	0.9224
Competitor density, 3 miles	0.0033	0.0018 *	-7.8406	1.0033	0.0033	0.0011 ***	1.0033
Secondary educational attainment							
Vocational school	0.0253	0.0113 **	-60.6298	1.0257	0.0242	0.0095 **	1.0245
Gymnasium (13 yrs of schooling)	0.0176	0.0048 ***	-42.1360	1.0178	0.0171	0.0038 ***	1.0172
Realschule (10 yrs of schooling)	0.0028	0.0048	-6.5878	1.0028	0.0030	0.0041	1.0030
Income							
Income	-0.1665	0.0495 ***	31.5511	0.8467	-0.1589	0.0379 ***	0.8531
Income*Income	0.0044	0.0012 ***		1.0044	0.0042	0.0009 ***	1.0042
ZIP-code population density	-0.0030	0.0045	7.1907	0.9970	-0.0030	0.0033	0.9970
Migration into ZIP-code	-0.0243	0.0111	58.1195	0.9760	-0.0236	0.0072	0.9767
Car ownership	0.0181	0.0261	-43.2825	1.0183	0.0162	0.0266	1.0164
Internet availability	0.0036	0.0012 ***	-8.7057	1.0036	0.0036	0.0010 ***	1.0036
Internet usage	0.0015	0.0014	-3.5322	1.0015	0.0015	0.0010	1.0015
Constant	-18.9763	0.7946 ***					
Weibull shape parameter	1.9269	0.0163					
Log Likelihood		-19,107.04				-74,342.57	
Number of observations		32,269				32,269	

[1] Standard errors allow for clustering at the zip code level.

Table 6
Count Models of Number of Logins into Online Banking Service

	Neg. Binomial Fixed Effects Model[1]			Poisson Random Effects Model[1]			Neg. Bin. Cross-Sectional Model[1, 2]		
	Coef.	**Std. Err.[3]**	**Marg. Eff.**	**Coef.**	**Std. Err.[3]**	**Marg. Eff.**	**Coef.**	**Std. Err.[3]**	**Marg. Eff.**
Male	-0.2144	0.0600 ***	-0.2144	0.0766	0.0655	0.0766	0.0929	0.0659	0.3248
Age									
Age	0.0248	0.0130 *	0.0077	0.0656	0.0305 **	0.0040	-0.0067	0.0156	-0.0186
Age*Age	-0.0003	0.0002 *		-0.0009	0.0004 **		0.0000	0.0002	
Banking									
Duration customer rel.	0.0033	0.0007 ***	0.0033	0.0087	0.0014 ***	0.0087	0.0002	0.0014	0.0006
OB adoption < 6 months	-0.1063	0.0205 ***	-0.1063	-0.1127	0.0315 ***	-0.1127	0.1529	0.1278	0.5768
Brokerage account	0.0834	0.0210 ***	0.0834	0.0768	0.0214 ***	0.0768	1.2836	0.1600 ***	2.9243
Checking account	0.3040	0.0388 ***	0.3040	0.2104	0.0326 ***	0.2104	1.6205	0.3291 ***	3.0674
Bank density, 3 miles	-0.0011	0.0326	-0.0011	0.0961	0.0415 **	0.0961	0.0749	0.0341 **	0.2646
School education									
Vocational school	0.0084	0.0195	0.0084	0.0382	0.0197 *	0.0382	0.0170	0.0280	0.0600
Schooling: 13 years	0.0083	0.0093	0.0083	0.0092	0.0089	0.0092	-0.0043	0.0085	-0.0151
Schooling: 10 years	0.0082	0.0086	0.0082	-0.0080	0.0087	-0.0080	0.0118	0.0119	0.0416
Income									
Income	-0.0790	0.0590	-0.0458	-0.2129	0.1183 *	-0.1256	0.0684	0.0947	0.1041
Income*Income	0.0016	0.0014		0.0052	0.0029 *		-0.0012	0.0025	
ZIP-code population density	-0.0060	0.0054	-0.0060	-0.0004	0.0151	-0.0004	0.0018	0.0083	0.0063
Migration into ZIP-code	0.0025	0.0025	0.0025	0.0024	0.0029	0.0024	0.0042	0.0286	0.0147
Car ownership	-0.0458	0.1080	-0.0458	-0.1294	0.0702 *	-0.1294	-0.2051	0.1002 **	-0.7249
Internet activity	0.0013	0.0027	0.0013	0.0001	0.0018	0.0001	-0.0015	0.0024	-0.0053
Constant	0.2822	1.0478		0.3703	2.1180		-2.0629	1.7156	
Dispersion parameter (ln(alpha))									
Constant				1.3583	0.0157 ***		0.9996	0.0893 ***	
Male							0.1135	0.0546 **	
Age							0.0107	0.0020 ***	
Log Likelihood		-178,583.17			-261,987.28			-14,493.90	
Number of obs. (customers)		91,399 (4,191)			122,682 (6,963)			6,963	

[1] Models correct for selection using Internet Availability, Competitor Density, and Adoption of Telephone Banking as instruments.

[2] Sample based on last observation for each customer.

[3] Standard errors based on 50 bootstrap replications.

Table 7
Count Models of Number of Online Transactions

	Neg. Binomial Fixed Effects Model[1]			Poisson Random Effects Model[1]			Neg. Bin. Cross-Sectional Model[1, 2]		
	Coef.	**Std. Err.[3]**	**Marg. Eff.**	**Coef.**	**Std. Err.[3]**	**Marg. Eff.**	**Coef.**	**Std. Err.[3]**	**Marg. Eff.**
Male	-0.0731	0.0640	-0.0731	-0.1428	0.0406 ***	-0.1428	-0.1016	0.0545 *	-0.1202
Age									
Age	-0.0133	0.0141	-0.0044	0.0059	0.0235	0.0165	0.0339	0.0126 ***	0.0244
Age*Age	0.0001	0.0002		0.0001	0.0003		-0.0002	0.0002	
Banking									
Duration customer rel.	0.0052	0.0010 ***	0.0052	0.0080	0.0012 ***	0.0080	0.0009	0.0007	0.0011
OB adoption < 6 months	-0.0987	0.0219 ***	-0.0987	-0.0387	0.0249	-0.0387	-0.0595	0.0898	-0.0678
Brokerage account	0.1095	0.0249 ***	0.1095	0.0379	0.0189 **	0.0379	1.7619	0.1529 ***	1.1647
Checking account	0.2442	0.0493 ***	0.2442	0.2120	0.0415 ***	0.2120	3.1125	0.4691 ***	1.2985
Bank density, 3 miles	0.0332	0.0216	0.0332	0.0801	0.0581	0.0801	0.0057	0.0352	0.0066
School education									
Vocational school	0.0063	0.0206	0.0063	0.0031	0.0148	0.0031	-0.0155	0.0207	-0.0181
Schooling: 13 years	0.0053	0.0100	0.0053	-0.0073	0.0047	-0.0073	-0.0119	0.0082	-0.0139
Schooling: 10 years	0.0095	0.0098	0.0095	0.0196	0.0066 ***	0.0196	0.0332	0.0070 ***	0.0388
Income									
Income	-0.0001	0.0549	-0.0066	-0.0188	0.1042	-0.0099	0.1420	0.0607 **	0.0131
Income*Income	-0.0001	0.0013		0.0004	0.0027		-0.0038	0.0015 **	
ZIP-code population density	-0.0040	0.0052	-0.0040	-0.0033	0.0102	-0.0033	-0.0023	0.0079	-0.0027
Migration into ZIP-code	-0.0007	0.0025	-0.0007	0.0027	0.0026	0.0027	0.0042	0.0256	0.0049
Car ownership	-0.0010	0.0999	-0.0010	-0.0316	0.0967	-0.0316	-0.0352	0.1123	-0.0411
Internet activity	0.0011	0.0021	0.0011	-0.0021	0.0012 *	-0.0021	-0.0027	0.0022	-0.0031
Constant	-0.0756	1.1662		1.1434	1.6199		-4.8481	1.1892 ***	
Dispersion parameter (ln(alpha))									
Constant				1.3922	0.0167 ***		0.6903	0.1041 ***	
Male							0.1797	0.0546 ***	
Age							0.0148	0.0026 ***	
Log Likelihood		-128,189.86			-175,906.41			-10,266.44	
Number of obs. (customers)		81,194 (4,191)			122,682 (6,963)			6,963	

[1] Models correct for selection using Internet Availability, Competitor Density, and Adoption of Telephone Banking as instruments.

[2] Sample based on last observation for each customer.

[3] Standard errors based on 50 bootstrap replications.

Table 8
Random-Effects Model of Customer Revenue Generation

Dependent Variable[1]	Checking Acct Revenue			Brokerage Acct Revenue			Total Revenue		
	Coef.	**Std. Err.[2]**		**Coef.**	**Std. Err.[2]**		**Coef.**	**Std. Err.[2]**	
Male	3.7740	1.4364	***	29.1420	28.0399		20.5393	6.5128	***
Age									
Age	1.4163	0.5773		-13.7140	7.6671	*	12.1417	1.8616	***
Age*Age	-0.0109	0.0081		0.2661	0.1234	**	-0.1145	0.0257	***
Banking									
Duration customer rel.	-0.1188	0.0611	*	-1.0570	0.8374		-0.0838	0.1694	
Brokerage account	3.6189	1.0034	***				70.1874	14.5571	***
Checking account				-18.7039	54.2373		36.9822	16.8338	**
Bank density, 3 miles	2.8523	1.6323	*	52.4385	39.1252		7.2975	4.8224	
School education									
Vocational school	1.1065	0.7509		25.8643	12.7011	**	7.2713	2.7383	***
Schooling: 13 years	0.9795	0.5184	*	-2.2256	3.8865		0.8246	0.9114	
Schooling: 10 years	-1.0068	0.2608	***	-9.3741	6.3108		-5.5287	1.2524	***
Income									
Income	-3.7915	3.1746		65.8316	50.9320		16.3446	11.3328	
Income*Income	0.0921	0.0751		-1.5414	1.2362		-0.3228	0.2876	
ZIP-code population density	-0.0453	0.2897		3.7855	2.8822		0.3774	0.7847	
Migration into ZIP-code	0.0340	0.0950		2.0139	4.7976		0.6041	0.4377	
Car ownership	13.1515	11.6956		-13.7274	47.7614		15.3585	17.4569	
Internet activity	-0.1081	0.0640	*	0.2731	0.7916		-0.1649	0.2154	
ln(*No. Domestic Transactions*)	-0.5884	0.2581	**						
ln(*No. Brokerage Transactions*)				106.0404	22.1977	***			
ln(*No. Online Transactions*)							5.8722	1.9554	***
Constant	-12.6043	44.9143		-1309.2840	809.5865		-671.3837	185.7099	***
Distribution parameters									
Sigma, u_i	59.9453			320.6268			242.8867		
Sigma, e_{it}	28.7862			221.8154			180.9822		
R-squared		0.02			0.14			0.07	
Number of obs. (customers)		36,639 (3,713)			1,615 (443)			42,132 (4,068)	

[1] Models correct for selection of customers with checking accounts, brokerage accounts, and online banking, respectively.

[2] Standard errors based on 50 bootstrap replications.

Figure 1
Time of Adoption and Usage of Online Banking

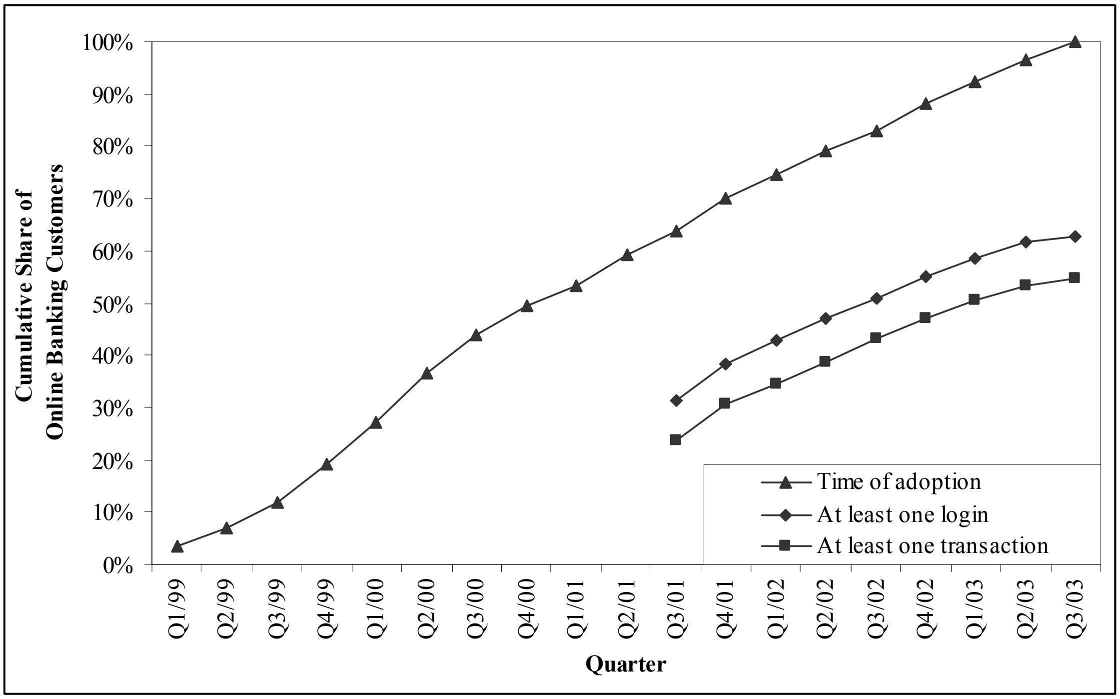
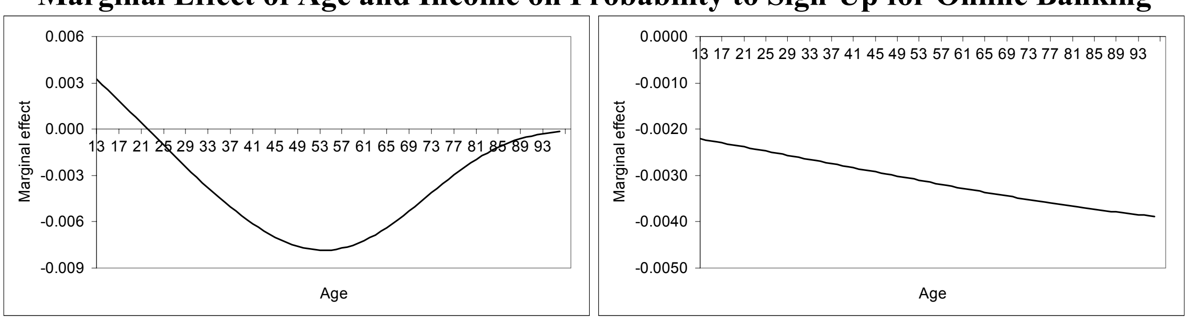
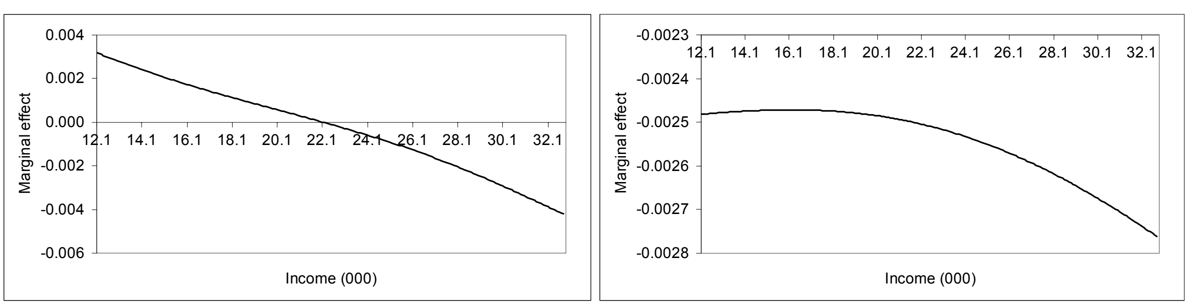


Figure 2
Marginal Effect of Age and Income on Probability to Sign-Up for Online Banking



All Adopters **Early Adopters**



All Adopters **Early Adopters**

Figure 3
Predicted Median Time until Sign-Up for Online Banking, All Adopters

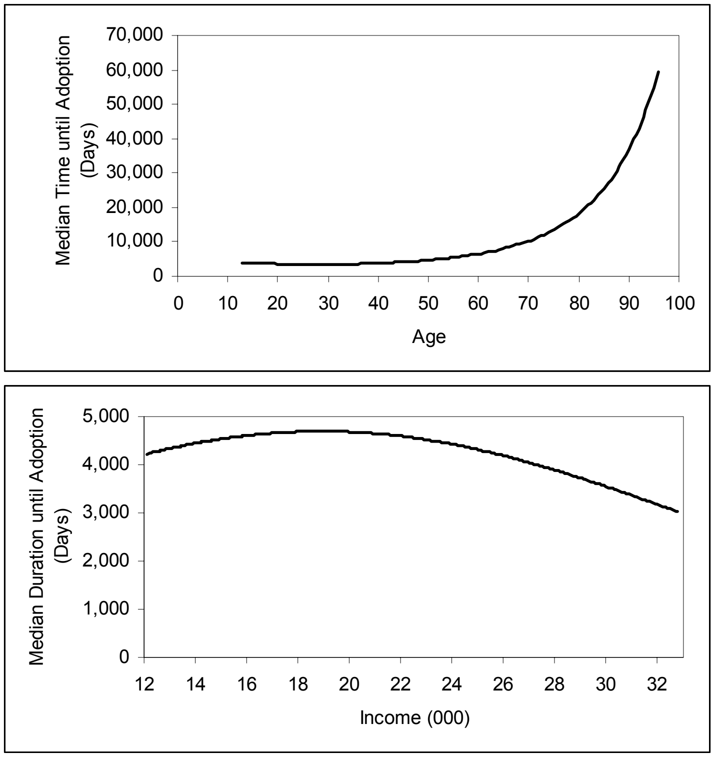


Figure 4
Marginal Effect of Age and Income on Number of Logins

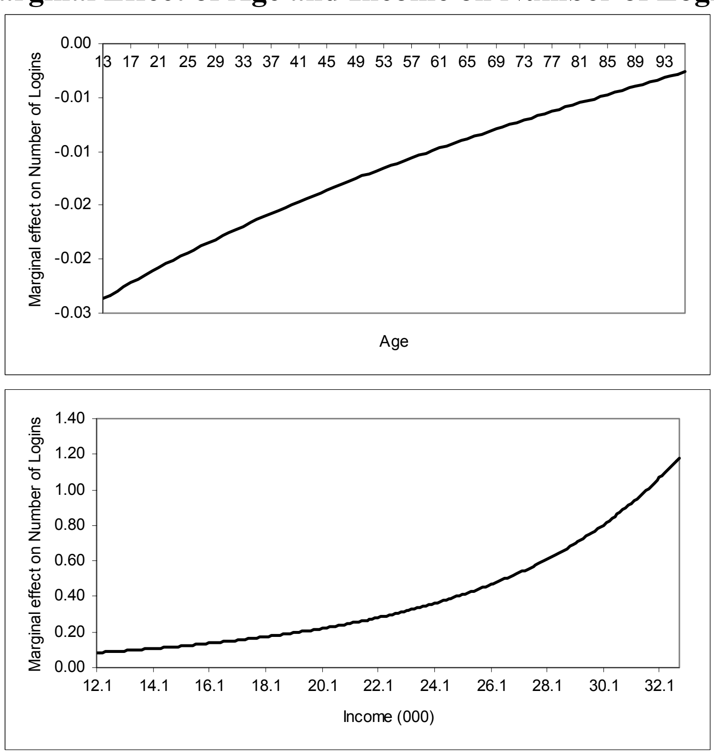
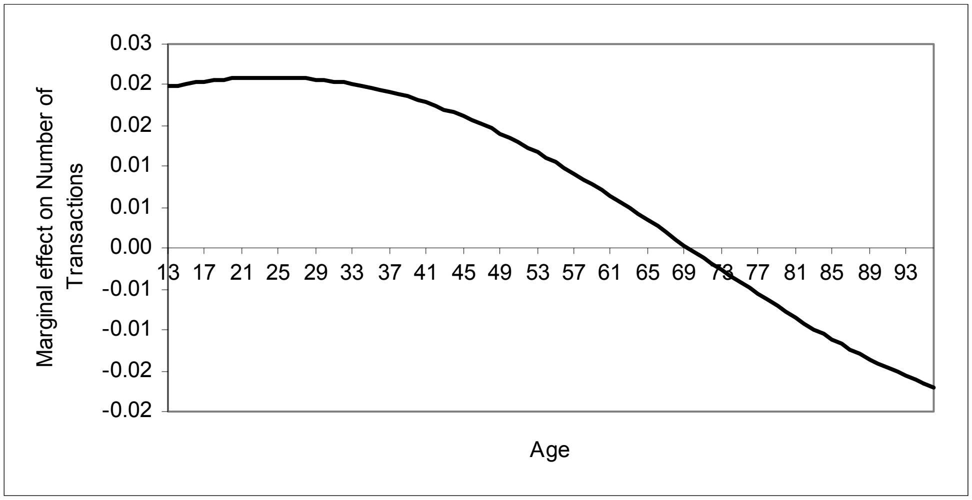


Figure 5

Marginal Effect of Age and Income on Number of Online Transactions



Bibliography

Ansari, Asim, Carl Mela and Scott Neslin (2005). "Customer Channel Migration." Mimeo, Graduate School of Business, Columbia University.

Aron, Debra and David Burnstein (2003). "Broadband Adoption in the United States: An Empirical Analysis." Mimeo, Northwestern University.

Astebrow, Thomas (2004). "Sunk costs and the depth and probability of technology adoption." *Journal of Industrial Economics* 52(3), 381-399.

Battisti, Guiliana and Paul Stoneman (2003). "Inter- and intra-firm effects in the diffusion of new process technology." *Research Policy* 32, 1641-1655.

Bell, David and Sangyoung Song (2004). "Neighborhood Effects and Trial on the Internet: Evidence from Online Grocery Retailing." Mimeo, The Wharton School, University of Pennsylvania.

Brown, Jeffrey and Austan Goolsbee (2002). "Does the Internet Make Markets More Competitive? Evidence from the Life Insurance Industry." *Journal of Political Economy* 110: 481-507.

Brynjolfsson, Erik and Michael Smith (2000). "Frictionless Commerce? A Comparison of Internet and Conventional Retailers." *Management Science* 46: 563-585.

Campbell, Dennis (2003). "The Cost Structure and Customer Profitability Implications of Electronic Distribution Channels: Evidence from Online Banking." Mimeo, Harvard Business School, Harvard University.

Dekimpe, Marnik, Philip Parker, Miklos Sarvary (2000): "Global Diffusion of Technological Innovations: A Coupled-Hazard Approach." *Journal of Marketing Research* 37: 47-59.

Ellison, Glenn and Sara Ellison (2004). "Search, Obfuscation, and Price Elasticities on the Internet." *NBER Working Paper* No. W10570.

Emre, Onsel, Ali Hortacsu and Chad Syverson (2005). "E-commerce and the Market Structure of Retail Industries." *NET Institute Working Paper* No. 05-24.

Fairlie, Robert (2004). "Race and the Digital Divide." *Contributions to Economic Analysis & Policy* 3(1). http://www.bepress.com/bejeap/contributions/vol3/iss1/art15

Forman, Chris, Avi Goldfarb, and Shane Greenstein (2004). "Geographic location and the diffusion of internet technology." *Electronic Commerce Research and Applications* 144, 1-13.

Forman, Chris, Avi Goldfarb, and Shane Greenstein (2005). "How Did Location Affect Adoption of the Commercial Internet? Global Village vs. Urban Leadership." Mimeo, Carnegie Mellon University.

Forrester Research (2005) "How German Consumers Use Banking Channels."

Gentzkow, Matthew (2006). "Valuing New Goods in a Model with Complementarities: Online Newspapers." Mimeo, Graduate School of Business, University of Chicago.

Goettler, Ronald and Karen Clay (2006). "Price Discrimination with Experience Goods: Sorting-Induced Biases and Illusive Surplus." Mimeo, Tepper School of Business, Carnegie Mellon University.

Goldfarb, Avi and Jeff Prince (2006). "Internet Adoption and Usage Patterns are Different: Implications for the Digital Divide." Mimeo, University of Toronto.

Goolsbee, Austan (2001). "Competition in the computer industry: Online versus retail." *Journal of Industrial Economics* 49: 487-499.

Goolsbee, Austan and Peter Klenow (2005). "Valuing Consumer Products By The Time Spent Using Them: An Application To The Internet." *SIEPR Policy Paper* No. 05-010.

Griliches, Zvi (1957). "Hybrid Corn: An Exploration in the Economics of Technological Change." *Econometrica* 25: 501-522.

Hitt, Lorin and Frances Frei (2002). "Do Better Customers Utilize Electronic Distribution Channels? The Case of PC Banking." *Management Science* 48: 732-748.

Israel, Mark (2005). "Services as Experience Goods: An Empirical Examination of Consumer Learning in Automobile Insurance." *American Economic Review* 95: 1444-63.

Jank, Wolfgang and P. K. Kannan (2005). "Understanding Geographical Markets of Online Firms Using Spatial Models of Customer Choice." *Marketing Science* 24: 623-634.

Mansfield, Edwin (1961). "Technical Change and the Rate of Imitation." *Econometrica* 29: 741-766.

Mortimer, Julie and Alan Sorensen (2005). "Supply Responses to Digital Distribution: Recorded Music and Live Performances." Mimeo, Department of Economics, Harvard University.

Morton, Fiona Scott, Florian Zettelmeyer, and Jorge Silva-Risso (2001). "Internet Car Retailing," *Journal of Industrial Economics* 49: 501-519.

Oberholzer, Felix and Koleman Strumpf (2005). "The effect of file sharing on record sales: An empirical analysis." Mimeo, Harvard Business School, Harvard University.

Osborne, Matthew (2005). "Consumer Learning, Habit Formation and Heterogeneity: A Structural Examination." Mimeo, Department of Economics, Stanford University.

Rob, Rafael and Joel Waldfogel (2004). "Piracy on the High C's: Music Downloading, Sales Displacement, and Social Welfare in a Sample of College Students." *Journal of Law & Economics*, forthcoming.

Sinai, Todd and Joel Waldfogel (2004). "Geography and the Internet: is the Internet a substitute or a complement for cities?" *Journal of Urban Economics* 56: 1-24.

Sinha, Rajiv and Murali Chandrashekaran (1992). "A Split Hazard Model for Analyzing the Diffusion of Innovations," *Journal of Marketing Research* 29: 116-27.

Thomas, Jacqueline and Ursula Sullivan (2005). "Managing Marketing Communications with Multichannel Customers." *Journal of Marketing* 69: 239-251.

Zhu, Kevin and Kenneth Kraemer (2005). "Post-Adoption Variations in Usage and Value of E-Business by Organizations: Cross-Country Evidence from the Retail Industry." *Information Systems Research* 16(1), 61-84.