Internet Banking: An Exploration in Technology Diffusion and Impact

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Abstract

This paper studies endogenous diffusion and impact of a cost-saving technological innovation – Internet banking. Our theory suggests that when the innovation was initially introduced, large banks would adopt it early and gain a further increase of size. Over time, as the innovation diffused into smaller banks, the aggregate bank size distribution shifts towards a new steady state with a higher mean. Applying the theory in an empirical study of Internet banking diffusion among state-chartered banks across 50 US states, we examine the technological, economic and institutional factors governing the process. The empirical findings allow us to disentangle the interrelationship between Internet banking adoption and change of average bank size, and explain the variation of diffusion rates across geographic regions.

JEL classification: G20; L10; O30

Keywords: Technology diffusion; Bank size distribution; Internet banking

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1 Introduction

Technology diffusion is a complex process through which potentialities of technological innovations are turned into productivity. Characteristics of the economic environment where diffusion takes place may affect the pace of diffusion, and the diffusion itself may also have feedback on the environment.

To better understand this process, economists need to study a series of important questions – For example, who are the early adopters of technological innovations, what factors determine the different diffusion rates across adopter groups and geographic regions, and what impact the diffusion may have on the economic environment. The ongoing diffusion of Internet banking provides us a good opportunity to closely examine these issues.

1.1 Questions on Internet Banking Diffusion

In the US, the Internet era in the banking industry started in 1995 when Wells Fargo first allowed its customers to access account balances online and the first Internet-only bank, Security First Network Bank, opened.¹ Ever since then, banks have steadily increased their online presence. A major driving force for adopting Internet banking is the potential productivity gains. On one hand, the Internet has made it much easier for banks to reach and serve their consumers, even over long distances. On the other hand, it provides cost savings for banks to conduct standardized, low-value-added transactions (e.g., bill payments, balance inquiries, account transfer) through the online channel, while focusing their resources on specialized, high-value-added transactions (e.g., small business lending, personal trust services, investment banking) through branches.

Figure 1 plots the diffusion of Internet banking.² It shows that 35 percent of depository

¹Our study focuses on the diffusion of Internet banking among traditional brick-and-mortar banks. Internet-only banks, as a very different business model, are hence not included. In fact, Internet-only banks account for a tiny fraction of the US banking population, less than 0.5% even during the dot-com boom years. See Wang (2007) and DeYoung (2005) for studies on Internet-only banks.

²Data Source: Call Report (1999-2007). Systematic data on Internet banking became available in 1999 when FDIC-insured depository institutions were required to report their website address. Since 2003, depository institutions have also been required to report whether their website allows customers to execute transactions on their accounts. In this paper, we carefully check the data accuracy and verify that a bank is counted as adopting Internet banking only if it reports a valid website address.

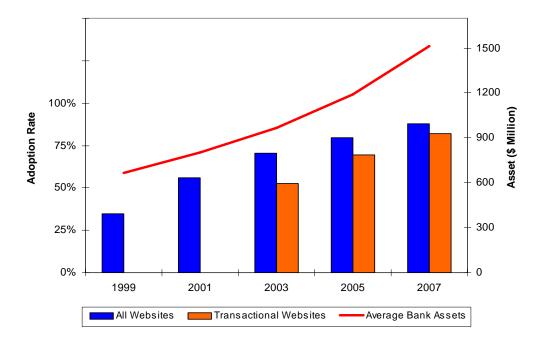


Figure 1: Diffusion of Internet Banking and Growth of Average Bank Size

institutions reported a website address in 1999, rising to 88 percent in 2007. Moreover, 53 percent of depository institutions reported websites with transactional capability in 2003, rising to 82 percent in 2007.³ In addition, the adoption of Internet banking varies significantly across geographic regions. Figure 2 presents the adoption of Internet banking across five regions of the US in 2003.⁴ The Northeast and the West had the highest adoption rates, while the central regions of the country had the lowest. Also, banks of large size tended to adopt Internet banking earlier. In 2003, 96 percent of banks with assets over \$300 million reported that they had a website, compared to only 51 percent of banks with assets under \$100 million. All these observations point to an important question: what determines the different diffusion rates across banking groups and geographic regions?

Meanwhile, the diffusion of Internet banking has taken place in a continuously changing environment. Since early 1990s, several major reforms of US banking regulation were introduced. Among the expected effects was a change in the size distribution of banks.

³Though data on transactional websites is not available for the whole sample of commercial banks before 2003, an independent survey conducted by the OCC shows that 6% national banks adopted transactional websites in 1998, and the ratio rose to 37% in 2000 (see Furst et al., 2001).

⁴Data Source: Call Report (2003).

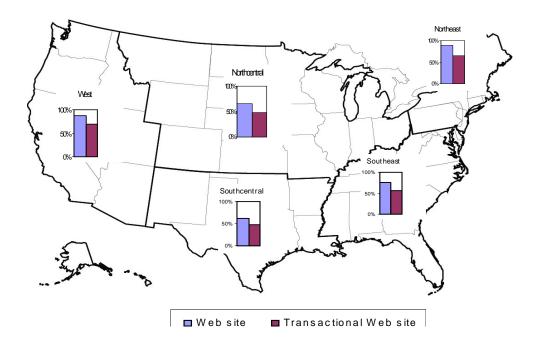


Figure 2: Regional Adoption for Internet Banking (2003)

In particular, the Riegle-Neal Act, passed in September 1994, allowed banks and bankholding companies to more easily establish branches across state lines. The branching deregulation has encouraged substantial geographical consolidation of banks and contributed to a rising average bank size (See Figure 1). This suggests further interesting questions: Given that bank size is an important factor for adopting Internet banking, how much has banking deregulation affected Internet banking adoption? At the same time, how much, if any, has Internet banking adoption influenced the bank size distribution?

1.2 The Hypothesis

Motivated by the aforementioned observations and questions, we try to provide a general framework to study the endogenous diffusion and impact of Internet banking. Our theory suggests that when a cost-saving technological innovation, such as Internet banking, is initially introduced, large banks have an advantage to adopt it first and gain a further increase of size. Over time, due to environmental changes (e.g., demand growth, technological progress and industry deregulation), the innovation gradually diffuses into smaller banks. As a result, the aggregate bank size distribution shifts towards a new steady state, driven by important interactions between technology adoption and average bank size.

Applying this theory in an empirical study of Internet banking diffusion among statechartered banks across 50 US states, we examine the technological, economic and institutional factors governing the process.⁵ Using instrument variables in our simultaneousequation estimation, we are able to disentangle the complex interrelationship between Internet banking adoption and change of average bank size, and explain the variation of diffusion rates across US geographic regions.

1.3 Related Literature

Several studies have looked at the Internet and related technology diffusion in the banking industry. Courchane, Nickerson and Sullivan (2002) develop and estimate a model for early adoption of Internet banking. They found that relative bank size and demographic information predictive of future demand positively influence Internet banking adoption. Furst, Lang, and Nolle (2000) estimate a logit model for Internet banking adoption in a sample of national banks. They found that larger banks are more likely to adopt Internet banking as well as banks that are younger and better performing. Some other studies analyzed the feedback of technology on bank performance but obtained mixed results. Sullivan (2000) studied performance characteristics of early adopters of Internet banking and found little difference from non-adopters. Berger and Mester (2003) found that banks enjoyed rising profits during the 1990s, and attributed this to banks' increasing market power gained by adopting new technologies. However, few existing studies have explicitly considered the endogenous interactions between technology adoption and bank performance measures.

This paper is a first attempt to study the diffusion and impact of Internet banking with an industry equilibrium model. Built upon the recent work of Wang (2008) and Olmstead and Rhode (2001), we revise the popular threshold diffusion model to account

 $^{^{5}}$ We use data to estimate Internet banking adoption and bank size distribution at state level. In order to avoid the complication of interstate banking, we focus on state-chartered banks. They account for 75% of total commercial banks in the US, and can be reasonably assumed to mainly serve the home state markets. National banks that typically serve many states are not included in our sample.

for the interaction between Internet banking adoption and bank size distribution. The approach that we develop in the paper goes beyond the Internet banking and connects to a broad literature in industry dynamics (e.g., Jovanovic 1982, Hopenhayn 1993), firm size distribution (e.g., Lucas 1979, Sutton 1997), and technology diffusion (e.g., Griliches 1957, Jovanovic and Lach 1997, Manuelli and Seshadri 2003, Comin and Hohijn 2004, Wang 2007, 2008).

1.4 Road Map

The paper is organized as follows. Section 2 presents a model of technology diffusion in a competitive industry. In particular, we explore the interactions between technology adoption and change of firm size distribution. Section 3 applies the theory in an empirical study on Internet banking diffusion among state-chartered banks across 50 US states. Section 4 concludes.

2 The Model

In this section, we construct a theoretical model to study the diffusion and impact of a cost-saving technological innovation in the Internet banking context.

2.1 Environment

The industry is composed of a continuum of banks which produce homogenous banking services. Banks behave competitively, taking market prices as given. We assume banks are heterogenous in productivity, which yields size differences. At a point of time t, the market demand takes a simple inelastic form – consumers are willing to pay P_t for the amount Q_t of banking services. Over time, P_t and Q_t might be shifted by economic forces, such as changes in population, consumer income or substitute services.⁶

⁶Our empirical study will focus on state-chartered banks, which is a subsample of the overall banking population. Therefore, it is reasonable to assume that P and Q are exogenously determined by overall market conditions.

2.2 Pre-Innovation Equilibrium

Before the technological innovation arrives, the industry is at a steady state. Taking the market price as given, an individual bank maximizes its profit under the existing technology:

$$\pi_0 = \underset{y_0}{Max} Py_0 - \alpha y_0^\beta$$

where π_0 is the profit, P is the price, y_0 is the output, and $\alpha > 0$ and $\beta > 1$ are cost parameters.

Solving the maximization problem yields

$$y_0 = \left(\frac{P}{\alpha\beta}\right)^{\frac{1}{\beta-1}}.\tag{1}$$

Given that banks are heterogenous in cost (i.e., α), there is a distribution G of bank size measured by output. Historically, bank size y_0 fits well with the log-logistic distribution (See Figure 3 for an example)⁷, which has the cdf function

$$\Pr(y_0 \le x) = G_{y_0}(x) = 1 - \frac{1}{1 + b_1 x^{b_2}} \tag{2}$$

with the mean $E(y_0)$ and Gini coefficient g given as

$$E(y_0) = b_1^{-1/b_2} \Gamma(1 + \frac{1}{b_2}) \Gamma(1 - \frac{1}{b_2}), \qquad g = \frac{1}{b_2},$$

where Γ denotes the gamma function $\Gamma(\mu) \equiv \int_0^\infty t^{\mu-1} \exp(-t) dt$.

Rewriting the log-logistic distribution into a more intuitive form, we have

$$G_{y_0}(x) = 1 - \frac{1}{1 + (\eta x / E(y_0))^{1/g}},$$
(3)

where $\eta = \Gamma(1+g)\Gamma(1-g)$.

⁷The log-logistic distribution is an easily tractable representative of the larger group of positively skewed distributions. It also connects our study to the typically observed logistic diffusion curves. See Wang (2008) for more discussion.

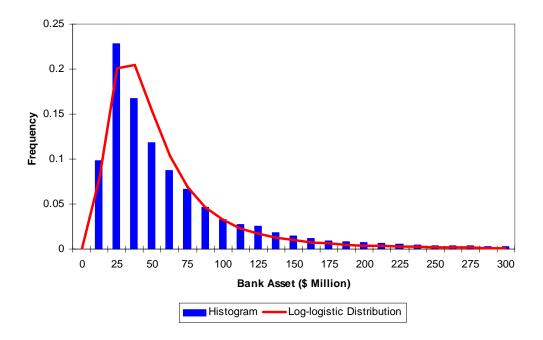


Figure 3: Bank Size Distribution (State-Chartered Banks, 1990)

At equilibrium, industry demand equals supply, so that

$$E(y_0)N = Q,$$

where N is the number of banks.

Note that our assumption of log-logistic size distribution is robust to environmental changes. For example, shocks to price P, mean productivity $E(\alpha^{\frac{1}{1-\beta}})$, or demand Q may affect the mean bank size $E(y_0)$ and/or the number of banks N, but not other properties of the distribution.⁸

2.3 Post-Innovation Equilibrium

2.3.1 Individual Bank Decision

At time T, the technological innovation, Internet banking, becomes available. Thereafter, at each period, an individual bank decides whether to adopt the innovation or not (0=

⁸Note that $\alpha^{\frac{1}{1-\beta}}$ decreases in α for $\beta > 1$. Hence, $\alpha^{\frac{1}{1-\beta}}$ can be interpreted as a productivity measure.

do not adopt, 1 = adopt):

$$\pi = Max\{\pi_0, \pi_1\}$$
where $\pi_0 = \underset{y_0}{Max}Py_0 - \alpha y_0^{\beta}, \quad \pi_1 = \underset{y_1}{Max}Py_1 - \frac{\alpha}{\gamma}y_1^{\beta} - k$

Note that $\gamma > 1$ is the cost saving by adopting the innovation and k is the period cost of adoption.

Solving the maximization problem yields

$$y_0 = \left(\frac{P}{\alpha\beta}\right)^{\frac{1}{\beta-1}} , \quad \pi_0 = \frac{\beta-1}{\beta} P y_0;$$

$$y_1 = \left(\frac{\gamma P}{\alpha\beta}\right)^{\frac{1}{\beta-1}} , \quad \pi_1 = \frac{\beta-1}{\beta} P y_1 - k$$

An individual bank adopts Internet banking iff $\pi_1 \ge \pi_0$, and hence there is a threshold size y_0^* for adoption:

$$\pi_1 = \pi_0 \Longrightarrow y_0^* = \frac{k}{P(\frac{\beta-1}{\beta})(\gamma^{\frac{1}{\beta-1}} - 1)}.$$

The size threshold for adoption suggests that large banks have an advantage in adopting the innovation. Considering the randomness of environmental parameters in reality, this result is expected to hold statistically. We show in Figure 4 that it is in fact true that large banks have been more likely to adopt Internet banking.⁹

2.3.2 Aggregate Adoption

Given the bank size distribution G defined in Eq (3) and the adoption threshold y_0^* , the aggregate adoption rate of Internet banking is

$$F = 1 - G_{y_0}(y_0^*) = \frac{1}{1 + (\eta y_0^* / E(y_0))^{1/g}},$$
(4)

where
$$y_0 = (\frac{P}{\alpha\beta})^{\frac{1}{\beta-1}}, \qquad y_0^* = \frac{k}{P(\frac{\beta-1}{\beta})(\gamma^{\frac{1}{\beta-1}}-1)}.$$

We then derive Proposition 1 as follows.

⁹Data Source: Call Report (1999 - 2007). A bank is counted as adopting Internet banking if it reports a valid website address.

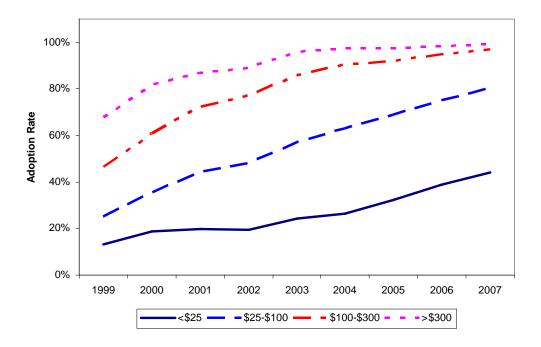


Figure 4: Internet Banking Adoption by Bank Assets (Million)

Proposition 1 The adoption rate F rises with consumer willingness-to-pay P, mean bank productivity $E(\alpha^{\frac{1}{1-\beta}})$, cost saving γ , but falls with adoption cost k.

Proof. Equation 4 suggests that $\partial F/\partial P > 0$, $\partial F/\partial E(\alpha^{\frac{1}{1-\beta}}) > 0$, $\partial F/\partial \gamma > 0$ and $\partial F/\partial k < 0$.

2.3.3 Average Bank Size

Note $E(y_0)$ is not directly observable after Internet banking is introduced. The observed mean bank size is indeed

$$E(y) = \int_0^{y_0^*} y_0 dG(y_0) + \int_{y_0^*}^{\infty} y_1 dG(y_0) = E(y_0) + \left[\gamma^{\frac{1}{\beta-1}} - 1\right] \int_{y_0^*}^{\infty} y_0 dG(y_0).$$

Given that y_0 follows the log-logistic distribution G, we have

$$\int_{y_0^*}^{\infty} y_0 dG(y_0) = E(y_0) [1 - \beta (1 + g, 1 - g; G(y_0^*))]$$

where β is the incomplete beta function defined as

$$\beta(a,b;x) \equiv \frac{\Gamma(a+b)}{\Gamma(a)\Gamma(b)} \int_0^x t^{a-1} (1-t)^{b-1} dt \quad \text{with} \quad a > 0, b > 0, x > 0,$$

$$\beta(a,b;0) = 0 \qquad \text{and} \qquad \beta(a,b;1) = 1.$$

Therefore, the observed mean bank size E(y) can be derived as

$$E(y) = E(y_0)\{1 + [\gamma^{\frac{1}{\beta-1}} - 1][1 - \beta(1+g, 1-g; 1-F)]\}.$$
(5)

Proposition 2 then follows.

Proposition 2 The mean bank size E(y) rises with consumer willingness-to-pay P, mean bank productivity $E(\alpha^{\frac{1}{1-\beta}})$, cost saving γ , but falls with adoption cost k.

Proof. Given Proposition 1, Eq (5) suggests that $\partial E(y)/\partial P > 0$, $\partial E(y)/\partial \gamma > 0$, $\partial E(y)/\partial E(\alpha^{\frac{1}{1-\beta}}) > 0$ and $\partial E(y)/\partial k < 0$.

2.4 Industry Dynamics and Long-run Equilibrium

Equations (4) and (5) describe the post-innovation industry equilibrium at a point of time. Note that we have so far omitted time subscripts of all variables. To discuss the industry dynamics, we now add them back. As we will see, the diffusion path closely follows a logistic curve.

Consider a banking industry under continuous environmental changes (e.g., demand growth, technological progress and industry deregulation). As a result, consumer willingnessto-pay P_t , mean bank productivity $E(\alpha_t^{\frac{1}{1-\beta}})$, Internet banking cost saving γ_t and adoption cost k_t may all change constantly. Therefore, we may specify simple laws of motion as follows

$$P_t = P_0 e^{z_p t}, \quad \gamma_t^{\frac{1}{\beta-1}} - 1 = (\gamma_0^{\frac{1}{\beta-1}} - 1) e^{z_\gamma t},$$

$$k_t = k_0 e^{z_k t}, \qquad E(\alpha_t^{\frac{1}{1-\beta}}) = E(\alpha_0^{\frac{1}{1-\beta}}) e^{z_\alpha t}.$$

Then, the diffusion path of Internet banking can be derived from Eq (4)

$$F_t = \frac{1}{1 + (\eta y_{0,t}^* / E(y_{0,t}))^{1/g}} = \frac{1}{1 + [\eta y_{0,0}^* / E(y_{0,0})]^{1/g} e^{\frac{1}{g} \{z_k - z_\alpha - z_\gamma - \frac{\beta}{(\beta-1)} z_p\}t}}.$$
 (6)

We may compare the diffusion formula derived above with the traditional logistic model (e.g., Griliches 1957), which assumes that the hazard rate of adoption rises with cumulative adoption due to contagion effects

$$\frac{\dot{F}_t}{1 - F_t} = vF_t \Longrightarrow F_t = \frac{1}{\left[1 + \left(\frac{1}{F_0} - 1\right)e^{-vt}\right]} \tag{7}$$

where F_t is the fraction of potential adopters who have adopted the innovation at time t, and v is a constant contagion parameter.

Comparing Eq (6) with Eq (7), we recognize that our diffusion formula is equivalent to the logistic model under very reasonable assumptions. In particular, the diffusion parameters traditionally treated as exogenous terms now have clear economic meanings: the contagion parameter v is determined by the growth rates of consumer willingnessto-pay, industry deregulation and technological progress; the initial condition F_0 is the fraction of banks that find it profitable to adopt the innovation at the initial period:

$$v = \left(\frac{\beta}{(\beta-1)}z_p + z_\gamma + z_\alpha - z_k\right)/g, \qquad F_0 = \frac{1}{1 + [\eta y_{0,0}^*/E(y_{0,0})]^{1/g}}.$$

Over time, as more banks adopt the innovation, the mean bank size keeps rising and the aggregate size distribution of banks shifts towards a new steady state. In the long run, as all banks have adopted the innovation, the cumulative distribution of bank size converges to $G_{y_{1,t}}(x)$ which is again a log-logistic distribution but with a higher mean

$$G_{y_{1,t}}(x) = 1 - \frac{1}{1 + (\frac{\Gamma(1+g)\Gamma(1-g)}{E(y_{1,t})}x)^{1/g}}, \qquad E(y_{1,t}) = E(y_{0,t})\gamma_t^{\frac{1}{\beta-1}}.$$

Figure 5 illustrates the industry dynamic path. Before Internet banking is introduced, the banking industry stays at a pre-innovation size distribution, drawn with a dotted line.

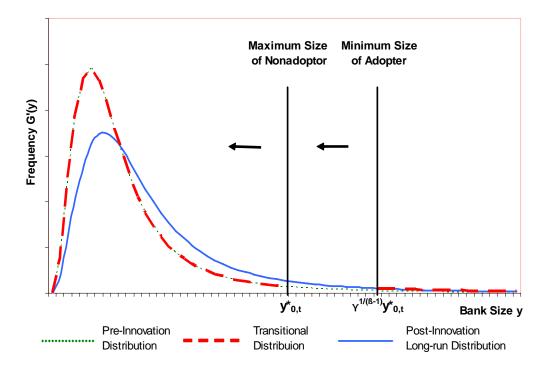


Figure 5: Illustration of the Industry Dynamics

After Internet banking becomes available, in the long run, the banking industry converges to a post-innovation long-run size distribution, drawn with a solid line. In between, the bank size distribution is at a transitional path, drawn with a dashed line. During the transition, at a point of time t, there is a size threshold $y_{0,t}^*$, which splits the original size distribution. For banks with size $y_{0,t} \ge y_{0,t}^*$, the size distribution resembles the postinnovation long-run distribution for the range $y_{1,t} > \gamma^{\frac{1}{\beta-1}}y_{0,t}^*$, so $\gamma^{\frac{1}{\beta-1}}y_{0,t}^*$ is the minimum size of adopters. Meanwhile for banks with size $y_{0,t} < y_{0,t}^*$ the size distribution resembles the pre-innovation one, so $y_{0,t}^*$ is the maximum size of nonadoptors. There will be no bank in the size range between $y_{0,t}^*$ and $\gamma^{\frac{1}{\beta-1}}y_{0,t}^*$. Over time, $y_{0,t}^*$ falls due to environmental changes (e.g., demand growth, technological progress and banking deregulation). As a result, Internet banking diffuses into smaller banks and the bank size distribution gradually converges to the post-innovation long-run distribution.

3 Empirical Study

In this section, we apply our theory in an empirical study on the diffusion and impact of Internet banking. The sample that we consider includes state-chartered banks in each of 50 US states, which totally account for 75% commercial banks in the US. The data on bank website adoption started in 1999 when FDIC-insured depository institutions were required to report their website address. Since 2003, depository institutions have also been required to report whether their website allows customers to execute transactions on their accounts. This information allows us to identify Transactional Websites from All Websites (Informational or Transactional). Because the Transactional Websites are more expensive and offer more functionality, their adoption pattern and impact on bank size might be different from All Websites. In the following study, we consider the adoption of All Websites (Informational or Transactional) from 2001-2006 and Transactional Websites from 2003-2006.¹⁰

3.1 Simultaneous Equations

The diffusion and impact of Internet banking can be characterized by a simultaneous equation system, which includes an adoption equation and a bank size equation as follows.

Note that the adoption equation (4) can be rewritten into a log-linear form:

$$g\ln(\frac{F}{1-F}) = -\ln\eta - \ln\frac{\beta}{\beta-1} - \ln k + \ln P + \ln(\gamma^{\frac{1}{\beta-1}} - 1) + \ln E(y_0).$$
(8)

An empirical approximation of the bank size equation (5) can be written as

$$\ln E(y) = \ln E(y_0) + b_1 [g \ln(\frac{F}{1-F})] + b_2 \ln(\gamma^{\frac{1}{\beta-1}} - 1).$$
(9)

Therefore, Eqs (8) and (9) imply

$$g\ln(\frac{F}{1-F}) = a_0 + a_1\ln E(y) + a_1[(1-b_2)\ln(\gamma^{\frac{1}{\beta-1}} - 1) + \ln P - \ln k]$$
(10)

¹⁰The 2007 data of some explanatory variables are not available, so our sample ends in 2006. The definitions and summary statistics of our empirical variables are shown in Tables 1 and 2.

where $a_0 = -(\ln \eta + \ln \frac{\beta}{\beta - 1})/(1 + b_1), a_1 = 1/(1 + b_1).$

Also, Eq (1) suggests

$$y_0 = (\frac{P}{\alpha\beta})^{\frac{1}{\beta-1}} \Longrightarrow \ln E(y_0) = \frac{1}{\beta-1} \ln P - \frac{1}{\beta-1} \ln \beta + \ln E(\alpha^{\frac{1}{1-\beta}}).$$

Hence we can rewrite Eq (9) as

$$\ln E(y) = b_0 + b_1 \left[g \ln\left(\frac{F}{1-F}\right)\right] + b_2 \ln\left(\gamma^{\frac{1}{\beta-1}} - 1\right) + \frac{1}{\beta-1} \ln P + \ln E(\alpha^{\frac{1}{1-\beta}})$$
(11)

where $b_0 = \frac{1}{1-\beta} \ln \beta$.

The two equations (10) and (11) are determined simultaneously. Note that the variable k is in Eq (10) but not in (11), and $E(\alpha^{\frac{1}{1-\beta}})$ is in Eq (11) but not in (10). Therefore, they help to define exclusion restrictions that identify structural parameters.

3.2 Empirical Specifications

In the empirical study, we estimate the following simultaneous equations based on Eqs (10) and (11) using state-level data of Internet banking adoption and average bank size, where each state is indexed by j and each year is indexed by t:¹¹

$$g_{j,t}\ln(\frac{F_{j,t}}{1-F_{j,t}}) = a_0 + a_1\ln(E(y)_{j,t}) + \sum_i a_i\ln(X_{i,j,t}) + \sum_l a_l\ln(I_{l,j,t}) + \varepsilon_{j,t} \quad (\text{Adoption})$$

$$\ln(E(y)_{j,t}) = b_0 + b_1[g_{j,t}\ln(\frac{F_{j,t}}{1 - F_{j,t}})] + \sum_i b_i \ln(X_{i,j,t}) + \sum_l b_l \ln(S_{l,j,t}) + \mu_{j,t}$$
(Size)

- F is state-level adoption of Internet banking (All Websites and Transactional Websites separately); g is the Gini coefficient of bank size distribution,
- E(y) is a measure of state-level average bank size,

 $^{^{11}{\}rm Note}$ that our sample includes only state-chartered banks. Bank related data are unweighted averages of all sample banks in a particular state.

- X are variables shared in both equations, e.g., variables affecting P and/or γ ,
- I are variables only in the Adoption equation, e.g., variables affecting k only,
- S are variables only in the Size equation, e.g., variables affecting $E(\alpha^{\frac{1}{1-\beta}})$ only.

The dependent variables in the two equations are as follows (See Tables 1 and 2 for details).

(1) Log odds ratio for Internet banking adoption adjusted by the Gini coefficient, constructed using the following variables: WEB – Adoption rate for All Websites (informational or transactional), TRANS– Adoption rate for Transactional Websites and GINIASST– Gini coefficient for bank assets.

(2) Average bank size, measured by ASST – Average bank assets.

As our theory suggests, there are three groups of explanatory variables X, I and S:

X: Variables in both Adoption and Size equations

METRO – Ratio of banks in metropolitan areas to all banks,

LNSPEC – Specialization of lending to consumers,¹²

MEDFAMINC – Real median family income in 1967 dollars,

POPDEN – Population density,

AGE – Average age of banks,

HHINET – Household access rate for the Internet,

BHC – Ratio of banks in bank holding companies to total banks,

WAGERATIO - Wage ratio of computer analyst to teller,

DEPINT – Ratio of deposits in local branches of out-of-state banks,¹³

REGION and YEAR – Dummies.

I: Variables only in Adoption equation (Instruments for Internet Banking Adoption)IMITATE – Years since the first bank in the state adopted a transactional website,

 $^{^{12}}$ Defined by consumer loans plus 1-4 family mortgages divided by total loans.

¹³Note that out-of-state banks include national banks and state-chartered banks headquartered in other states.

COMINET – Internet adoption rate among urban commercial firms in 2000.

S: Variables only in Size equation (Instruments for Average Bank Size) ASST90 – Average bank asset in 1990,

INTRAREG – A dummy variable for whether the state had intrastate branching restrictions after 1995.

Variables in X affect both Internet banking adoption and average bank size. Take HHINET for example: If more households have access to the Internet, local banks may get more cost savings γ from adopting Internet banking. However, Internet access also allows households to reach non-local banking services (e.g., national banks), which may then lower demand and consumer willingness-to-pay P for local banking services. AGE is another example: More established banks typically achieve higher productivity $E(\alpha^{\frac{1}{1-\beta}})$, and so may have an advantage in adopting Internet banking. However, they may also face higher Internet banking adoption cost k compared to younger banks since they have to adapt Internet banking to their legacy computer systems.

The decision on exclusion restrictions I and S is a matter of economic judgement. We include two variables in I: the number of years since the first bank in the state adopted a transactional website (IMITATE) and Internet adoption rate among urban commercial firms of the state (COMINET). They are expected to affect the bank size only through the Internet banking adoption: Higher values of IMITATE may help Internet banking adoption by providing more local expertise on bank-specific website installation; Higher values of COMINET may delay Internet banking adoption by competing away local resources for Internet installation and maintenance. We include two variables in S: a dummy variable for whether the state had intrastate branching restrictions after 1995 (INTRAREG) and average bank assets in 1990 (ASST90). They are expected to affect the adoption of Internet banking only through their effects on average bank size: INTRAREG may negatively affect the average bank size by imposing high regulation costs; ASST90 may be positively correlated with current average bank size through the persistence of underlying productivity variables.¹⁴

3.3 Estimation Results

Table 3 presents results of estimating the model where the Internet banking adoption rate is measured with All Websites for 2001-2006.¹⁵ For completeness we present estimates of reduced form equations but will focus on discussing estimated structural equations. Overall, the structural model has a good fit with a R^2 of 80 percent for the adoption equation and 81 percent for the size equation. Most of the signs of estimated coefficients, and all of those that are statistically significant, are consistent with our theoretical predictions.

We first turn to the structural equation for Internet banking adoption (Table 3, column 3). The coefficient on the fitted value of lnASST is positive and statistically significant, as our theory predicts. In the structural equation for average bank assets (Table 3, column 4), the coefficient on the fitted value of lnWEBODDS_GINI is also positive, as expected, and statistically significant. Quantitatively, given an average Gini coefficient equal to 0.6, our results imply that a 10 percent increase in average bank size would increase the adoption odds ratio by about 6 percent, and a 10 percent increase of adoption odds ratio would increase the average bank size by about 7.7 percent.

In the adoption equation, there is a significantly negative coefficient on lnCOMINET. This suggests that Internet banking adoption could be delayed if other industries rush adopting the Internet and compete for the resources. In the size equation, there is a significantly positive coefficient on lnASST90. This suggests a strong persistence in the asset size distribution. According to our theory, this could be driven by the underlying productivity of state banks.

Our measure of the location of banks in metropolitan areas (lnMETRO) has significant effects on both Internet banking adoption and bank asset size. Its effect on Internet bank-

 $^{^{14}}$ As discussed above, if historical average bank size captures the persistence of state banking productivity, it can serve as a valid instrumental variable for current average bank size. Our empirical tests show that this is supported by the data.

¹⁵For most empirical variables used in the estimation, we take the log transformation and prefix the variables with "ln" in the notation. Our period of study starts in 2001 because the information of COMINET becomes available in the year 2000.

ing adoption is negative, which is consistent with a higher demand for Internet Banking in locations with higher cost of travel to bank branches. Its effect on bank size is positive, which simply confirms that banks in urban areas enjoy more business.

The average age of a state's banks (lnAGE) is significantly related to both Internet banking adoption and bank asset size. The negative coefficient on lnAGE in the adoption equation implies that as the average age of a state's banks rises, the adoption rate falls. This results is consistent with previous findings that denovo banks were more likely to adopt Internet Banking than other banks (Furst, Lang, and Nolle 2000; Sullivan 2000). New banks may find it cheaper to install Internet banking technology in a package with other computer facilities compared to older banks who must add Internet banking to legacy computer systems. Meanwhile, the positive coefficient on lnAGE in the size equation indicates that bank scale rises with age, which can be reasonably explained by the accumulation of experience and reputation.

Access of households to the Internet (InHHINET) is statistically significant in explaining both website adoption and bank asset size in sample states. Greater household access to the Internet is associated with a higher website adoption, as expected. However, greater household access to the Internet is negatively related to a state's average bank assets. A possible explanation is that the Internet makes it easier for households to form relationship with non-local banks, which negatively affects the size of home-state banks.¹⁶

We also found that branch competition from out-of-state banks (lnDEPINT) significantly affects Internet banking adoption and state bank asset size. The estimates suggest that more deposits in local branches of out-of-state banks push more home-state banks to adopt Internet banking. Meanwhile, more branch competition from out-of-state banks leads to smaller size of home-state banks.

We next look at estimates using data for the period 2003-2006 when the transactional website data become available.¹⁷ Table 4 shows results for All Websites and Table 5

¹⁶Non-local banks most likely include large national banks that benefit most from using the Internet to operate on a nationwide basis.

¹⁷Note that the number of state observations may change with the sample range. In fact, in later years, some states had achieved full adoption of websites, so that the log-odds ratio can not be calculated. Hence, we lose a few state observations in our sample.

shows results for Transactional Websites, and we can compare the difference between these two types of websites. The results are largely consistent with our findings in Table $3.^{18}$ Moreover, we find that bank size (lnASST) has a bigger effect on adoption of All Website than Transactional Website. This is simply because Transactional Websites are counted as a subset of All Websites. Meanwhile, we also find that Transactional Website (lnTRANODDS_GINI) has a larger impact on average bank size compared with All Website (lnWEBODDS_GINI). This confirms our intuition that transactional websites allow banks to increase their scales more than the informational websites.

3.4 Robustness Check

Our empirical findings also provide supporting evidence for the validity of our instrumental variables and the robustness of our results.

We check the validity of our instrumental variables in the following steps, as shown in Tables 3-5. First, we look at the reduced form regressions with the instrumental variables as the explanatory variables. In both adoption equation and bank size equation, our instrumental variables have coefficients that are significantly different from zero with signs that support our identification story. Furthermore, we ran overidentification tests on the instrumental variables. For both adoption and bank size equations, we fail to reject the null hypothesis that our instruments are valid. F-tests also show that the instrumental variables have jointly significant explanatory power. Nevertheless, instruments for the asset structural equation have relatively low partial R^2 . Therefore, to address concerns for potential weak instruments, we also try Fuller's LIML estimators, which is more robust to weak instruments (See Murray, 2006). Results are consistent with those shown in Tables 3-5.

To check the robustness of our results, we experimented with alternative samples and estimation procedures. For example, we tried excluding states with less than nine statechartered banks and using random effects panel regression model. As it turns out, the results are similar.¹⁹

¹⁸The only exception is the coefficient for lnMETRO, which appears to be sensive to the sample range. ¹⁹All the robustness check results are included in the Appendix, which is available on request.

3.5 Implications and Discussions

Our findings offer useful insights for answering the questions raised at the beginning of the paper. First, we have shown that Internet banking adoption rates vary by bank groups. Particularly, large banks have an advantage in adopting Internet banking earlier. Then, the following question is: What may explain the variation of Internet banking diffusion rates across US geographic regions? More specifically, why do the Northeast and the West have the highest Internet banking adoption rates, while the central regions of the country have the lowest (See Figure 2)?

To answer the question, we present regional average of variables that are found significantly affecting Internet banking adoption in Table 7. Far West, Plains and New England are used to represent the West, Central and Northeast regions respectively.

Variables	Effects on Website Adoption	Far West	Plains	New England
OBS		6	7	6
WEB		0.88	0.54	0.97
TRANS		0.77	0.40	0.70
GINIASST		0.56	0.57	0.54
ASST	+	1,337	107	1,563
IMITATE	+	5.83	6.71	6.33
HHINET	+	63.48	58.77	62.87
COMINET	_	0.91	0.90	0.89
DEPINT	_	0.32	0.16	0.29
AGE	_	34.91	80.18	57.46

 Table 7: Mean Values of Selected Variables by Region

(Far West, Plains and New England 2003)

*See Table 1 for variable definitions and sources.

The data in Table 7 shows that in 2003 the Plains region has a similar number of states and a similar Gini coefficient of bank size distribution compared to the other two

regions, but the average Internet banking adoption rate was only about half the level of the other two regions. Compared with the Far West and New England, we notice that the Plains region has smaller mean bank size, lower household Internet access and older bank vintages. All these factors, as suggested by our analysis, may have contributed to slow diffusion of Internet Banking. Meanwhile, the data appears to reject several alternative explanations for slow Internet banking diffusion in the central regions, particularly, the imitation of early adopters, the commercial Internet adoption and branch competition from out-of-state banks. Similarly, we can compare variations of Internet banking diffusion rates between any other regions. The values of variables for all eight US regions are reported in Table 6.

Our findings also help answer another important question: Given that bank size is an important factor for adopting Internet banking, how much has banking deregulation affected Internet banking adoption? At the same time, how much, if any, has Internet banking adoption influenced the bank size distribution?

Our empirical results suggest that banking deregulation had a significant impact on Internet banking adoption. As shown by our reduced form regressions, intrastate branching regulation (INTRAREG) negatively affects Internet banking adoption, while interstate branching deregulation (InDEPINT) has positive effects. In the meantime, Internet banking adoption had a large impact on the bank size distribution. According to our findings, a 10 percent increase of adoption odds ratio would increase the average bank size by about 7.7 percent.²⁰ Therefore, should other things be fixed, the increase of website adoption should have a large quantitative impact on the average bank size (Note that the odds ratio increases from 2.45 in 2001 to 8.2 in 2006). However, this potential increase of average bank size was largely offset by the changes of other environmental variables, including the increase in household Internet access rate (HHINET) and the deposit ratio in local branches of out-of-state banks (DEPINT). Those changes have allowed non-local banks to compete away an increasingly large share of business from state banks. Particularly, the online competition from non-local banks has a much larger negative impact on the state

 $^{^{20}}$ In 2001, the national average odds ratio was 2.45. Accordingly, a 10 percent increase in the odds ratio represents an increase in the adoption rate from 70 percent to 72 percent.

bank size than the branch competition. Our estimates show that a 10 percent increase of household Internet access may decrease the average size of state banks by 36.7 percent (Note that the national average household Internet access rate rose from 45.5 percent in 2001 to 74.5 percent in 2006, a 63.7 percent increase). Quantitatively speaking, this effect alone has offset most potential size increase of state banks associated with adopting Internet banking. Meanwhile, the branch competition from out-of-state banks had a negative but much milder impact on the size of state banks.

4 Conclusion

This paper studies the endogenous diffusion and impact of Internet banking. Our theory suggests that when the innovation was initially introduced, large banks had an advantage to adopt it first and gain a further increase of size. Over time, due to environmental changes (e.g., demand growth, technological progress and banking deregulation), the innovation diffused into smaller banks. As a result, the aggregate bank size distribution shifts towards a new steady state with a higher mean. Overall, there exists important interactions between Internet banking adoption and average bank size.

Applying the theory in an empirical study of Internet banking diffusion among statechartered banks across 50 US states, we examine the technological, economic and institutional factors governing the process. The empirical findings allow us to disentangle the interrelationship between Internet banking adoption and change of average bank size, and explain the variation of diffusion rates across geographic regions. We find that factors significantly affecting Internet banking adoption include mean bank size, household access to the Internet, branch competition from out-of-state banks, imitation of early adopters, commercial adoption of Internet and average bank age. In particular, it is the first three factors that are primarily responsible for the slower diffusion of Internet banking in the central regions than the West and Northeast regions. We also find evidence that adopting Internet banking help state banks maintain their asset size. Otherwise, they could have become much smaller due to the online and branch competitions from non-local banks, especially those big national banks. The theoretical and empirical approach that we develop in the paper goes beyond the Internet banking. It provides a general framework to study the joint evolution of technology adoption and firm size distribution, and can be readily applied to other studies of technology diffusion and industry dynamics.

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Variable name	Definition	Source
TRANS	Adoption rate for transactional websites	Call Report
	-	-
TRANODDS	Odds ratio for adoption of transactional websites	Call Report
WEB	Adoption rate for informational or transactional websites	Call Report
WEBODDS	Odds ratio for adoption for informational or transactional websites	Call Report
GINIASST	Gini coefficient for bank assets	Call Report
ASST	Average bank assets	Call Report
METRO	Ratio of banks in metropolitan areas to all banks	Call Report
LNSPEC	Specialization of lending to consumers (consumer loans plus 1-4 family mortgages / total loans)	Call Report
MEDFAMINC	Median family income (in 1967 dollars)	U.S. Census Bureau
POPDEN	Population density	Statistical Abstract of
		the United States
IMITATE	Years since the first bank in the state adopted a transactional website	Online Banking
		Report
AGE	Average age of banks	Call Report
HHINET	Household access rate for Internet	Statistical Abstract of
		the United States
WAGERATIO	Ratio of computer analyst wage to teller wage	Bureau of Labor Statistics
INTRAREG	Indicator variable for whether the state had branching restrictions after 1995	Krozner and Strahan (1999)
BHC	Ratio of banks in bank holding companies to total banks	Call Report
DEPINT	Ratio of deposits in local branches of out-of-state banks to total	FDIC Summary of
	deposits	Deposits
COMINET	Adoption rate of high-speed internet among urban commercial firms in 2000	Forman, et.al. (2003)
asst90	Average bank assets in 1990	Call Report

Table 1: Empirical Variable Definitions and Sources

Regional dummy variables:

Southeast: AL, AR, FL, GA, KY, LA, MS, NC, SC, TN, VA, WV SE Far West: AK, CA, HI, NV, OR, WA FARWEST Rocky Mountain: CO, ID, MT, UT, WY ROCKYMTN Plains: IA, KS, MN, MO, NE, ND, SD PLAINS Southwest: AZ, NM, OK, TX SW New England: CT, MA, ME, NH, RI, VT NWENGLND MIDEAST Middle East: DC, DE, MD, NJ, NY, PA GRTLAKE Great Lakes: IL, IN, MI, OH, WI

Notes: Data for banks are unweighted averages for those located in individual states. Selected banks were state-chartered, fullservice, retail commercial banks. Regions are a set of geographic areas that are aggregations of the states defined by the Bureau of Economic Research. The regional classifications, which were developed in the mid-1950s, are based on the homogeneity of the states in terms of economic characteristics, such as the industrial composition of the labor force, and in terms of demographic, social, and cultural characteristics.

Bureau of Economic

Analysis

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		20	001			20	003				006	
VARIABLE	Maan	Ctd Day	Min	Ман	Маан	Ctd Davi	Min	Ман	Маан	Std.	Min	Ман
	Mean 0.636	Std. Dev.	Min 0.299	Max. 1.000	Mean	Std. Dev.	Min 0.443	Max 1.000	Mean	Dev.	Min 0.500	Max 1.000
WEB		0.181			0.757	0.162			0.864	0.123		
WEBODDS	2.448	2.163	0.428	9.500	4.334	4.342	0.794	21.999	8.214	8.111	1.000	34.002
TRANS					0.573	0.166	0.277	1.000	0.795	0.136	0.500	1.000
TRANODDS	0 (15	0.152	0.000	0.010	1.596	1.248	0.382	7.000	4.098	4.220	0.752	22.998
GINIASST	0.615	0.153	0.288	0.918	0.618	0.153	0.298	0.922	0.627	0.160	0.153	0.918
ASST*	\$686	\$1,321	\$70	\$7,371	\$838	\$1,648	\$78	\$9,486	\$873	\$1,372	\$101	\$6,608
METRO	0.499	0.281	0.101	1.000	0.759	0.190	0.264	1.000	0.771	0.186	0.275	1.000
LNSPEC	0.393	0.119	0.143	0.657	0.365	0.120	0.130	0.609	0.327	0.117	0.112	0.594
MEDFAMINC**		\$14.38	\$70.55	\$128.44	\$94.79	\$14.46	\$70.00	\$127.52	\$96.56	\$14.42	\$70.92	\$129.48
POPDEN	364.7	1315.0	1.1	9403.2	367.6	1315.5	1.1	9405.1	372.1	1324.4	1.2	9471.2
IMITATE	4.706	1.101	2.000	7.000	6.706	1.101	4	9	9.706	1.101	7	12
AGE	55.580	22.967	6.923	96.714	56.563	23.282	5.100	95.667	55.064	24.751	1.500	98.667
HHINET	45.493	6.181	30.316	60.354	57.927	5.831	43.549	69.422	74.485	4.794	60.103	81.320
WAGERATIO	2.977	0.290	2.305	3.732	3.031	0.255	2.417	3.595	3.015	0.214	2.440	3.535
BHC	0.754	0.141	0.412	1.000	0.772	0.139	0.308	1.000	0.760	0.180	0.000	1.000
DEPINTST	0.243	0.190	0.001	0.756	0.278	0.187	0.002	0.741	0.357	0.215	0.005	0.966
INTRAREG	0.235	0.428	0	1	0.235	0.428	0	1	0.235	0.428	0	1
COMINET	0.891	0.036	0.722	0.928	0.891	0.036	0.722	0.928	0.891	0.036	0.722	0.928
ASST90*	\$289	\$500	\$30	\$2,451	\$289	\$500	\$30	\$2,451	\$289	\$500	\$30	\$2,451
SE	0.235	0.428	0	1	0.235	0.428	0	1	0.235	0.428	0	1
FARWEST	0.118	0.325	0	1	0.118	0.325	0	1	0.118	0.325	0	1
ROCKYMTN	0.098	0.300	0	1	0.098	0.300	0	1	0.098	0.300	0	1
SW	0.078	0.272	0	1	0.078	0.272	0	1	0.078	0.272	0	1
NWENGLND	0.118	0.325	0	1	0.118	0.325	0	1	0.118	0.325	0	1
MIDEAST	0.118	0.325	0	1	0.118	0.325	0	1	0.118	0.325	0	1
GRTLAKE	0.098	0.300	0	1	0.098	0.300	0	1	0.098	0.300	0	1
PLAINS	0.137	0.348	0	1	0.137	0.348	0	1	0.137	0.348	0	1

Table 2: Summary Statistics

Notes: Sample includes the 50 states in the U.S. and the District of Columbia. See Table 1 for variable definitions and sources. *In millions. **In thousands

	Reduced Forms		Structural Equations		
VARIABLES	InWEBODDS_GIN	II lnASST	Inwebodds_GINI	lnASST	
lnASST (fitted)			0.3679***		
			(0.0605)		
InWEBODDS_GINI (fitted)				1.2808***	
				(0.3087)	
Inimitate	0.3972**	0.5383**	0.1926		
	(0.1779)	(0.2543)	(0.1426)		
Incominet	-2.2973***	-2.8548***	-1.1531*		
	(0.6622)	(0.8620)	(0.6107)		
INTRAREG	-0.1149*	-0.1377		0.0088	
	(0.0626)	(0.1083)		(0.1137)	
lnASST90	0.2719***	0.7812***		0.4322***	
	(0.0602)	(0.0781)		(0.1068)	
Inmetro	-0.2174**	0.1218	-0.2455***	0.4006***	
	(0.0890)	(0.1128)	(0.0818)	(0.1465)	
Inlnspec	-0.2792*	-0.6412**	-0.0311	-0.2964	
	(0.1458)	(0.2710)	(0.1219)	(0.2272)	
Inmedfaminc	-0.4978	0.0470	-0.5503	0.6921	
	(0.4074)	(0.5244)	(0.3619)	(0.5564)	
Inpopden	0.1249**	0.2273***	0.0351	0.0729	
	(0.0633)	(0.0671)	(0.0598)	(0.0824)	
lnAGE	-0.2199**	0.5645***	-0.4268***	0.8546***	
	(0.1003)	(0.1643)	(0.0816)	(0.1349)	
Inhhinet	1.5416***	-1.5919**	2.0760***	-3.5605***	
	(0.4759)	(0.6528)	(0.4062)	(0.7886)	
Inbhc	0.6981**	1.4143***	0.1147	0.5153	
	(0.2752)	(0.4084)	(0.2169)	(0.3968)	
lnwgratio	0.4026	1.4879***	-0.1049	0.9649*	
	(0.2832)	(0.5020)	(0.2797)	(0.5107)	
Indepint	0.1012***	-0.0854**	0.1354***	-0.2150***	
	(0.0294)	(0.0330)	(0.0270)	(0.0440)	
Constant	-7.8632***	2.4482	-8.5836***	12.4446***	
	(1.7970)	(1.8808)	(1.7069)	(3.1743)	
Observations	258	258	258	258	
R^2	0.754	0.815	0.804	0.807	
Instrument Partial R ²	0.057***	0.400***			
Overidentification test: $\chi(1)$		0.100	1.119	0.0214	
	/ Robust standard er	rors in narent		0.0217	
1					

Table 3: Simultaneous Equation Model of Adoption of Informational or Transactional Websites and of Average Bank Assets Instrumental variables estimation, estimation period = 2001 to 2006

*** p < 0.01, ** p < 0.05, * p < 0.1Estimated coefficients for year and regional dummy variables not shown.

Table 4: Simultaneous Equation Model of Adoption of Informational or Transactional Websites and of Average Bank Assets Instrumental variables estimation, estimation period = 2003 to 2006

	Reduced F	orms	Structural Equations		
VARIABLES	lnWEBODDS_GINI	lnASST	lnwebodds_gini	lnASST	
lnASST (fitted)			0.3528***		
			(0.0780)		
InWEBODDS GINI (fitted)			. ,	1.0515***	
_ ()				(0.2348)	
Inimitate	0.8101**	1.2463***	• 0.3368		
	(0.3131)	(0.4501)	(0.2297)		
Incominet	-3.5293***	-2.6460**	-2.4497***		
	(0.8071)	(1.1335)	(0.6791)		
INTRAREG	-0.1810**	-0.1989		-0.0065	
	(0.0908)	(0.1348)		(0.1205)	
lnASST90	0.2780***	0.8602***	:	0.5590***	
	(0.0861)	(0.0913)		(0.1102)	
Inmetro	-0.1587	-0.2227	0.0136	0.0272	
	(0.2563)	(0.2740)	(0.1852)	(0.2520)	
Inlnspec	-0.2971	-0.4129	-0.1321	-0.2348	
	(0.1943)	(0.3356)	(0.1483)	(0.2299)	
Inmedfaminc	-0.9404	-0.4396	-0.7973*	0.5969	
	(0.5854)	(0.6115)	(0.4834)	(0.5194)	
Inpopden	0.1584	0.2047**	0.0713	0.0912	
	(0.1049)	(0.0868)	(0.0861)	(0.0905)	
lnage	-0.2699	0.3456	-0.3895***	0.7487***	
	(0.1659)	(0.2734)	(0.1071)	(0.1686)	
Inhhinet	3.0006***	-0.6099	3.0522***	-3.6728***	
	(0.8891)	(0.8612)	(0.7092)	(0.8765)	
Inbhc	1.3554***	2.3430***		0.8310*	
	(0.3502)	(0.4227)	(0.3080)	(0.4458)	
lnwgratio	0.9434**	1.8928**	0.3319	0.7732	
	(0.4456)	(0.8021)	(0.3739)	(0.5741)	
Indepint	0.0716*	-0.1207**	0.1186***	-0.1934***	
	(0.0420)	(0.0482)	(0.0390)	(0.0497)	
Constant	-13.3038***	-0.5512	-12.5824***	12.8979***	
	(2.9372)	(2.8723)	(2.4946)	(3.4394)	
Observations	164	164	164	164	
R^2	0.734	0.824	0.801	0.847	
Instrument Partial R ²	0.105***	0.452***			
Overidentification test: $\chi(1)$.)		1.839	2.401	
<i>7</i> . (Robust standard erre	ors in parentl	neses		
	***	<0.05 * <0	1		

*** p < 0.01, ** p < 0.05, * p < 0.1Estimated coefficients for year and regional dummy variables not shown.

Table 5: Simultaneous Equation Model of Adoption of Transactional Websites and of Average Bank Assets Instrumental variables estimation, estimation period = 2003 to 2006

	Reduced Fo	orms	Structural Equations		
VARIABLES	lnTRANODDS_GINI	lnASST	lnTRANODDS_GINI	lnASST	
lnASST (fitted)			0.1871***		
			(0.0697)		
Intranodds Gini (fitted)				1.2744***	
_ 、 ,				(0.3026)	
Inimitate	0.4291*	0.6427*	0.2808		
	(0.2210)	(0.3731)	(0.1953)		
Incominet	-3.5380***	-4.3862***	* -2.5320***		
	(1.0108)	(1.0728)	(0.8474)		
INTRAREG	-0.1631**	-0.1290		0.0797	
	(0.0716)	(0.1330)		(0.1517)	
lnASST90	0.1136*	0.7709***	k	0.6247***	
	(0.0638)	(0.0917)		(0.1184)	
lnmetro	0.2043	0.0581	0.3182*	-0.1892	
	(0.2169)	(0.2620)	(0.1832)	(0.3306)	
Inlnspec	-0.0995	-0.6008*	0.0335	-0.5023*	
	(0.1368)	(0.3188)	(0.1239)	(0.2649)	
Inmedfaminc	-0.4883	0.6498	-0.6608	1.2737*	
	(0.4737)	(0.5607)	(0.4521)	(0.6987)	
Inpopden	0.0443	0.3099***	* -0.0344	0.2638**	
	(0.0764)	(0.0873)	(0.0773)	(0.1104)	
lnAGE	-0.2024	0.6295***	* -0.3084***	0.9091***	
	(0.1334)	(0.1894)	(0.1056)	(0.1733)	
Inhhinet	2.2853***	-1.8812**	2.4816***	-4.7593***	
	(0.5759)	(0.8494)	(0.5420)	(1.0467)	
lnBHC	1.0747***	1.5511***		0.1746	
	(0.2173)	(0.4464)	(0.2418)	(0.5535)	
lnwgratio	0.2617	1.5545**	0.0556	1.1949*	
	(0.3701)	(0.6545)	(0.3278)	(0.6734)	
Indepint	0.0804**	-0.1166**	0.1077***	-0.2187***	
	(0.0339)	(0.0459)	(0.0365)	(0.0569)	
Constant	-8.9815***	0.2271	-8.4596***	11.5832***	
	(2.0871)	(2.4768)	(1.9295)	(3.7659)	
Observations	179	179	179	179	
R^2	0.735	0.791	0.748	0.749	
Instrument Partial R ²	0.125***	0.380***	-	-	
Overidentification test: $\chi(1)$		0.500	3.273*	0.0732	
	Robust standard er	rors in narent		0.0752	
	100000 Standard Ch	iono in purent			

Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1Estimated coefficients for year and regional dummy variables not shown.

	New					Rocky		
VARIABLE	England	Mideast	Southeast	Great Lakes	Plains	Mountain	Southwest	Far West
WEBAVE	0.967	0.894	0.718	0.722	0.539	0.749	0.64	0.882
WEBODDS	13.749	9.782	3.003	3.04	1.319	3.386	3.241	5.982
TRANS	0.695	0.686	0.522	0.533	0.399	0.559	0.485	0.768
TRANODDS	2.18	2.518	1.214	1.242	0.712	1.407	1.131	3.16
GINIASST	0.536	0.691	0.677	0.765	0.567	0.529	0.572	0.561
ASST*	\$1,562.9	\$2,536.5	\$568.6	\$558.6	\$106.7	\$174.6	\$144.5	\$1,336.7
METRO	0.857	0.958	0.69	0.782	0.51	0.688	0.766	0.958
LNSPEC	0.43	0.422	0.446	0.451	0.287	0.29	0.307	0.208
MEDFAMINC**	\$109.64	\$108.14	\$82.18	\$97.92	\$93.16	\$92.43	\$81.50	\$101.95
POPDEN	470.224	2038.934	132.326	191.489	39.186	20.1	50.044	95.351
IMITATE	6.333	7.167	7	7.8	6.714	6	6.5	5.833
AGE	57.461	53.753	55.134	76.431	80.18	44.053	44.975	34.906
HHINET	62.87	59.753	52.114	56.414	58.77	61.295	53.086	63.483
WAGERATIO	2.854	3.164	3.015	3.183	3.125	2.905	3.074	2.944
BHC	0.599	0.701	0.785	0.85	0.867	0.82	0.743	0.78
DEPINTST	0.294	0.274	0.313	0.184	0.164	0.305	0.379	0.319
INTRAREG	0	0.167	0.25	0	0.571	0.6	0.25	0
COMINET	0.891	0.881	0.893	0.899	0.901	0.849	0.892	0.906
ASST90*	\$324.9	\$922.1	\$136.5	\$138.1	\$42.6	\$73.4	\$195.2	\$579.2
Obs.	6	5	12	5	7	5	4	6

Table 6: Mean Values of Selected Variables by Region 2003

Notes: See Table 1 for variable definitions and sources. See Table 2 for the national average of variables. *In millions. **In thousands

Appendix: Additional results for robustness checks

Table 3a: Simultaneous Equation Model of Adoption of Informational or Transactional Websites and of Average Bank Assets Instrumental variables estimation, estimation period = 2001 to 2006 LIML estimates, λ =4

VARIABLES lnASST (fitted)	(1) lnWEBODDS_GINI 0.3673*** (0.0502)	(2) InASST			
lnwebodds_GINI (fitted)	(0.0593)	1.1331***			
Inimitate	0.1926	(0.2282)			
	(0.1426)				
Incominet	-1.1541*				
	(0.6102)				
INTRAREG		-0.0012			
		(0.1091)			
lnASST90		0.4692***			
		(0.0913)			
Inmetro	-0.2452***	0.3668***			
	(0.0816)	(0.1308)			
Inlnspec	-0.0316	-0.3485			
	(0.1215)	(0.2171)			
Inmedfaminc	-0.5501	0.6365			
	(0.3618)	(0.5243)			
Inpopden	0.0353	0.0915			
	(0.0597)	(0.0725)			
lnAGE	-0.4266***	0.8277***			
	(0.0815)	(0.1238)			
Inhhinet	2.0748***	-3.3363***			
	(0.4056)	(0.7095)			
lnBHC	0.1154	0.6045*			
	(0.2163)	(0.3582)			
Inwgratio	-0.1040	0.9901**			
	(0.2795)	(0.4919)			
Indepint	0.1352***	-0.2017***			
	(0.0269)	(0.0377)			
Constant	-8.5766***	11.3626***			
	(1.6999)	(2.6826)			
Observations	258	258			
R^2	0.804	0.825			
Robust standard errors in parentheses					

*** p<0.01, ** p<0.05, * p<0.1

Table 5a: Simultaneous Equation Model of Adoption of Transactional Websites and of Average Bank Assets Instrumental variables estimation, estimation period = 2003 to 2006 LIML estimates, λ =4

	(1)	(2)			
VARIABLES	lntranodds_gini	lnASST			
lnASST (fitted)	0.1867***				
	(0.0690)				
InTRANODDS_GINI (fitted		1.1460***			
		(0.2464)			
Inimitate	0.2809				
	(0.1953)				
Incominet	-2.5330***				
	(0.8472)				
INTRAREG		0.0671			
		(0.1469)			
lnASST90		0.6370***			
		(0.1127)			
lnmetro	0.3183*	-0.1712			
	(0.1833)	(0.3098)			
Inlnspec	0.0333	-0.5146*			
	(0.1238)	(0.2653)			
Inmedfaminc	-0.6606	1.2409*			
	(0.4519)	(0.6629)			
Inpopden	-0.0342	0.2662**			
	(0.0772)	(0.1037)			
lnage	-0.3084***	0.8809***			
	(0.1057)	(0.1608)			
Inhhinet	2.4811***	-4.5147***			
	(0.5418)	(0.9753)			
lnBHC	0.6713***	0.2899			
	(0.2408)	(0.5137)			
lnwgratio	0.0561	1.1812*			
	(0.3276)	(0.6460)			
Indepint	0.1076***	-0.2090***			
	(0.0364)	(0.0535)			
Constant	-8.4981***	11.1828***			
	(2.0311)	(3.5070)			
Observations	179	179			
\mathbb{R}^2	0.748	0.764			
Robust standard errors in parentheses					
*** p<0.0	01, ** p<0.05, * p<0.	1			

Table 3b: Simultaneous Equation Model of Adoption of Informational or Transactional Websites and of Average Bank Assets Instrumental variables estimation, estimation period = 2001 to 2006 States with 10 or more sample banks

VARIABLES lnASST (fitted)	(1) lnwebodds_gini	(2) InASST	(3) lnWEBODDS_GINI 0.4356*** (0.0520)	(4) InASST
lnwebodds_gini (fitted)			(0.0320)	1.5255*** (0.4068)
Inimitate	0.5113***	0.7031***	0.1950	(0.1000)
	(0.1775)	(0.2616)	(0.1484)	
Incominet	-1.1627*	-2.3347**	-0.0829	
	(0.6441)	(0.9387)	(0.5974)	
INTRAREG	-0.1122*	-0.1450		0.0302
	(0.0616)	(0.1127)		(0.1224)
lnASST90	0.3895***	0.9243***		0.3313**
	(0.0603)	(0.0821)		(0.1659)
Inmetro	-0.2305***	0.1261	-0.2681***	0.4663***
	(0.0865)	(0.1383)	(0.0781)	(0.1594)
Inlnspec	0.0490	-0.3666	0.2212**	-0.3939**
	(0.1321)	(0.2766)	(0.1088)	(0.1900)
Inmedfaminc	0.1651	0.0678	0.1282	-0.1812
	(0.3578)	(0.4788)	(0.3197)	(0.5711)
Inpopden	0.0158	0.1260	-0.0418	0.0779
	(0.0499)	(0.0803)	(0.0442)	(0.0657)
lnAGE	-0.2350**	0.6044***	-0.4959***	0.9247***
	(0.0923)	(0.1901)	(0.0772)	(0.1439)
Inhhinet	1.2825***	-1.3770**	1.8052***	-3.3465***
	(0.4229)	(0.6594)	(0.3922)	(0.8209)
lnBHC	0.9523***	1.7594***	0.1320	0.3342
	(0.2705)	(0.3760)	(0.1968)	(0.5015)
lnwgratio	0.3705	1.4780***	-0.2479	0.9314*
	(0.2765)	(0.5526)	(0.3120)	(0.5528)
Indepint	0.0724**	-0.0960***	0.1161***	-0.2084***
	(0.0334)	(0.0355)	(0.0285)	(0.0498)
Constant	-10.3764***	0.4003	-10.3630***	16.4590***
	(1.6258)	(2.1234)	(1.4715)	(4.7427)
Observations	248	248	248	248
R^2	0.789	0.813	0.824	0.770
Instrument Partial R ²	0.047**	0.434***		
Overidentification test: $\chi(1)$			0.685	0.367
	Robust standard er	rors in parenth	neses	

*** p<0.01, ** p<0.05, * p<0.1

Table 5b: Simultaneous Equation Model of Adoption of Transactional Websites and of Average Bank Assets Instrumental variables estimation, estimation period = 2003 to 2006 States with 10 or more sample banks

VARIABLES lnASST (fitted)	(1) lntranodds_gini	(2) Inasst	(3) Intranodds_gini 0.1943*** (0.0659)	(4) Inasst
Intranodds_GINI (fitted)			(0.0003))	1.4031***
Inimitate	0.5761***	0.6279	0.4329***	(0.4400)
Incominet	(0.1872) -2.0900***	(0.3838) -3.5714***	(0.1658) -1.2234**	
	(0.5517)	(1.0621)	(0.5537)	
INTRAREG	-0.1251*	-0.0965		0.0845
lnASST90	(0.0751) 0.1364**	(0.1363) 0.8397***		(0.1618) 0.6494***
	(0.0680)	(0.0964)		(0.1371)
Inmetro	0.3916** (0.1900)	-0.0844 (0.2927)	0.5080*** (0.1459)	-0.6645** (0.3383)
Inlnspec	0.1597	-0.4741	0.2802**	-0.6222**
Inmedfaminc	(0.1070) 0.2183	(0.3360) 0.8687*	(0.1095) 0.0474	(0.2670) 0.6118
	(0.3907)	(0.5157)	(0.3878)	(0.6864)
Inpopden	-0.1050* (0.0533)	0.3417*** (0.1127)	-0.1909*** (0.0510)	0.4591*** (0.0964)
lnage	-0.2878***	0.5904***	-0.3914***	0.9357***
Inhhinet	(0.0803) 2.0790***	(0.1994) -2.5299***	(0.0717) 2.4252***	(0.1912) -5.5725***
	(0.5303)	(0.8745)	(0.5095)	(1.2681)
lnBHC	1.1925***	1.6377***	0.7831***	-0.0248
lnwgratio	(0.2243) 0.3015	(0.4188) 1.4983**	(0.2304) 0.0635	(0.6792) 1.1191
	(0.3078)	(0.6997)	(0.2823)	(0.7002)
Indepint	0.0558 (0.0341)	-0.1275*** (0.0487)	0.0833** (0.0347)	-0.2089*** (0.0582)
Constant	-10.4748***	1.4114	-10.3778***	16.4855***
Observations	(1.7218) 173	(2.8175) 173	(1.5061) 173	(4.8791) 173
R ²	0.776	0.790	0.786	0.740
Instrument Partial R^2	0.082***	0.372***	1.010	0.404
Overidentification test: $\chi(1)$	Robust standard er	rors in narantl	1.910	0.494
			1	

*** p<0.01, ** p<0.05, * p<0.1

Table 3c: Simultaneous Equation Model of Adoption of Informational or Transactional Websites and of Average Bank Assets Instrumental variables estimation, estimation period = 2001 to 2006 Random effects model

VARIABLES	(1) lnwebodds_gini	(2) lnASST
lnASST (fitted)	0.3014***	
InWEBODDS GINI (fitted)	(0.0820)	0.4991***
······		(0.1781)
Inimitate	-0.0849	· · · ·
	(0.2190)	
Incominet	-1.7692	
	(1.2353)	
INTRAREG	· · · ·	-0.0226
		(0.1714)
lnASST90		0.5863***
		(0.1039)
Inmetro	-0.3569***	0.2562***
	(0.0758)	(0.0833)
Inlnspec	-0.2369	-0.4052**
	(0.2156)	(0.1962)
Inmedfaminc	-0.3518	0.1968
	(0.4598)	(0.4487)
Inpopden	0.1470**	0.1895**
	(0.0740)	(0.0776)
lnAGE	-0.4312***	0.8429***
	(0.1339)	(0.1493)
Inhhinet	1.2108***	-0.8830**
	(0.4244)	(0.3631)
lnBHC	0.3412	0.1808
	(0.2441)	(0.2398)
lnWGRATIO	0.0330	-0.2716
	(0.3130)	(0.2411)
Indepint	0.0872***	-0.1136***
	(0.0325)	(0.0260)
Constant	-6.0374**	3.4307
	(2.5917)	(2.7162)
Observations	258	258
Overall R ²	0.788	0.823
Standa	ard errors in parenthes	
	0.01, ** p<0.05, * p<	
stimated coefficients for y	, 1 , 1	

Table 5c: Simultaneous Equation Model of Adoption of Transactional Websites and of Average Bank Assets Instrumental variables estimation, estimation period = 2003 to 2006 Random effects model

	(1)	(2)
VARIABLES	Intranodds_Gini	
lnASST (fitted)	0.1973**	
	(0.0974)	
InTRANODDS_GINI (fitted)		0.3685*
		(0.1940)
Inimitate	0.5294	
	(0.3641)	
Incominet	-2.8492**	
	(1.3494)	
INTRAREG		0.0996
		(0.2867)
lnASST90		0.6203***
		(0.1609)
Inmetro	0.1716	0.6281
	(0.3141)	(0.4473)
Inlnspec	-0.1060	-0.3297
	(0.2286)	(0.2331)
Inmedfaminc	-0.4880	0.4747
	(0.5026)	(0.5361)
Inpopden	-0.0263	0.1548
	(0.0823)	(0.1148)
lnAGE	-0.3103**	0.6633***
	(0.1557)	(0.1900)
Inhhinet	1.2917**	-1.2319***
	(0.6028)	(0.4677)
lnBHC	0.4936*	0.0992
	(0.2881)	(0.2814)
Inwgratio	0.3403	-0.4897*
	(0.3440)	(0.2603)
Indepint	0.0875**	-0.1266***
	(0.0436)	(0.0369)
Constant	-5.6984*	4.7986
	(2.9693)	(3.6007)
Observations	179	179
Overall R ²	0.724	0.756
Standard errors in parentheses		
*** p<0.01, ** p<0.05, * p<0.1		