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Strategic Online-Banking Adoption*

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Abstract

In this paper we study the determinants of banks' decision to adopt a transactional website for their customers. Using a panel of commercial banks in the United States for the period 2003-2005, we show that although bank-specific characteristics are important determinants of banks' adoption decision, competition plays a prominent role. The extent of competition is related to the geographical overlap of banks in different markets and their relative market share in terms of deposits. In more competitive markets banks are more likely to adopt earlier. Even more importantly, banks adopt earlier in markets where their competitors have already adopted.

JEL Codes: O31, G21, L10, C41.
Keywords: Duration Models, Technological Adoption, Online Banking, Competition.

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1 Introduction

The arrival of the internet has not only spurred the development of new industries in recent years but it has also changed the business model of many others. This is, for example, the case of the banking industry. In 1995, the Security First Network Bank was the first internet-only bank created. Around the same time, Wells Fargo was the first brick-and-mortar bank to establish its online presence. For most of the rest of the banks, however, online presence in the first few years often meant only the creation of a static corporative website. Banks soon started to develop software applications that first allowed customers to access their accounts and later allowed them to perform financial operations online. By the end of 2003, more than half of the commercial banks present in the U.S. offered *online-banking* services to their customers.

The purpose of this paper is to analyze the determinants of a bank's decision to adopt online banking. In particular, we focus on the strategic considerations of this adoption, mainly in response to the adoption decisions of competitors in the same markets. We show that banks that compete in markets where competitors have already adopted online banking are expected to adopt earlier. This effect persists even after controlling for the standard measures of the degree of competition in the market and whether banks operate in rural or metropolitan markets. Measures related to bank size, such as the volume of assets, are also significant, as are standard measures of a bank's financial health.

There is a considerable literature, particularly in the field of industrial organization, regarding the optimal adoption of new technologies by a firm. For example, Oster (1982) studies the introduction of the basic oxygen furnace used in steel making. He approaches this decision as technologically driven, independent of the decisions taken by competitors.[1] Later papers such as Hannan and McDowell (1984) introduced strategic considerations, mainly through the use of the Herfindahl index as a reduced form to measure competition.

Karshenas and Stoneman (1993) summarizes the determinants of the decisions to adopt a new technology in a competitive context. These determinants are structured around 4 different mechanisms: *rank*, *stock*, *order* and *epidemic effects*. Rank effects, mainly related to firm size, stem from the fact that adoption costs typically increase less than proportionally with the size of the firm and decrease over time. As a result, firms adopt according to their size: larger firms adopt earlier. Stock effects are related to the idea that the benefit from adopting a new technology may decrease as more firms have adopted it. Order effects arise when the return from adoption depends on the order in which firms have adopted, for example due to preemption effects: firms might adopt early to make adoption unprofitable to competitors. Finally, epidemic effects assume that the diffusion of new technologies is faster when more firms have adopted.

[1] Rose and Joskow (1990) study adoption decisions in markets where firms are local monopolies. In this case, the assumption that strategic interactions are absent is rather natural.

The decision to provide online-banking services is different from the *replacement* of an existing technology studied in the classical examples in the adoption literature. Instead, online banking coexists with the traditional channels that include not only bank branches but also telephone banking. For example, opening an account requires a visit to the branch, and this is also (together with ATMs) the main way to withdraw or deposit money. At the same time, online banking reduces the cost to provide a wide variety of products to customers. Hence, online banking can be understood as a service complementary to existing technologies.

In spite of its importance, the literature on adoption of online banking is still scarce. Very few papers have studied the demand for these services. One example is Chang (2004) which studies the consumer-adoption decision of this technology in South Korea. The author infers that risk aversion and customer inertia make bank investments in this new technology unlikely to be profitable. As a result, she concludes that bank adoption might arise due to the positive reputation effects it entails or preemptive motivations towards competitors.

Studies regarding the supply side for the U.S. include Furst et al. (2001), Sullivan and Nickerson (2004) and Sullivan and Wang (2005). Furst et al. (2001) studies the determinants of adoption using a cross-section of banks for 1999. The authors do not include strategic considerations. They show that profitability, bank size, presence in urban markets, and membership in a bank holding company are all positive and good predictors of the decision to adopt.

Sullivan and Nickerson (2004) embeds the strategic decision regarding the adoption of online banking in a real options environment. Their theoretical model shows that market leaders are more likely to adopt if competition consists of small firms or if uncertainty in the demand is small. They confirm these hypotheses using also a cross-section for 1999. Sullivan and Wang (2005) studies the pattern of diffusion of technological innovations in different states. They propose a theoretical model that is later tested using data of online-banking adoption. Using observations at the statewide level, they estimate slower patterns of adoption for those states where per capita income is lower, internet access is more scarce or banks are older. More important, adoption is also slower in states where banks are smaller. To the extent that rank effects make big banks more likely to adopt, the authors interpret this last result as supportive of the existence of epidemic effects.

Our paper departs from the previous literature in that we measure the strategic decision of firms to adopt online banking as a response to the adoption decisions of competitors. In the terminology introduced earlier, we measure the stock and order effects together. For this purpose we use a dataset on online adoption that has been available only recently. Starting in 2003, the Federal Deposit Insurance Corporation (FDIC) asked institutions to indicate in their quarterly *Call Reports* whether their websites allowed customers to execute transactions or not.[2]

[2]Call Reports also tracked the presence of an internet website since 1999.

We complement this dataset with information at the bank level using the Summary of Deposits also from the FDIC, and demand characteristics from the U.S. Census Bureau. As opposed to other papers in the literature, we benefit from the construction of a panel that allows us to estimate a duration model of the adoption decision over time.

To the extent that we are interested in determining the strategic component of adoption, it is essential to identify the relevant market in which banks operate, and the competitors they face. Unfortunately, there is no natural segmentation of markets. Instead, many banks compete at a national level, other at the state level and finally, many small banks are local. For this reason, in order to isolate the effect of online presence we adapt the concept of *Multimarket Contact* used in papers such as Evans and Kessides (1994) for the airline industry. The idea of this index is to weight the characteristics of each competitor according to how close a substitute their product is. In the case of the banking industry, two banks can be considered closer substitutes if, among other things, their network of branches overlaps more often.

Our index of Multimarket Contact is constructed as a weighted sum of indicator functions for a bank's competitors at the zip-code level. The indicator is 1 if the competitor has adopted online-banking and its weight in each zip code depends on the market share that it has in this particular zip code measured in terms of deposits. The Multimarket Contact index averages the zip-code values according to the share of the total deposits of the bank that each zip code represents. Obviously, this index is bank specific and it varies over time.

In this paper we use the Multimarket Contact index to address different issues from the ones studied in the literature. While papers such as Evans and Kessides (1994) and Waldfogel and Wulf (2006) relate the extent of multimarket contact with the probability that firms tacitly collude, in this paper we take this index as a proxy of the strategic motivation for banks to adopt online operations as a competitive response to the rivals' actions.

Our results support the hypothesis that competitive considerations play an important role in adoption decisions. However, competitive pressure can be reflected in several ways. First, and consistent with previous empirical studies, banks that operate in less competitive markets (measured by a higher concentration index) tend to adopt later. Second, our index allows us to conclude that for similar levels of competition in the market, adoption occurs faster in markets where rivals have already adopted.

Our estimations are robust to changes in the measures of the relevant market definition or the variable used to denote the online presence. In particular, the results hold if the relevant market is defined at the county level (as opposed to the zip-code level) of if our measure of online presence is replaced by the decision to create a corporate website (where transactions are not necessarily possible).

Section 2 briefly describes the sector and the evolution of online banking adoption in the United States. Section 3 discusses the measures of competition used in the paper. Section 4

presents the empirical strategy. Section 4 explains the construction of the database and section 5 discusses the main specification. Section 6 performs some robustness checks and section 7 concludes.

2 The Pattern of Online-Banking Adoption

Customers interact with their banks in several ways. Although most of the transactions traditionally occurred at the branch counter, new technologies have reduced the costs that customers had to bear. For example, ATMs became widespread around the mid-eighties, making some transactions easier. Telephone banking, initially human-operated and later voice-automated, reduced the need to visit a bank's physical branch. In recent years, particularly since 1995, the internet has made banking easier and allowed institutions to offer newer services to their customers, further reducing the need to stop by a branch office.

The cost of setting up a transaction website has decreased substantially in recent years. The cost of an online transaction is estimated to be as low as \$0.01 as opposed to the cost of a transaction at a branch of \$1.[3] These cost savings together with the widespread use of the internet has enticed smaller banks to adopt this technology. According to DeYoung (2001) around 1100 banks and thrifts operated a transactional web site in 1999. This number increased to around 4000 banks at the beginning of 2003. Since 2003, banks have adopted at a rate of about 5% per quarter. By the end of 2005 around 5700 banks (70% of the total) provided online banking to their customers. Figure 1 shows the evolution of adoption in recent years.

For the purposes of this paper, it is important to emphasize that internet-only banks (those that operate without any branch) have remained an oddity in the United States. In 2000 they accounted for less than 1% of the deposits and constituted less than 5% of all transactional websites. In 2004, there were less than 30 internet-only banks.[4] At the same time, the rest of the entrants during our sample period do not necessarily provide a transaction website.

Table 10 in the appendix shows the stark differences between those banks that adopted prior to the beginning of 2003 and those that were yet to adopt. Non-adopters were in general smaller in terms of deposits (and total assets) and had on average 80% fewer branches. They also faced fewer competitors and devoted a bigger proportion of their activities to non-urban markets.

The larger size of earlier adopters, consistent with the rank effects previously mentioned, is natural for several reasons. The main one is that the setup cost of online services is not particularly sensitive to the size of the bank. However, smaller banks face other challenges.

[3]See Economist (2000) and references therein.

[4]See DeYoung (2001) and Wang (2006). The last author argues that their little success is due to the complementarity between brick-and-mortar and online channels; While standarized products are easily distributed through the online channel, specialized products require a branch presence. As a result, internet-only banks are found to have on average a lower return on assets.

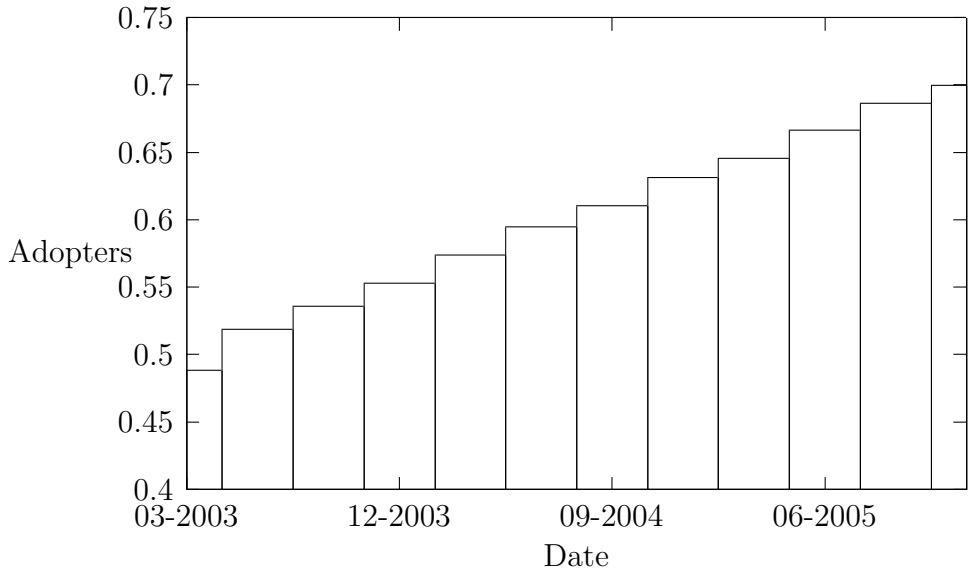

Figure 1: Proportion of banks that have adopted online-banking in the period 2003-2005.

For example, Nathan (1999) emphasizes that community banks (usually defined as banks with total assets of $1 billion or less) rely more on closer and more personalized contact for customer screening. Hence, the access to a wider market might be less profitable to them.

3 Measures of Competition

3.1 The Index of Multimarket Contact

This paper originates from the idea that the decision to adopt online banking depends on the behavior of competitors over and above the level of market concentration previously considered in the literature. In the banking industry, expanding the number of branches and choosing their location has traditionally constituted one of the main channels of competition. Online banking provides a substitute to the creation of new bank branches, but at the same time it reduces customer transaction costs.

At least in the short run, the provision of online banking by an institution is likely to steal customers from competitors that operate in similar geographic areas, where overlapping of their branch network is important. Our index accounts for this factor by giving different weights to banks that coincide in different areas and have a different volume of deposits. In particular, if bank i has branches in the set M_i of zip codes and a set of banks B_s operate in zip code s, we compute the Multimarket Contact Index (MMC) as

$$MMC_i = \sum_{s \in M_i} \frac{D_{is}}{\sum_{r \in M_i} D_{ir}} \times \sum_{j \in B_s \setminus \{i\}} I_j \frac{D_{js}}{\sum_{k \in B_s \setminus \{i\}} D_{ks}}$$

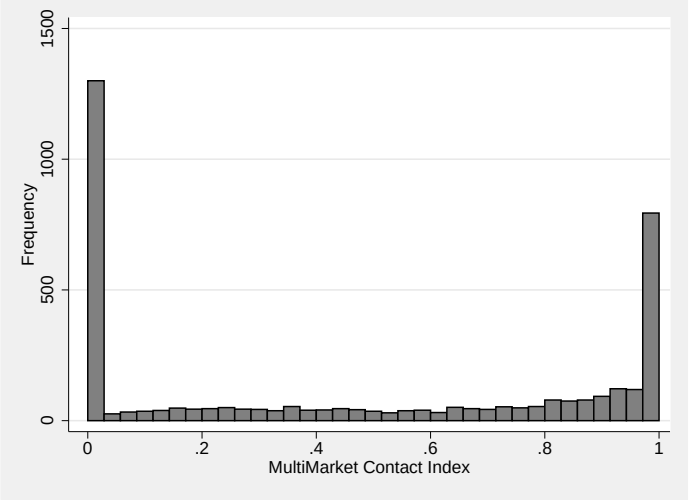

Figure 2: The MMC index for the first quarter of 2003 among all banks that had not adopted.

where D_{js} denotes the sum of deposits of bank j in zip code s and I_j is an indicator function that takes the value 1 if bank j has adopted online banking in a previous period and 0 otherwise.[5]

Notice that the index excludes the bank for which it is computed. This exclusion avoids some spurious correlation originating in our estimations from the period in which the firm decides to adopt and the corresponding change in multimarket contact.

This index can also be interpreted as the share of deposits controlled by the competitors of bank i in the markets where this bank operates. The weights assigned to each competitor are increasing in its market share in that particular zip code. These weights are also increasing in the share that this zip code represents in the total volume of deposits of bank i.

Figure 2 graphs the histogram of the MMC index for the first period of the sample. It is worth noticing that this index is bimodal and it clearly distinguishes between markets in which competitors have not adopted and those in which essentially all competitors have adopted.

	$MMC < 0.2$	$MMC > 0.8$
Adoption (I=1)	427(28%)	747(55%)
No Adoption (I=0)	1099(72%)	614(45%)

Table 1: Adoption in the period 2003-2005 for different values of initial 2003 MMC.

During the sample period under study, 40% of the banks that had not adopted by the first quarter of 2003 had adopted by the fourth quarter of 2005. The pattern of adoption, however, was different for those banks that operated in markets where competitors have already adopted and those that were yet to adopt. As Table 1 shows, adoption in markets where MMC is close

[5]This index is bank and period specific. However, in order to ease of exposition we have excluded the time subscript in the formula.

to 1 is almost twice as likely than in those markets where MMC is close to 0.

3.2 The Herfindahl-Hirschman Index

The adoption decision by competitors is not necessarily the only strategic interaction between firms in their decision of future adoption. In particular, adoption is likely to depend significantly on the characteristics of the markets in which each bank operates. Besides demand-side considerations that are likely to condition the profitability of online banking (consumer internet access, education attainment, level of income, etc), this profitability is likely to depend on the level of competition in each market. Standard theories, for example, would suggest that competition spurs innovation as a way to achieve cost reductions or to differentiate products.

In this paper, we measure competition using the Herfindahl-Hirschman Index (HHI). As opposed to the usual analysis of competition among firms that operate in the same market, different banks have activities in different zip codes. As a result, the measures of competition will be in this case bank-specific, reflecting the average conditions among all the markets in which each firm operates. For this reason we compute the HHI for bank i as the weighted sum of all the HHIs in the zip codes where this bank operates. Similarly to the MMC computed earlier, the weights correspond to the share of total deposits of bank i in each of the zip codes. In particular, the formula is given by

$$HHI_i = \sum_{s \in M_i} \frac{D_{is}}{\sum_{r \in M_i} D_{ir}} \times \sum_{j \in B_s} \left(\frac{D_{js}}{\sum_{k \in B_s} D_{ks}} \right)^2 .$$

4 The Empirical Model

In the empirical model, we estimate the determinants of the timing of adoption. The decision to adopt is dynamic in nature. When a firm decides whether to adopt in a particular moment in time or not, it takes into account the cost to be incurred and the increase in present value of profits compared to the best alternative of future adoption. This decision is in essence an optimal stopping-time problem.

We denote the present value of profits of firm i (net of the cost of adoption) when it adopts in period t as V_{it}^A. Similarly, we denote the present value of profits of not adopting in t, and instead waiting until the best future period, as V_{it}^{NA}. We posit a reduced-form model for the difference in profits between these two options as a latent variable y_{it}^* which depends on a vector of exogenous variables affecting the adoption decision as follows

$$y_{it}^* = \alpha + \beta x_{it} + \gamma w_{it} + \delta z_{it} + \varepsilon_{it}.$$

The vector of variables x_{it} corresponds to bank-specific characteristics, w_{it} are market characteristics, z_{it} are measures of competition, and ε_{it} is an error term.[6] Notice that both market

[6] These regressors can be interpreted as the relevant state variables in the dynamic problem.

characteristics and measures of competition are bank-specific, since they are weighted according to the deposits of each bank across all the zip codes where it operates.

We do not observe the latent variable y_{it}^* and instead we observe the outcome of the adoption decision, y_{it}. We define this variable to be equal to 1 if the firm i possesses online-banking capabilities and 0 if it has not adopted yet. We assume that a bank adopts in period t if and only if its present value of profits of adopting is higher than the present value of profits of waiting. That is, $y_{it} = 1$ if and only if $y_{it}^* = V_{it}^A - V_{it}^{NA} \geq 0$. Furthermore, we assume that the adoption decision is irreversible. Thus, banks do not provide (to the econometrician) any additional information after they have adopted.

We estimate a discrete hazard model of duration until the adoption decision. Let T_i be the random-variable representing the period of adoption for each bank i. The hazard rate of adopting in period t, the probability of adoption in period t conditional on not having adopted before, is defined as

$$h_{it} \equiv \Pr\left(T_i = t | T_i \geq t; x_{it}, w_{it}, z_{it}\right).$$

The unconditional probability of adoption in period t corresponds to

$$\begin{aligned} \Pr\left(T_i = t\right) &= h_{it} \prod_{s=1}^{t-1} \left(1 - h_{is}\right) \\ &= \frac{h_{it}}{1 - h_{it}} \prod_{s=1}^{t} \left(1 - h_{is}\right), \end{aligned}$$

and the unconditional probability that the firm adopts at a future date is

$$\Pr\left(T_i > t\right) = \prod_{s=1}^{t} \left(1 - h_{is}\right).$$

Building on Allison (1982), papers such as Jenkins (1995) show that this model can be easily estimated using the following log-likelihood function:

$$\log \mathcal{L} = \sum_{i=1}^{N} \sum_{t=1}^{S_i} \left[y_{it} \log h_{it} + \left(1 - y_{it}\right) \log(1 - h_{it})\right],$$

where S_i is the actual number of periods bank i is present in the sample. This is the likelihood function of a static discrete-choice model for y_{it} that can be estimated using standard packages. However, it is particular in the way in which observations are organized. The model stacks all the observations for a particular bank for all the periods before it adopts, and it drops observations of that bank in all periods after adoption.

For the purpose of this paper we use a logit specification for this discrete-choice model, which in this case implies that

$$h_{it} = \frac{\exp\left(\alpha + \beta x_{it} + \gamma w_{it} + \delta z_{it}\right)}{1 + \exp\left(\alpha + \beta x_{it} + \gamma w_{it} + \delta z_{it}\right)}.$$

5 Data

Our dataset consists of quarterly date for all commercial banks in the U.S. during the period 2002:1-2005:4. These data were obtained from the Call Reports made available by the Federal Reserve Bank of Chicago.

Since the second quarter of 1999, the Call Reports provide the address of a bank's website if it exists. Most important for this analysis, starting in the first quarter of 2003, they also report whether the bank's website offers transactional capabilities, such as downloading statements, transferring money between account, or paying bills. We use this variable as the indicator for the adoption of online-banking. This variable is also used in the construction of the multimarket contact index. In our robustness analysis we alternatively use as a measure of internet presence the mere existence of a corporate website, which may or may not allow customers to perform transactions online.

From the Call Reports data we obtain bank-specific variables used in the vector x_{it}. These variables include: (log) total assets to measure bank size, the number of branches, and the (log) age of the bank. We also obtain standard measures of profitability and bank financial health, such as the return on assets, the share of non-performing loans, the loans to assets ratio, and the equity to assets ratio.

We also obtain annual branch-level data for each bank in the sample using the Summary of Deposits from the FDIC. This dataset includes the deposits per branch for all banks as of June of each year. This dataset provides information about the geographical location of each branch, including the postal address, and whether the bank is located in a metropolitan area or not.

The Summary of Deposits also reports information on whether the bank belongs to a multi-bank holding company, a one-bank holding company or it is an independent bank. We include these variables as additional bank characteristics in the vector x_{it}. We take the indicator for an independent bank as the reference category, while we include the other two as dummy variables.

We match the deposits data from the Summary of Deposits with the bank level information from the Call Reports and we use them to construct the measures of competition in the vector z_{it}, i.e., the HHI and MMC index introduced earlier in the paper.

Finally, we also control for several market characteristics in the vector w_{it}. First, we account for whether the bank operates in metropolitan or rural areas averaging the share of deposits that corresponds to branches located in metropolitan areas over all of the bank's branches. Second, we obtain annual demographic information at the state level from the American Community Survey of the U.S. Census Bureau for 2002-2005. These variables include population, median family income, and the share of people aged 25 and older who have completed a bachelor's degree. We complete this information with the share of households with internet access from the Current Population Survey also from the Census Bureau, available only for 2003. For banks

that operate in more than one state, all the demographic variables are weighted according to the share of the deposits that each state represents for the bank.

Summary statistics of the above variables are presented in Table 10 in the appendix. The initial database has observations for 7788 banks present in the first quarter of 2003. We eliminated 7 banks with coding errors in the indicator for online-banking adoption resulting in 7,781 observations in the first period. We then eliminate 3,680 banks that had already adopted (they already had a transactional website) in the first period of the sample. The resulting bank panel has 4,101 banks that have not adopted by the first quarter of 2003. Of these banks, 298 do not appear in all periods of the sample, probably as a result of bank failures or acquisitions.[7] For each bank we observe at most 11 quarters until the adoption decision is made, since by construction we do not observe any adoption in the first period.

In the logit regressions, future observations of banks are eliminated from the sample after they decide to adopt. In total, the resulting unbalanced panel has about 34,000 observations.

6 Results

The results of the baseline estimation are reported in Table 2 for four different specifications. In model (1) we include only bank-specific variables in addition to the multimarket contact index. In model (2) we also include the Herfindahl index to control for market concentration, and in model (3) we control also for demographic variables. Whereas models (1) to (3) include a second-order polynomial for a time trend, model (4) introduces time fixed effects. In what follows, we discuss the average marginal effects presented in column (1) of Table 3, but qualitatively there are little differences between the 4 models presented. All financial ratios, as well as the MMC index, are measured in decimal points (0.01 is equivalent to 1 percentage point). The HHI is normalized to be between 0 and 1.

The effects of the bank-specific variables are similar across model specifications. The size of the bank in terms of (log) assets has the expected positive effect on the decision to adopt. Namely, larger banks are likely to adopt earlier, since the cost of adoption is quite independent of the size of the bank. Because assets are measured in logs, the interpretation of the coefficient of 0.0147 is that, on average (across all observations) an increase of 5% in assets increases the probability of adoption by approximately 7.3 basis points per quarter and the effect is statistically significant. Membership to either a one-bank or a multi-bank holding company is also positive and statistically significant. Banks in one-bank holding company are about 2 percentage points more likely to adopt than stand-alone banks, whereas banks in a multi-bank holding are about 3 percentage points more likely than stand-alone banks.

A standard measure of banks' health, the share of non-performing loans, has a strongly

[7] Our estimation results do not change significantly if those banks are excluded from the sample.

Table 2: Bank Adoption of a Transactional Website

	(1)	(2)	(3)	(4)
time	0.00159	0.00267	0.00807	
	(0.047)	(0.078)	(0.235)	
time^2	0.00241	0.00239	0.00217	
	(0.848)	(0.842)	(0.761)	
MMC Index (trans. website zip)	0.61049	0.49040	0.47233	0.47049
	(8.173)***	(4.914)***	(4.703)***	(4.680)***
Branch Count	-0.00118	-0.00130	-0.00087	-0.00093
	(0.475)	(0.520)	(0.347)	(0.369)
Loans to Assets Ratio	1.59494	1.58769	1.44145	1.44584
	(9.448)***	(9.405)***	(8.394)***	(8.413)***
Return on Assets	-9.14164	-9.17728	-8.78176	-8.89620
	(6.376)***	(6.392)***	(6.152)***	(6.200)***
Nonperforming Loans Ratio	-12.27413	-12.19324	-11.66629	-11.64710
	(5.798)***	(5.759)***	(5.521)***	(5.506)***
(log) Total Assets	0.31700	0.31355	0.29880	0.29953
	(12.548)***	(12.282)***	(11.350)***	(11.358)***
Equity to Assets Ratio	-2.81854	-2.73352	-2.94602	-2.99691
	(4.180)***	(4.063)***	(4.371)***	(4.432)***
Multigroup	0.56654	0.57003	0.59615	0.59283
	(6.556)***	(6.597)***	(6.824)***	(6.781)***
Unigroup	0.49193	0.48929	0.51414	0.51105
	(6.948)***	(6.912)***	(7.157)***	(7.110)***
(log) Age	-0.02849	-0.01348	0.00024	0.00057
	(1.100)	(0.495)	(0.008)	(0.020)
Herfindahl Index (zip)		-0.27571	-0.35809	-0.35877
		(1.816)*	(2.317)**	(2.320)**
Metropolitan Share			0.10324	0.10286
			(1.679)*	(1.671)*
(log) Median Income Per Capita			0.02919	0.02851
			(0.938)	(0.915)
University			-0.01786	-0.01881
			(1.900)*	(1.998)**
Internet Access			0.02882	0.02938
			(3.848)***	(3.917)***
Constant	-7.68376	-7.48103	-8.23771	-8.10149
	(22.436)***	(20.691)***	(17.070)***	(16.685)***
Observations	34201	34201	34201	34201
Time dummies	No	No	No	Yes
Log-likelihood	-6400.318	-6398.670	-6387.818	-6371.213
Pseudo-R2	0.061	0.061	0.063	0.065

Absolute value of z statistics in parentheses
* significant at 10%; ** significant at 5%; *** significant at 1%

Table 3: Bank Adoption of a Transactional Website (Average Marginal Effects)

	(1)	(2)	(3)	(4)
Multigroup	0.03127	0.03149	0.03318	0.03289
	(5.563)***	(5.593)***	(5.744)***	(5.717)***
Unigroup	0.02200	0.02189	0.02295	0.02279
	(7.132)***	(7.093)***	(7.341)***	(7.294)***
time	0.00007	0.00012	0.00037	
	(0.047)	(0.078)	(0.235)	
time^2	0.00011	0.00011	0.00010	
	(0.848)	(0.842)	(0.761)	
MMC Index (trans. website zip)	0.02832	0.02275	0.02189	0.02178
	(8.075)***	(4.893)***	(4.685)***	(4.662)***
Branch Count	-0.00005	-0.00006	-0.00004	-0.00004
	(0.475)	(0.520)	(0.347)	(0.369)
Loans to Assets Ratio	0.07399	0.07366	0.06681	0.06692
	(9.319)***	(9.278)***	(8.303)***	(8.323)***
Return on Assets	-0.42411	-0.42578	-0.40703	-0.41179
	(6.347)***	(6.363)***	(6.127)***	(6.174)***
Nonperforming Loans Ratio	-0.56944	-0.56571	-0.54073	-0.53912
	(5.766)***	(5.728)***	(5.494)***	(5.479)***
(log) Total Assets	0.01471	0.01455	0.01385	0.01386
	(12.306)***	(12.053)***	(11.174)***	(11.184)***
Equity to Assets Ratio	-0.13076	-0.12682	-0.13655	-0.13872
	(4.167)***	(4.051)***	(4.356)***	(4.416)***
(log) Age	-0.00132	-0.00063	0.00001	0.00003
	(1.099)	(0.495)	(0.008)	(0.020)
Herfindahl Index (zip)		-0.01279	-0.01660	-0.01661
		(1.815)*	(2.314)**	(2.317)**
Metropolitan Share			0.00478	0.00476
			(1.678)*	(1.671)*
(log) Median Income Per Capita			0.00135	0.00132
			(0.937)	(0.914)
University			-0.00083	-0.00087
			(1.899)*	(1.997)**
Internet Access			0.00134	0.00136
			(3.839)***	(3.909)***

Absolute value of z statistics in parentheses
* significant at 10%; ** significant at 5%; *** significant at 1%

negative and statistically significant effect on the decision to adopt. On average, an increase of 1 percentage points in the share of non-performing loans reduces the probability of adoption by about 56 basis points per quarter. In other words, banks with a better loan portfolio would tend to adopt earlier. To the extent that online banking can be used as a way to capture new customers, an immediate explanation of this result is that banks that are better at screening projects (and have a lower non-performing loans ratio) obtain a higher revenue per customer, and this entices them to adopt earlier.

A common measure of profitability is the return on assets. Our results indicate that this variable has a negative and statistically significant effect on the adoption decision. An increase of 1 percentage points in the return on assets decreases the probability of adoption by about 42 basis points per quarter. This suggests that less profitable banks are hard pressed to adopt online banking sooner, perhaps as a way of exploring new business opportunities in an attempt to improve profitability.

The probability of adoption is also positively related to the ratio of loans to assets. A 1 percentage point increase in this ratio increases the probability of adoption by about 7 basis points per quarter. One possible interpretation of this result is that more aggressive banks hold a bigger loan portfolio and, in their strategy, online banking is a channel to attract more resources. Similarly, the ratio of equity to assets (a measure of leverage or capitalization) might be a proxy for conservative banking. Under this interpretation, our results would suggest that more conservative banks tend to be less interested in adopting online banking sooner. An increase of 1 percentage points in the equity to assets ratio reduces the probability of adoption by about 13 basis points per quarter.

Because online banking and bank branches are substitute strategies for expansion, we could expect growing banks to adopt earlier at the same time that they open new branches. This effect would have biased the results towards a positive effect on the probability of adoption. But in our results, this issue does not arise because the number of branches is not statistically significant.

The age of a bank is measured in log years to account for the skewedness in the age distribution. This variable is not statistically significant, however.

In all models the effect of the MMC index is positive and highly significant. That is, the adoption by more competitors in the relevant markets make a bank more likely to adopt. This effect persists in all specifications in spite of the introduction of the Herfindahl index in models (2) to (4). The effect of the MMC index on adoption can be interpreted as follows: on average, an increase of 10 percentage points in the share of deposits controlled by a bank's competitors which have already adopted increases the probability of adoption by more than 20 basis points per quarter. To put this effect in perspective, it is important to remember that the observed probability of adoption is about 5% per quarter.

The Herfindahl index has a negative impact on the probability of adoption. As a result, banks that operate in geographical areas where the market is more concentrated are likely to adopt later. The effect is noticeable and statistically significant.

We have included demographic variables in specifications (3) and (4) to account for demand factors. Internet access at the state level has the expected positive effect. The effect of our income measure is also positive although not statistically significant. Finally, the share of population with a college degree has a statistically significant negative effect. We forgo interpreting this variable, as this measure of education is negatively correlated with income per capita in the data, and the use of state-level demographic variables may not adequately capture characteristics of markets that are defined at the zip-code level.

One possible caveat of our analysis is the existence of omitted variables correlated with the decision to adopt and with the MMC index that could bias our results. These variables could include structural characteristics of the markets where these banks operate (for example, rural versus urban areas). To address this issue we included in models (3) and (4), the proportion of bank business (in terms of deposits) conducted in metropolitan areas. This variable is statistically significant with a positive effect as expected. Its introduction, however, does not affect the coefficient of the MMC.

Finally, an important concern is whether the results are driven by a small number of banks and, specially, banks that have been in the market for a only few years and for which the information in the financial ratios does not reflect the banks' long-run financial standing. Similar kinds of concerns might arise for large banks, that operate at a national scale, and in markets with a different competitive structure than, smaller, community banks. We therefore restricted the sample eliminating de-novo banks (5 years or younger) and those with assets in excess of 1 billion dollars. The sample is reduced by about two thousand observations, but the (unreported) results do not display noticeable differences with the tables we show here.

7 Robustness Analysis

In this section we perform several sensitivity checks to study the robustness of the results to changes in the measures that we use. In particular, we focus on changes in our measure of multimarket contact and in the variable used to account for internet presence. We also conduct some preliminary work on the determinants of adoption in bank groups.

7.1 County Level Data

As a first robustness check we change the market definition from zip codes to counties. In other words, competitors are now taken from banks that operate branches in the same county as the observation bank. New multimarket contact and Herfindahl-Hirschman indexes are computed

according to formulas analogous to those in section 3. We estimate the same model with these new definitions and the results are presented in table 4 and 5.

Our results are in line with those obtained using a finer market definition. The effects of the different control variables maintain the same sign and comparable magnitudes. Some variables lose statistical significance, while others that were not statistically significant become so with the county-level measures. It is interesting to notice that the Herfindahl index is no longer significant in any of the specifications considered, whereas the log age, as opposed to the results in the benchmark models, is now significant and negatively correlated with the probability of adoption. The MMC index remains statistically significant in all specifications and its average marginal effect is slightly larger than in the baseline cases.

7.2 A Different Measure of Internet Presence

So far we have defined internet adoption as the existence of a transactional website. However, a simpler definition of a bank's internet presence can be formulated with the existence of a corporate website which provides only basic information about the bank, such as contact telephone numbers, e-mail addresses, or information on the location of the bank branches and does not necessarily imply the capability of allowing online transactions.

Starting in the second quarter of 1999, the Call Report data contained information about the existence of a bank's website. Using this information, in this section we replace our measure of internet presence with the existence of a bank website and maintain the zip-code level definition of banking markets. Due to lack of annual data on the demand variables for previous years, we restrict our estimation to the period 2002 to 2005. An additional advantage of restricting our analysis to the latter years is that the variable for existence of a website is not very reliable in the early part of the sample.[8]

The results from this estimation are presented in Table 6. Table 7 shows the average marginal effects. The results in this case are similar to those presented in the previous section. Bank size measures have a positive impact on the creation of a corporate website, while both measures of competition, the Herfindahl Index and the Index of Multimarket Contact have the expected sign and are both statistically significant. The MMC in this case is computed using this alternative definition of internet adoption. It is worth emphasizing that the impact of changes in this variable is in this case smaller, suggesting that the adoption by competitors of a simple bank website, which does not necessarily allows for online transactions, has a modest effect on the adoption decision. In contrast, the effect of the usual market concentration measure is essentially unchanged.

Again, there are no differences between the use of a time-trend and time dummies to account

[8]The Call Report question asked for the bank's website address, but instead this variable was often populated with an e-mail address from a generic internet service provider.

Table 4: Bank Adoption of a Transactional Website (County Level)

	(1)	(2)	(3)	(4)
time	-0.00163	-0.00047	0.00322	
	(0.048)	(0.014)	(0.094)	
time^2	0.00233	0.00227	0.00213	
	(0.819)	(0.799)	(0.749)	
MMC Index (trans. website cty)	0.79171	0.75465	0.74104	0.73674
	(7.180)***	(6.639)***	(6.409)***	(6.367)***
Branch Count	-0.00239	-0.00249	-0.00227	-0.00232
	(0.955)	(0.992)	(0.906)	(0.924)
Loans to Assets Ratio	1.56354	1.55589	1.45152	1.45574
	(9.303)***	(9.263)***	(8.492)***	(8.510)***
Return on Assets	-10.02533	-10.03061	-9.83025	-9.94482
	(6.902)***	(6.895)***	(6.782)***	(6.821)***
Nonperforming Loans Ratio	-11.98273	-11.76204	-11.48029	-11.46571
	(5.712)***	(5.611)***	(5.471)***	(5.457)***
(log) Total Assets	0.36235	0.36477	0.36367	0.36438
	(15.419)***	(15.483)***	(14.712)***	(14.717)***
Equity to Assets Ratio	-2.93546	-2.87085	-3.04989	-3.10510
	(4.325)***	(4.231)***	(4.465)***	(4.533)***
Multigroup	0.59156	0.59578	0.60338	0.60018
	(6.844)***	(6.891)***	(6.913)***	(6.872)***
Unigroup	0.50560	0.50524	0.51383	0.51083
	(7.162)***	(7.158)***	(7.178)***	(7.132)***
(log) Age	-0.06103	-0.05703	-0.05934	-0.05905
	(2.440)**	(2.267)**	(2.299)**	(2.286)**
Herfindahl Index (cty)		-0.30948	-0.30936	-0.30798
		(1.550)	(1.475)	(1.468)
Metropolitan Share			0.03698	0.03713
			(0.580)	(0.582)
(log) Median Income Per Capita			0.02594	0.02506
			(0.831)	(0.802)
University			-0.01628	-0.01723
			(1.732)*	(1.830)*
Internet Access			0.02154	0.02209
			(2.902)***	(2.973)***
Constant	-8.28280	-8.22753	-8.76735	-8.68617
	(24.008)***	(23.704)***	(18.465)***	(18.159)***
Observations	34201	34201	34201	34201
Time dummies	No	No	No	Yes
Log-likelihood	-6405.913	-6404.685	-6399.270	-6382.747
Pseudo-R2	0.060	0.060	0.061	0.064

Absolute value of z statistics in parentheses
* significant at 10%; ** significant at 5%; *** significant at 1%

Table 5: Bank Adoption of a Transactional Website (Average Marginal Effects, County Level)

	(1)	(2)	(3)	(4)
Multigroup	0.03294	0.03322	0.03370	0.03342
	(5.762)***	(5.796)***	(5.802)***	(5.776)***
Unigroup	0.02259	0.02258	0.02294	0.02277
	(7.351)***	(7.347)***	(7.365)***	(7.319)***
time	-0.00008	-0.00002	0.00015	
	(0.048)	(0.014)	(0.094)	
$time^2$	0.00011	0.00011	0.00010	
	(0.819)	(0.799)	(0.749)	
MMC Index (trans. website cty)	0.03672	0.03500	0.03435	0.03411
	(7.114)***	(6.586)***	(6.361)***	(6.320)***
Branch Count	-0.00011	-0.00012	-0.00011	-0.00011
	(0.955)	(0.992)	(0.906)	(0.924)
Loans to Assets Ratio	0.07252	0.07216	0.06728	0.06739
	(9.178)***	(9.139)***	(8.396)***	(8.414)***
Return on Assets	-0.46503	-0.46521	-0.45567	-0.46038
	(6.862)***	(6.854)***	(6.744)***	(6.783)***
Nonperforming Loans Ratio	-0.55582	-0.54552	-0.53216	-0.53078
	(5.681)***	(5.582)***	(5.444)***	(5.430)***
(log) Total Assets	0.01681	0.01692	0.01686	0.01687
	(14.969)***	(15.028)***	(14.327)***	(14.335)***
Equity to Assets Ratio	-0.13616	-0.13315	-0.14137	-0.14374
	(4.310)***	(4.217)***	(4.449)***	(4.516)***
(log) Age	-0.00283	-0.00265	-0.00275	-0.00273
	(2.438)**	(2.266)**	(2.297)**	(2.284)**
Herfindahl Index (cty)		-0.01435	-0.01434	-0.01426
		(1.550)	(1.474)	(1.467)
Metropolitan Share			0.00171	0.00172
			(0.580)	(0.582)
(log) Median Income Per Capita			0.00120	0.00116
			(0.831)	(0.802)
University			-0.00075	-0.00080
			(1.732)*	(1.829)*
Internet Access			0.00100	0.00102
			(2.899)***	(2.969)***

Absolute value of z statistics in parentheses
* significant at 10%; ** significant at 5%; *** significant at 1%

Table 6: Bank Adoption of a Corporate Website

	(1)	(2)	(3)	(4)
time	0.10956	0.11060	0.11317	
	(4.317)***	(4.356)***	(4.442)***	
time^2	-0.00518	-0.00520	-0.00519	
	(3.186)***	(3.198)***	(3.192)***	
MMC Index (website)	0.40911	0.30093	0.30254	0.22682
	(5.565)***	(2.932)***	(2.914)***	(2.140)**
Branch Count	0.00293	0.00278	0.00331	0.00222
	(0.674)	(0.639)	(0.764)	(0.485)
Loans to Assets Ratio	1.18605	1.17049	1.03265	1.09852
	(6.838)***	(6.733)***	(5.842)***	(6.119)***
Return on Assets	-7.25941	-7.25862	-6.78074	-7.53924
	(5.801)***	(5.781)***	(5.458)***	(6.027)***
Nonperforming Loan Ratio	-8.84860	-8.84208	-8.22537	-8.80613
	(4.578)***	(4.576)***	(4.299)***	(4.521)***
(log) Total Assets	0.43343	0.42942	0.40416	0.41287
	(14.554)***	(14.289)***	(13.170)***	(13.132)***
Equity to Assets Ratio	-2.87398	-2.78248	-3.02088	-3.00872
	(4.205)***	(4.059)***	(4.397)***	(4.315)***
Multigroup	0.52325	0.52421	0.53751	0.51523
	(6.195)***	(6.207)***	(6.324)***	(5.981)***
Unigroup	0.41695	0.41527	0.44295	0.42747
	(5.712)***	(5.690)***	(5.992)***	(5.727)***
(log) Age	-0.10128	-0.08837	-0.06458	-0.06458
	(3.662)***	(3.051)***	(2.176)**	(2.138)**
Herfindahl		-0.24259	-0.29561	-0.35920
		(1.511)	(1.803)*	(2.148)**
Metropolitan Share			0.20010	0.19481
			(3.254)***	(3.126)***
(log) Median Income Per Capita			0.02217	0.01895
			(0.666)	(0.563)
University			-0.00720	-0.01614
			(0.708)	(1.566)
Internet Access			0.02895	0.03409
			(3.741)***	(4.329)***
Constant	-8.45041	-8.25101	-9.31284	-9.77422
	(22.565)***	(20.730)***	(17.890)***	(18.319)***
Observations	30244	30244	30244	30244
Time dummies	No	No	No	Yes
Log-likelihood	-5974.089	-5972.950	-5955.464	-5736.136
Pseudo-R2	0.064	0.064	0.067	0.101

Absolute value of z statistics in parentheses
* significant at 10%; ** significant at 5%; *** significant at 1%

Table 7: Bank Adoption of a Corporate Website (Average Marginal Effects)

	(1)	(2)	(3)	(4)
Multigroup	0.02992	0.02998	0.03078	0.02843
	(5.399)***	(5.409)***	(5.493)***	(5.254)***
Unigroup	0.02034	0.02026	0.02156	0.02025
	(5.770)***	(5.747)***	(6.049)***	(5.797)***
time	0.00544	0.00549	0.00561	
	(4.306)***	(4.345)***	(4.430)***	
$time^2$	-0.00026	-0.00026	-0.00026	
	(3.181)***	(3.193)***	(3.187)***	
MMC Index (website)	0.02031	0.01494	0.01499	0.01095
	(5.531)***	(2.927)***	(2.909)***	(2.138)**
Branch Count	0.00015	0.00014	0.00016	0.00011
	(0.674)	(0.640)	(0.764)	(0.485)
Loans to Assets Ratio	0.05887	0.05810	0.05116	0.05303
	(6.788)***	(6.687)***	(5.811)***	(6.089)***
Return on Assets	-0.36033	-0.36033	-0.33594	-0.36393
	(5.778)***	(5.758)***	(5.439)***	(6.005)***
Nonperforming Loan Ratio	-0.43921	-0.43893	-0.40751	-0.42508
	(4.563)***	(4.561)***	(4.287)***	(4.509)***
(log) Total Assets	0.02151	0.02132	0.02002	0.01993
	(14.190)***	(13.942)***	(12.908)***	(12.915)***
Equity to Assets Ratio	-0.14265	-0.13813	-0.14967	-0.14524
	(4.190)***	(4.047)***	(4.381)***	(4.302)***
(log) Age	-0.00503	-0.00439	-0.00320	-0.00312
	(3.656)***	(3.048)***	(2.175)**	(2.137)**
Herfindahl		-0.01204	-0.01465	-0.01734
		(1.511)	(1.802)*	(2.147)**
Metropolitan Share			0.00991	0.00940
			(3.249)***	(3.123)***
(log) Median Income Per Capita			0.00110	0.00091
			(0.666)	(0.563)
University			-0.00036	-0.00078
			(0.708)	(1.566)
Internet Access			0.00143	0.00165
			(3.733)***	(4.318)***

Absolute value of z statistics in parentheses
* significant at 10%; ** significant at 5%; *** significant at 1%

for wide-spread time-varying shocks. But in contrast to the baseline case, time trend coefficients are significant here. This result has an interesting interpretation in terms of the cost of adoption of a corporate website. Holding all other factors constant, over time, the cost of adoption decreases, but at a decreasing rate.

The direction and magnitude of the effects of a bank's financial ratios is comparable to the baseline cases, as are the effects of the demand variables.

7.3 Adoption in Bank Groups

The results from section 6 indicate that a bank's membership to either a one-bank or a multi-bank holding company is an important determinant of the adoption decision. In this section we explore this issue further and characterize some of the differences between independent banks and those that are members of a holding company.

Presumably, when the technology for the provision of online banking was first introduced, once a bank realized the investment in the new technology, it was less costly to disseminate it among other banks members of the same holding group, that would have incentives to adopt faster. Our sample starts in 2003, about eight years after the introduction of online banking. The costs of setting up a transaction have fallen considerably over this period and one would expect that the benefits of synergies among members of a holding group would have fallen accordingly. The results from tables 2 and 3 indicate that they have not.

In table 8 we examine the adoption decision for independent and holding group member banks separately. We summarize the categories for holding groups with an indicator variable for whether the banks are members of a holding group or independent. Column (1) in this table presents the logit coefficients of a model similar to model (4) of table 2, in which the variables 'Multigroup ' and 'Unigroup' are replaced by the categorical variable "Member of Bank Holding Company." Columns (2) and (3) in table 8 present the regression coefficients for the samples of holding company members and independent banks, respectively. Finally, columns (4) to (6) present the average marginal effects of these three regressions.

Our results indicate that membership in a holding group increases the incentives to adopt online banking by about 2 percentage points, according to column (4) in table 8. Furthermore, when we examine the regressions for the two categories separately we find that even though a similar set of variables have statistically significant effects, in columns (5) and (6), the effects appear to be twice as large (in absolute value) for banks that are members of a holding group. This is also true for the competition effect captured by the MMC index.

In an omitted regression that includes the interactions of the holding company dummy with the significant regressors in column (1), a log-likelihood ratio test of the joint significance of the holding company dummy and the interactions also rejects the null hypothesis of no effects of holding group membership.

An interpretation of these results is that, in recent years, the synergies among holding group members continue to generate benefits of adoption, and that these benefits are unrelated to the costs of investing in the new technology.

8 Concluding Remarks

In this paper we have shed some light on the determinants of the adoption of online banking operations among U.S. banks. In contrast with the existing literature, we regard the adoption decision as a strategic dynamic choice. For this reason we have specified a discrete hazard model, which has the virtue of being easily estimated using standard techniques.

One of the contributions of this paper has been to address the determinants of competition in a context where firms interact in a geographical environment. In our model firms adopt online banking simultaneously across all markets where they operate. By controlling for the level of concentration in the market we can isolate the strategic component of the adoption decision, which turns out to be significant in the variety of specifications we propose.

Throughout the paper we have said very little regarding the channel through which this competition affects adoption. As mentioned in the introduction, according to Karshenas and Stoneman (1993) three reasons might relate the decision of one bank to adopt to the decisions of competitors. These are stock, order and epidemic effects. Epidemic effects might be important, although the fact that online banking has existed for almost ten years is likely to reduce its impact. In the early years studied by Sullivan and Wang (2005) banks learned about the technological possibilities of online banking from observing their competitors and imitation was important. However, in latter years the technology has become quite standard and strategic considerations (stock and order effects) matter more.

Because our sample includes mainly small banks (with only about 3 branches on average), it is unlikely that their adoption is motivated by order (preemptive) effects. However, stock effects are a sensible explanation for our results. In markets where big banks have already adopted, small institutions may be forced to also adopt online banking as a way to preserve their market share against products perceived as superior.

This paper is a first approach to the study of these strategic considerations. Further research in this area might pursue the specification of a structural dynamic model of adoption. Although at a cost of a higher technical complexity, structural estimation could help to quantify the effect of each motivation.

Finally, the setup in this paper can be applied to other contexts. Many adoption decisions are irreversible and implemented in several markets at the same time. An example could be the adoption of new inventory systems for retailers that operate in several markets, to the extent that competitors partially overlap across different markets.

Table 8: Bank Adoption of a Transactional Website by Banks in a Holding Co.

	Logit Coefficients			Average Marginal Effects		
	(1)	(2)	(3)	(4)	(5)	(6)
MMC Index (trans. website zip)	0.47429	0.48874	0.43234	0.02196	0.02540	0.01309
	(4.715)***	(4.439)***	(1.670)*	(4.697)***	(4.422)***	(1.664)*
Herfindahl Index (zip)	-0.35044	-0.29659	-0.39173	-0.01622	-0.01542	-0.01186
	(2.265)**	(1.706)*	(1.067)	(2.263)**	(1.705)*	(1.065)
Branch Count	-0.00080	-0.00159	-0.01749	-0.00004	-0.00008	-0.00053
	(0.319)	(0.618)	(0.796)	(0.319)	(0.618)	(0.796)
Loans to Assets Ratio	1.45022	1.60284	1.02650	0.06714	0.08331	0.03107
	(8.435)***	(8.303)***	(2.613)***	(8.344)***	(8.204)***	(2.593)***
Return on Assets	-8.84269	-15.76932	-5.65259	-0.40936	-0.81961	-0.17110
	(6.166)***	(4.868)***	(3.107)***	(6.140)***	(4.849)***	(3.080)***
Nonperforming Loans Ratio	-11.63163	-13.12785	-8.12356	-0.53847	-0.68232	-0.24590
	(5.494)***	(5.445)***	(1.808)*	(5.467)***	(5.415)***	(1.801)*
(log) Total Assets	0.30222	0.34700	0.20759	0.01399	0.01804	0.00628
	(11.474)***	(11.605)***	(3.165)***	(11.293)***	(11.398)***	(3.135)***
Equity to Assets Ratio	-2.91552	-3.07033	-2.13129	-0.13497	-0.15958	-0.06451
	(4.332)***	(3.712)***	(1.812)*	(4.318)***	(3.703)***	(1.805)*
(log) Age	-0.00028	0.04463	-0.11575	-0.00001	0.00232	-0.00350
	(0.010)	(1.383)	(1.884)*	(0.010)	(1.382)	(1.877)*
Metropolitan Share	0.10067	0.07777	0.18676	0.00466	0.00404	0.00565
	(1.636)	(1.153)	(1.208)	(1.635)	(1.152)	(1.206)
(log) Median Income Per Capita	0.02896	0.03368	0.01757	0.00134	0.00175	0.00053
	(0.929)	(0.956)	(0.256)	(0.928)	(0.956)	(0.256)
University	-0.01854	-0.01543	-0.03616	-0.00086	-0.00080	-0.00109
	(1.970)**	(1.513)	(1.463)	(1.969)**	(1.512)	(1.460)
Internet Access	0.02933	0.03028	0.03133	0.00136	0.00157	0.00095
	(3.912)***	(3.658)***	(1.665)*	(3.903)***	(3.650)***	(1.660)*
Member of Bank Holding Company	0.52925			0.02165		
	(7.536)***			(8.537)***		
Constant	-8.15129	-8.41313	-6.34155			
	(16.826)***	(15.205)***	(6.093)***			
Observations	34201	25159	9042	34201	25159	9042
Time dummies	Yes	Yes	Yes			
Log-likelihood	-6371.939	-5160.116	-1197.817			
Pseudo-R2	0.065	0.060	0.064			

Absolute value of z statistics in parentheses
* significant at 10%; ** significant at 5%; *** significant at 1%

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A Data Appendix

Table 9: Variable Definitions and Sources

Variable	Variable Code
Summary of Deposits	
Branch Count	Authors' calculations
Branch Deposits	DEPSUMBR
Metropolitan Branch Flag	CBSA_METROB
Zip Code Branch	ZIPBR
State Code Branch	STNUMBR
Multi-Bank Holding Company Flag	HCTMULT
One Bank Holding Company Flag	HCTONE
No Bank Holding Company Flag	HCTNONE
Call Reports	
Opening Date	rssd9950
Total Deposits	rcfd2200
Non-accrual or 90 days Past-due Loans	rcfd1403 + rcfd1407
Total Loans and Leases	rcfd2122
Total Assets	rcfd2170
Net Income (numerator of ROA)	riad4340
Quarterly Avg. Assets (denominator of ROA)	rcfd3368
Total Equity	rcfd3210
Transactional Website	rcfd4088
Corporate Website	text4087
U.S. Census Bureau	
Population	Table GCT-T1-R: 2002-2005
Share of Households with Internet Access	P23-208 Table 1B: 2003
Median Family Income	Table R2002: 2002-2005
Share of People 25 Years and Over Who Have Completed a Bachelor's Degree	Table R1402: 2002-2005

Table 10: Summary Statistics as of March 2003

Variable	stat.	Adoption = 0	Adoption = 1	Total
Number of banks		4101	3680	7781
Age (years)	Mean	67.2	62.1	64.8
	Med.	79.2	69.2	73.2
MMC (trans. website)	Mean	0.4792	0.7330	0.5993
	Med.	0.4690	0.8536	0.7647
MMC (website)	Mean	0.5611	0.8110	0.6793
	Med.	0.7266	0.9389	0.8881
Herfindahl Index	Mean	0.6184	0.4516	0.5395
	Med.	0.5707	0.4114	0.4831
Number of branches	Mean	2.8	15.8	9.0
	Med.	2.0	4.0	2.0
Number of competitors	Mean	2.4	3.8	3.0
	Med.	1.5	3.2	2.3
Number of zip codes	Mean	2.5	12.2	7.1
	Med.	2.0	3.0	2.0
Multi-bank holding	Mean	0.2	0.3	0.2
	Med.	0.0	0.0	0.0
One-bank holding	Mean	0.6	0.5	0.6
	Med.	1.0	1.0	1.0
Total Assets (mill.)	Mean	188.8	1710.2	908.4
	Med.	58.3	169.3	94.0
Equity to Asset Ratio	Mean	0.1213	0.1016	0.1120
	Med.	0.1028	0.0908	0.0962
Loan to Asset Ratio	Mean	0.5808	0.6430	0.6103
	Med.	0.5962	0.6652	0.6322
Non-Performing Loans	Mean	0.0137	0.0099	0.0119
	Med.	0.0074	0.0062	0.0067
Return on Assets	Mean	0.0096	0.0111	0.0103
	Med.	0.0107	0.0114	0.0110
Median Family Income (thous.)	Mean	51.1	51.9	51.5
	Med.	50.8	51.3	51.2
Metropolitan Share	Mean	0.4267	0.6209	0.5186
	Med.	0.0000	0.9753	0.6377
Population (mill.)	Mean	8.5	9.3	8.8
	Med.	5.5	5.8	5.7
Pop. with College degree (%)	Mean	25.3	25.6	25.5
	Med.	24.5	24.5	24.5
Internet use (%)	Mean	53.4	54.1	53.7
	Med.	53.0	53.7	53.6

Note: Mean and median statistics are taken at the bank level.