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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. When the innovation is initially introduced, large banks have an advantage to adopt it first and enjoy further growth of size. Over time, as the innovation diffuses into smaller banks, the aggregate bank size distribution increases stochastically towards a new steady state. Applying the theory to an empirical study of Internet Banking diffusion across 50 US states, we examine the technological, economic and institutional factors governing the process. Our findings disentangle the interrelationship between Internet Banking adoption and growth of average bank size, and explain the variation of diffusion rates across geographic regions.

Keywords: Technology Diffusion, Bank Size Distribution, Internet Banking

JEL Classification: G20, L10, O30

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1 Introduction

Technology diffusion is an indispensable process through which technological potential of innovative activities can be actually turned into productivity. Various characteristics of the economic environment in which diffusion takes place may affect the pace of diffusion, while the diffusion itself may also have feedbacks on the environment.

To better understand this process, many important questions have to be answered. Among them, economists are most curious about the following: who are the early adopters of technological innovations, what factors determine the various diffusion rates across adopter groups and geographic regions, and what feedbacks, if any, the diffusion may have on the economic environment. The ongoing diffusion of Internet Banking (IB) provides us a good opportunity to look closely at these questions.

1.1 Diffusion of Internet Banking: Questions

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 presence on the Web. A major driving force of adopting IB is the potential for productivity gains that it offers. 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-

[1] Our study focuses on the diffusion of Internet Banking among traditional brick-and-mortar banks. The Internet-only bank, as a very different business model, is hence not included. In fact, the Internet-only banks count for a very small fraction of the US banking population, less than 0.5% even during the dot-com boom years. For a direct study on the Internet-only banks, see Wang (2005).

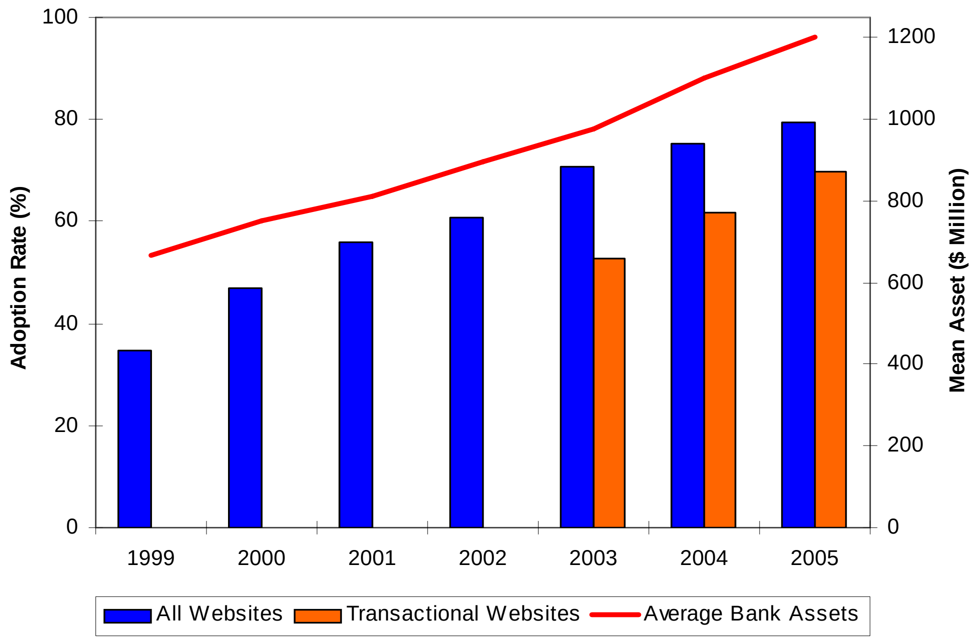

Figure 1: Diffusion of Internet Banking and Growth of Average Bank Size

value-added transactions (e.g., bill payments, balance inquiries, account transfer) through the online channel, while focus their resources into specialized, high-value-added transactions (e.g., small business lending, personal trust services, investment banking) through branches.

Figure 1 plots the diffusion trends of IB.[2] It shows that 35 percent of depository institutions reported a Website address in 1999, rising to 80 percent in 2005. Moreover, 53 percent of depository institutions reported Websites with transactional capability

[2]Data Source: Call Report (1999-2004). Systematic data on Internet banking became available in 1999 when FDIC-insured depository institutions were required to report their Website address. Data became more useful in 2003 when depository institutions were also required to report whether their Website allows customers to execute transactions on their accounts. In this paper, we take extra effort to check the data for accuracy to make sure that banks are counted as having a Website only if it report a valid Website address.

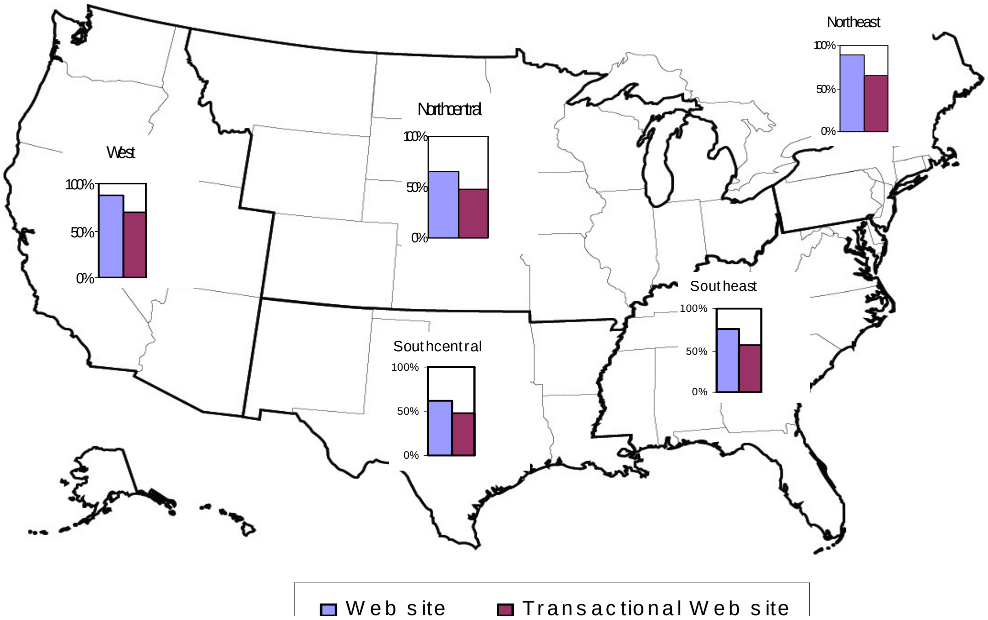

Figure 2: Regional Adoption for Internet Banking (2003)

in 2003, rising to 70 percent in 2005.[3] However, the adoption of IB varies significantly across geographic regions. Figure 2 presents the adoption of IB 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 with large size tend to adopt IB 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. These observations raise an important question: what explain these variations of diffusion rates across banking groups and geographic regions?

Meanwhile, the diffusion of IB has taken place in a continuously changing environ-

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

[4] Data Source: Call Report (2003).

ment of US banking industry. Over the past decade, several reforms of US banking regulatory framework were introduced and expected to affect the size distribution of banks. In particular, the Riegle-Neal Interstate Banking and Branching Efficiency Act was passed in September 1994. The act allows banks and bank-holding companies to freely establish branches across state lines. This new flexibility in branching regulation has opened the door to the possibility of substantial geographical consolidation in the banking industry. As a result, there has been a strong trend towards higher average bank size (Figure 1). This suggests further interesting questions: if bank size is an important factor in the adoption of IB, then how much has banking deregulation affected IB adoption? At the same time, how much, if any, has adoption of IB influenced the increase of average bank size?

1.2 The Hypothesis

Motivated by the aforementioned observations and questions, this paper tries to provide a general framework to study, theoretically and empirically, the endogenous diffusion and impact of Internet Banking. The theory suggests that when a cost-saving technological innovation, e.g., IB, is initially introduced, large banks have an advantage to adopt it first and enjoy further growth of size. Over time, due to environmental changes (demand change, technological progress and industry deregulation), the innovation gradually diffuses into smaller banks. As a result, the aggregate bank size distribution increases stochastically towards a new steady state, and there are important interactions between the IB adoption and growth of average bank size.

Applying the theory to an empirical study of Internet Banking diffusion across 50 US states, we examine the technological, economic and institutional factors governing the process. Using simultaneous-equation regressions, we are able to disentangle the complex interrelationship between IB adoption and growth of average bank size, and explain the variation of diffusion rates across US geographic regions.[5]

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 IB adoption at the early stages when there is considerable uncertainty about consumers' demand. They find that relative bank size and demographic information predictive of future demand positively influence IB adoption. Furst, Lang, and Nolle (2000) estimate a logit model for the determinants of IB adoption in a sample of national banks. They find that larger banks are more likely to adopt IB as well as banks are younger, better performing, located in urban areas, and members of a bank holding company. Some other studies analyze the reverse effect of technology on bank performance but obtain mixed results. Sullivan (2000) studies performance characteristics, including costs and profitability, of early adopters of IB and finds little difference from non-adopters. Berger and Mester (2003) find that banks enjoyed rising profits during the 1990s, and attribute this to banks' increasing market power gained by adopting new technologies. However, few of the 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

[5] In the empirical study, we use state-level aggregate data to estimate the IB adoption and bank size distribution. Only state-chartered banks are included to avoid the complication of interstate banking. The state-chartered banks count for 75% of total commercial banks in the US, and they can be reasonably assumed to mainly serve the home state markets.

with an equilibrium structural model. Built upon the recent work of Wang (2004) and Olmstead and Rhode (2001), we revise the popular threshold diffusion model to account for the interaction between technology adoption and firm size. Our theory explicitly considers the heterogeneity of banks' productivity and derives an empirically plausible bank size distribution. Based on that, we then characterize the endogenous diffusion of IB and its reverse impact on the average bank size. Using the theory to construct a simultaneous-equation estimation that applies to an original dataset of IB diffusion across 50 US states, the empirical results confirm our theoretical findings.

The approach that we develop in the paper goes far beyond the Internet Banking by providing a general framework to study technology diffusion and evolution of firm size distribution. Hence, it is also connected to a broad literature in related fields, namely theories of industry dynamics (Hopenyahn 1992, Jovanovic and MacDonald 1994, Klepper 1996), firm size distribution (Lucas 1979, Sutton 1997, Axtell 2000) and studies of technology diffusion (Griliches 1957, Mansfield 1961, David 1969, Davies 1979, Manuelli and Seshadri 2003, Comin and Hohijn 2004).

1.4 Road Map

The paper is organized as follows. Section 2 presents the model, in which we study competitive industry dynamics with endogenous technology diffusion. In particular, we explore the dynamic interactions between technology adoption and change of bank size distribution. Section 3 applies the model to an empirical study on the diffusion of Internet Banking across 50 US states. Using simultaneous-equation regressions, we disentangle the complex interrelationship between IB adoption and growth of average bank size, and explain the variation of diffusion rates across US geographic regions. Section 4 offers final remarks.

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 IB context.

2.1 Environment

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

2.2 Pre-Innovation Equilibrium

Before the technology innovation arrives, the industry is at a steady state. Taking the prices as given, an individual bank maximizes its profit using 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, we have

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

[6] P and Q are assumed to be exogenously determined by the aggregate market condition. In fact, this is not an unreasonable assumption given our focus on state-chartered banks, a subsample of the overall banking population.

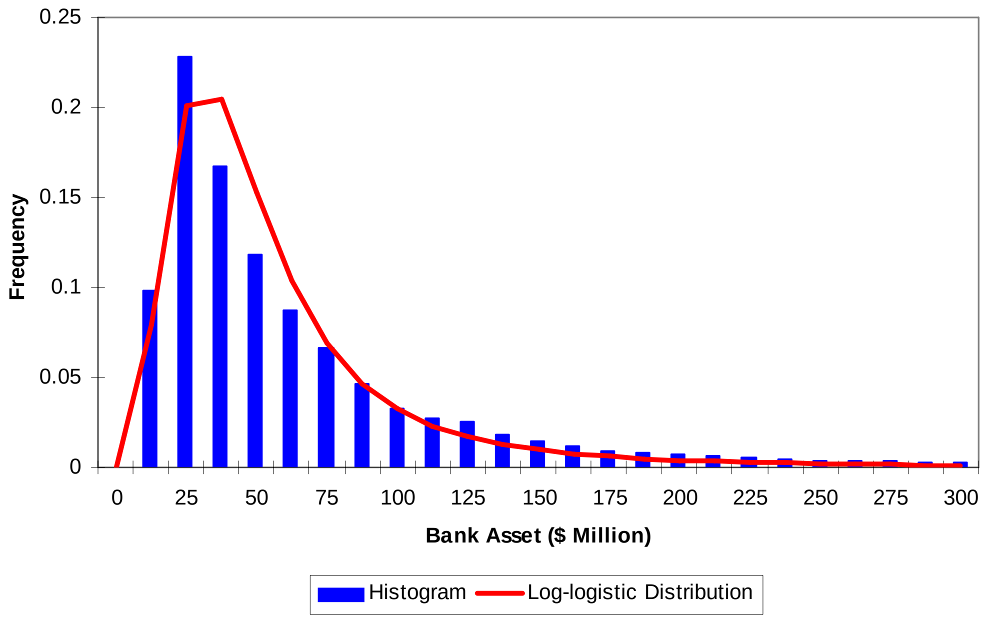

Figure 3: Bank Size Distribution (State-Chartered Banks, 1990)

Given individual bank's heterogeneity of productivity, e.g., α, there is a bank size distribution G. Historically, bank size y_0 fits well with a log-logistic distribution[7], whose cdf function is given as

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

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 $\Gamma(\mu) \equiv \int_0^\infty t^{\mu-1}\exp(-t)dt$.

[7]We pick the log-logistic distribution here is not only because it serves as an easily tractable representative of the larger group of positively skewed distributions, but also because it connects our study to the typically observed logistic diffusion curves. See Wang (2004) for a detailed discussion.

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

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

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

Figure 3 presents an example fitting the log-logistic distribution to the size frequency of US state-chartered banks in 1990. As can be seen, the log-logistic distribution offers a good description of the actual bank size distribution.

At equilibrium, aggregate demand equals supply, so that

$$N \int_0^\infty y_0 dG(y_0) = Q$$

where N is the total number of banks.

Notice that the assumption of log-logistic size distribution is robust to changes of the market environment. For example, any shocks to the price P and the mean bank productivity[8] $E(\alpha^{\frac{1}{1-\beta}})$ only affect the mean of the size distribution but nothing else; any shocks to the total demand Q only affect the number of banks N through bank entry and exit, but not the size distribution.

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 maximizes its profit and decides whether to adopt the innovation or not (0= do not adopt, 1= adopt):

$$\begin{aligned} \pi &= Max\{\pi_0, \pi_1\} \\ with \qquad \pi_0 &= \underset{y_0}{Max} P y_0 - \alpha y_0^\beta; \qquad \pi_1 = \underset{y_1}{Max} P y_1 - \frac{\alpha}{\gamma} y_1^\beta - k \end{aligned}$$

[8]Given $\beta > 1$, $\alpha^{\frac{1}{1-\beta}}$ decreases with α. Hence, $\alpha^{\frac{1}{1-\beta}}$ can be interpreted as a productivity measure.

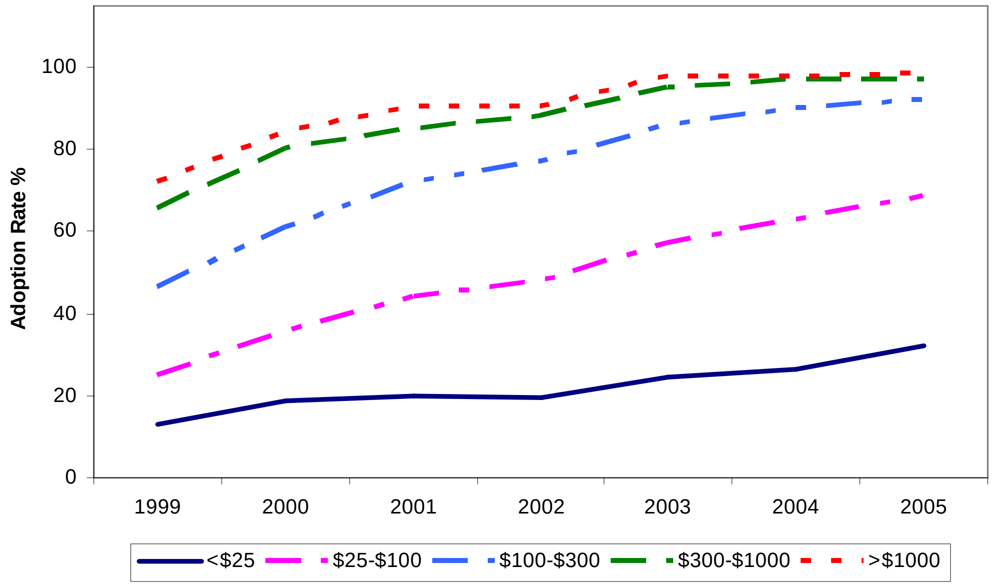

Figure 4: Diffusion of Web Sites by Bank Assets (Million)

where γ is the cost saving by adopting the innovation, k is the period cost of adoption.

Solving the maximization problem, we have

$$\begin{aligned} y_0 &= \left(\frac{P}{\alpha\beta}\right)^{\frac{1}{\beta-1}} \quad ; \quad \pi_0 = \frac{\beta-1}{\beta}Py_0; \\ y_1 &= \left(\frac{\gamma P}{\alpha\beta}\right)^{\frac{1}{\beta-1}} \quad ; \quad \pi_1 = \frac{\beta-1}{\beta}Py_1 - k. \end{aligned}$$

An individual bank will adopt IB if $\pi_1 \geq \pi_0$, and 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 requirement for adoption suggests that large banks have an advantage in adopting the innovation. Using bank assets as a size approximation, we show in Figure 4 that it is indeed what happened in the diffusion of Internet Banking.[9]

[9]Data Source: Call Report (1999 - 2004).

2.3.2 Aggregate Adoption

Given the log-logistic bank size distribution G defined in Equation 3 and the threshold y_0^* for adoption, the aggregate adoption rate of the IB innovation is :

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

Recall

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

Then Proposition 1 follows.

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

Notice $E(y_0)$ is not something directly observable. The observed mean bank size is indeed

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

Given that y_0 takes a 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 can be derived as follows

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

Given the results of Proposition 1, it is straightforward to get Proposition 2.

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, Equation 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. Notice that we have so far omitted time subscripts of all variables. To discuss the industry dynamics, we now make them explicit. As a result, we are going to see that the diffusion path closely follows a logistic curve.

In fact, over time, consumer willingness-to-pay P_t may change with income or substitute services, and mean bank productivity $E(\alpha_t^{\frac{1}{1-\beta}})$, IB cost saving γ_t and IB adoption cost k_t may change with banking deregulation and technology progress. Taking these time changes into account, let us consider a simple law of motion with constant growth as follows

$$P_t = P_0 e^{z_p t}; \quad E(\alpha_t^{\frac{1}{1-\beta}}) = E(\alpha_0^{\frac{1}{1-\beta}})e^{z_\alpha t}; \quad \gamma_t^{\frac{1}{\beta-1}} - 1 = (\gamma_0^{\frac{1}{\beta-1}} - 1)e^{z_\gamma t}; \quad k_t = k_0 e^{z_k t}.$$

Then, the diffusion path of IB can be derived from Equation 4

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

We may compare the diffusion formula derived here with the traditional logistic model. The logistic model, based on a behavioral assumption of social contagion, assumes that the hazard rate of adoption rises with cumulative adoption

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

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

Comparing Equation 6 with Equation 7, we realize 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 willingness-to-pay, industry deregulation, technology progress; the initial condition F_0 is the fraction of banks that find it profitable to adopt the innovation at the initial period:

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

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

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

Figure 5 illustrates the industry dynamic path. Before the IB innovation arrives, the banking industry stays at a pre-innovation size distribution, drawn with a dotted

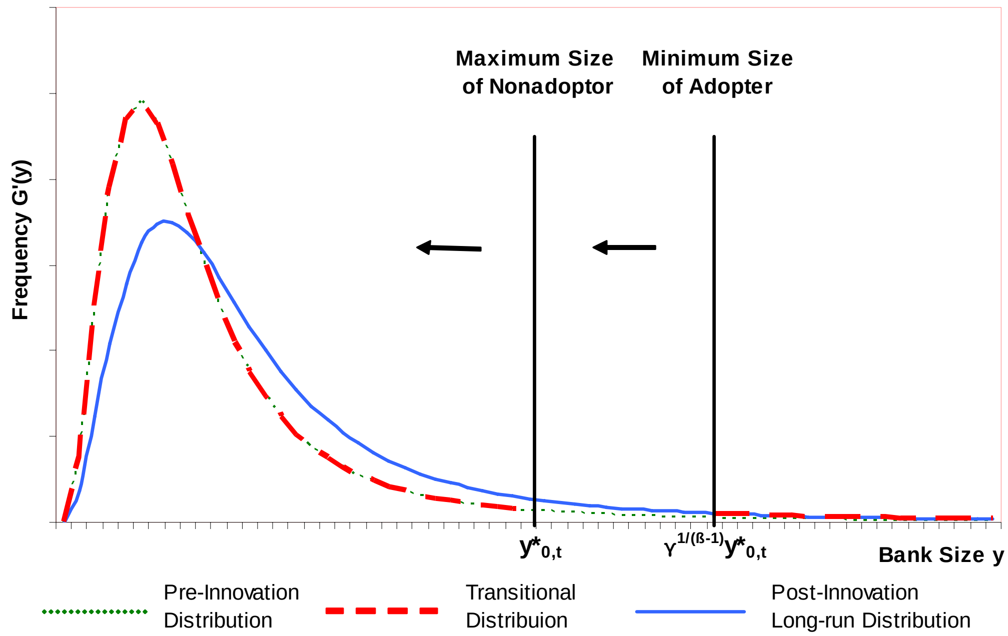

Figure 5: Illustration of the Industry Dynamics

green line. After the IB innovation, in the long run, the banking industry converges to a post-innovation long-run size distribution, drawn with a solid blue line. In between, the banking size distribution is at a transitional path, drawn with a dashed red line. During the transition, at a point of time t, there is an critical size requirement $y^*_{0,t}$, which splits the size distribution into two parts. For banks with size $y_{0,t} \geq y^*_{0,t}$, the size distribution resembles the post-innovation long-run distribution for the range $y_{1,t} > \gamma^{\frac{1}{\beta-1}} y^*_{0,t}$, while for banks with size $y_{0,t} < y^*_{0,t}$ the size distribution resembles the pre-innovation one. Over time, $y^*_{0,t}$ falls due to environmental changes (demand change, technology progress and banking deregulation). As a result, the IB innovation 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 the theoretical model to an empirical study of US banking industry and investigate the diffusion and impact of Internet Banking.

The data we use covers Internet Banking adoption (Informational Websites and Transactional Websites) among state-chartered banks across 50 US states for years 2003-2005, which includes about 5600 out of the total 7500 commercial banks in the US. The reason that we choose state-chartered banks is because it is more reasonable to define the state that they receive the charter as the market they serve. The reason that we start with the years 2003 is because 2003 is the first year when depository institutions were required to report their transactional Websites.

3.1 Simultaneous Equations

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

Recall Equation 1

$$F = 1 - G(y_0^*) = \frac{1}{1 + (\eta y_0^*/E(y_0))^{1/g}}.$$

It can be rewritten into a log-linear form:

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

Recall Equation 2

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

An empirical approximation of Equation 2 can be written as

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

Therefore, Equation 8 and 9 imply

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

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

Also, Equation 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 Equation 9 as

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

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

The two Equations 10 and 11 are determined simultaneously and have to be estimated with simultaneous-equation regressions. Since the variable k is in Equation 10 but not Equation 11, and $E(\alpha^{\frac{1}{1-\beta}})$ is in Equation 11 but not Equation 10, they can be used to define exclusion restrictions and identify structural parameters.

3.2 Empirical Specifications

In the empirical study, we estimate the following simultaneous equations[10] based on Equations 10 and 11 using state-level data 2003-2005, where each state is indexed by j and each year is indexed by t:

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

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

[10]Our regression model is similar to Olmstead and Rhode (2001), but we derive it from an explicit theoretical model.

- F is state-level adoption of IB (All Websites and Transactional Websites separately); g is the Gini coefficient of state-chartered bank size distribution;
- $E(y)$ is a measure of state-level average bank size;
- X are variables shared in both equations, e.g., variables affecting P and 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 (Detailed explanations and sources of empirical variables are summarized in Table 1).

(1) Log odds ratio for IB adoption adjusted by the Gini coefficient, constructed using the following variables: TRANSAVE – Adoption rate for Transactional Websites; WEBAVE – Adoption rate for All Websites (informational or transactional) ; GINIASST– Gini coefficient for bank assets;

(2) Average Bank Size, constructed by ASSTAVE – Bank assets[11].

As seen in the theory, there are four groups of exogenous variables: consumer willingness-to-pay P, mean bank productivity $E(\alpha^{\frac{1}{1-\beta}})$, IB cost saving γ and IB adoption cost k. We have to find relevant empirical variables to proxy them. The following is a preliminary grouping.

(1) Consumer willingness-to-pay P: METROAVE – Ratio of banks in metropolitan areas to all banks in state; LNSPAVE – Specialization of lending to consumers (consumer loans plus 1-4 family mortgages / total loans); RPCY – Real income per capita; POPDEN – Population density;

[11] Using Bank deposits as an alternative measure of bank size, we get consistent regression results.

(2) Mean Bank Productivity $E(\alpha^{\frac{1}{1-\beta}})$: AGEAVE – Average age of banks; INTRAREG – Indicator variable for whether the state had intrastate branching restrictions after 1995; BHCAVE – Ratio of banks in bank holding companies to total banks; DEPINTST – Ratio of deposits in out-of-state banks to total deposits; ASST90 – Bank assets in 1990;

(3) IB Cost Saving γ: INETADOPT – Household access rate for the Internet;

(4) IB Adoption Cost k: IMITATE – Years since the first bank in the state adopted a transactional Website; WAGERATIO – Wage ratio of computer analyst to teller;

(5) Region dummies and Years.

Notice that the above is a preliminary grouping of variables. Some of the variables may belong to more than one group. Take INETADOPT for example: if more households have access to the Internet, local banks may get more cost savings γ from adopting IB. However, the Internet access also allows the households to reach non-local banking services, e.g., out-of-state banks, then may also lower the demand and consumer willingness-to-pay P for local banking service. Another example is AGEAVE: more established banks typically achieve higher productivity $\alpha^{\frac{1}{1-\beta}}$, so may have higher incentive to adopt IB. However, they may also face higher IB adoption cost k compared to younger banks since they have to adapt the IB to their legacy system. Therefore, we have to be cautious to design and interpret our empirical study.

In particular, making the exclusion restrictions that define I and S becomes 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 the ratio of computer analyst wage to teller wage (WAGERATIO). They are expected to affect the bank size only through the IB adoption. In S, we use four variables: an indicator variable for whether the state had intrastate branching restrictions after

1995 (INTRAREG); the ratio of banks in bank holding companies to total banks (BHCAVE); the ratio of deposits in out-of-state banks to total deposits (DEPINTST); and bank assets in 1990 (ASST90). They are expected to affect the adoption of IB only through their effects on average bank size.

3.3 Data and Estimation Details

Our dataset consists of state-chartered, full service retail banks across 50 states of the U.S. for 2003-2005. Table 2 shows summary statistics for all empirical variables.

As the theory suggests, we use Gini-adjusted log-odds ratio as the dependent variable. However, by the year 2004 and 2005, some states had achieved full adoption of transactional Websites, so that the log-odds ratio can not be calculated. Hence, there are 137 observations in the transactional IB estimation instead of 150. For the same reason, there are 122 observations in the all IB (informational or transactional) estimation. Also, for most empirical variables used in the estimation, we take the log transformation and prefix the variables with "ln" in the notation.

To get robust estimates, we tried various definitions of dependent variables. For example, we use Transactional Websites and All Websites (informational or transactional) as alternative measures of IB adoption, and use Bank Assets and Bank Deposits as alternative measures of bank size. We also compare the estimation results between simple OLS regressions and simultaneous-equation regressions. Tables 3-4 report regression results with alternative model setups using Transactional Websites and Bank Assets as dependent variables; Tables 5-6 use All Websites (informational or transactional) and Bank Assets as dependent variables.

3.4 Estimation Results

Table 3 and 5, using alternative measures of IB adoption, report simple OLS regression results on two structural equations without taking care of the potential simultaneity problem. The coefficients of IB adoption and bank size are both found to be statistically significant. It confirms our hypothesis that IB adoption and bank size are simultaneously determined, and suggests that the OLS estimates may be inconsistent. It turns out that the OLS tends to underestimate the interactions between the IB adoption and firm size, as we show in Table 4 and 6.

Table 4 presents results of estimating the model using instrumental variables where the IB adoption rate is measured with Transactional Websites. 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-square of 75 percent for the adoption equation and 79 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 turn first to the structural equation for IB adoption (Table 4, column 3). The coefficient on the fitted value of lnASSTAVE is positive and statistically different from zero, as our theory predicts. In the structural equation for average bank assets (Table 4, column 4), the coefficient on the fitted value of lnTRANSAVE*GINIASST is also positive, as expected, though not statistically different from zero. However, we should have confidence with the positive effect, since the simple OLS regressions in Table 3 have shown that zero effect is not consistent with the data. Moreover, when adoption rates are measured using All Websites (informational or transactional), the coefficient turns statistically significant (Table 6, column 4).

There is a significantly positive coefficient on lnIMITATE. The result implies that the longer the state has had a bank with a Transactional Website, the higher the state's Internet Banking adoption rate. The leadership of the early adopter may have helped prepare other banks and customers to use Internet Banking through lowering the adoption cost, financially or perceptionally. The wage ratio lnWAGERATIO turns out to be statistically insignificant, which suggests that it might not be an ideal instrument.

Estimates show strong persistence in the asset size distribution. The significantly positive coefficient on lnASST90 implies that the average bank assets of a state in 1990 is a good predictor of average assets later. Estimates suggest that interstate competition (lnDEPINTST) has a significantly negative influence on the asset size of a state's banks. Neither intrastate branching restrictions (INTRAREG) after 1995 nor BHC membership (lnBHCAVE) have a statistically significant effect on bank assets in the structural equation, but BHC membership is shown to have significantly positive effects on IB adoption and bank assets in the reduced form regressions.

Explanatory variable that describe bank characteristics have a mixed impact on Website adoption and average asset size. Our measure of the location of banks in metropolitan areas (lnMETRO) has a significantly positive effect on IB adoption, but its effect on bank size is not statistically significant. The significantly negative coefficient on lnLNSPAVE in the asset size equation implies that greater specialization of a state's banks in consumer lending is associated with a smaller average bank assets. Perhaps banks achieve greater average size with lending focused on other areas, such as commercial loans. The significantly positive coefficient on lnLNSPAVE in the Website adoption equation suggests that greater specialization of a state's banks in consumer lending is associated with a higher adoption rate. This is consistent with findings that early bank Websites offered services aimed at retail customers and later added features useful to businesses (Sullivan (2004)).

The average age of a state's banks is significantly related to both Website adoption and asset size. The negative coefficient on lnAGEAVE in the Website 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 system. Many new banks may also pursue consumers with demographics that favor Internet Banking and therefore adopt appropriate technology.

With one exception, explanatory variables that describe the market characteristics of a state have expected signs and are statistically significant for both the Website adoption and the asset size equation. A state's per capita income (lnRPCY) is positively related to the average asset size of banks but is not significantly related to Website adoption. Population density (lnPOPDEN) is also positively related to asset size but negatively related to Website adoption. The latter result implies that adoption of Internet Banking is higher where population is less dense, which is consistent with a higher demand for Internet Banking in locations with higher cost of travel to bank branches. Access of households to the Internet (lnINETADPT) is statistically significant in explaining both Website adoption and asset size in sample states. Greater household access to the Internet is associated with a higher Website adoption rate, 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 may make it easier for households to form relationship with non-local banks, which may have a negative impact on the size of local state banks.

Using All Websites (informational or transactional) as an alternative measure of IB adoption, Table 6 reports regression results that are largely consistent with Table 4. We will discuss more details in the next session.

3.5 Empirical Findings on IB Diffusion

The estimation results have confirmed our theoretical findings. First, there are important interrelationship between IB adoption and average bank size. Quantitatively, as shown in Table 4, a 10 percent increase in average bank size would increase the Gini-adjusted adoption odds ratio by about 1.5 percent, and a 10 percent increase of adoption odds ratio would increase the average bank size by about 7.6 percent. The effects become even stronger when IB adoption rates are measured using All Websites (informational or transactional). One plausible explanation is that the adoption of All Websites might be a proxy for adoption of the new IT technology in general, therefore it captures a larger difference between the adopters and non-adopters than the specific adoption of Transaction Websites.

Since the IB adoption and bank size are endogenous variables, they are determined by underlying technological, economic and institutional factors. In the theory, we have grouped those factors into four basic categories that affect, respectively, consumer willingness-to-pay P, mean bank productivity $E(\alpha^{\frac{1}{1-\beta}})$, IB cost saving γ and IB adoption cost k. The empirical findings then reveal their quantitative effects.

At the beginning of this paper we asked: what explains the variation of IB diffusion rates across US geographic regions? To be specific, why do the Northeast and the West have the highest IB adoption rates, while the central regions of the country have the lowest? To answer this question, we present regional average of variables that are found significantly affecting IB adoption in our regressions in Table 7, in which we use Far West, Plains and New England to represent the West, Central and Northeast regions respectively.

Table 7: Mean Values of Selected Variables Across Regions

(Far West, Plains and New England 2003)

Variable*	Definition	Effects on IB	Far West	Plains	New England
OBS.	Number of States		6	7	6
TRANSAVE	% of Trans Web		0.768	0.399	0.695
WEBAVE	% of Website		0.882	0.539	0.967
GINIASST	Gini of Bank Size		0.561	0.567	0.536
ASSTAVE	Mean Bank Asset	+	1,337	107	1,563
LNSPAVE	Loan Specialization	+	0.208	0.287	0.430
RPCY	Per Capita Income	+	57.8	54.6	62.9
IMITATE	Years since 1st T-Web	+	5.83	6.71	6.33
INETADPT	% of HH Internet	+	63.48	58.77	62.87
BHCAVE	% of Bank Holding Co.	+	0.780	0.867	0.599
ASST90	Mean Bank Asset 1990	+	579.2	42.6	324.9
DEPINTST	% of Interstate Dep	−	0.319	0.164	0.294
POPDEN	Population Density	−	95.7	39.2	470.4
AGEAVE	Average Bank Age	−	34.91	80.18	57.46

*See Table 1 for details of 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 IB adoption rate in the Plains region was only about half of that of the other two regions. Compared with the Far West and New England, the Plains region has smaller mean bank size, lower per capita income, lower household access to Internet and older bank vintages. All these factors appear to have contributed to slow diffusion of Internet Banking.

However, at the same time, the data reject several alternative explanations of slow IB diffusion in the Central regions. In particular, it is not caused by the imitation of early adopters, percentage of BHC membership, competition from out-of-state banks or population density. In fact, all those factors work in favor of adopting Internet Banking in the Central region.

In a similar way, we can also compare variations of IB diffusion rates between any other regions. Average value of variables for all eight US regions are reported in Table 7a in the Appendix.

4 Final Remarks

This paper studies the endogenous diffusion and impact of Internet Banking. When a cost-saving innovation, such as Internet Banking, is initially introduced, large banks have an advantage to adopt it first and enjoy further growth of size. Over time, due to environmental changes (demand change, technology progress and banking deregulation), the innovation diffuses into smaller banks. As a result, the aggregate bank size distribution increases stochastically towards a new steady state, and there exists important interactions between the IB adoption and the average bank size. Applying the theory to an empirical study of the diffusion of IB across 50 US states, we examine the technological, economic and institutional factors governing the process. Using simultaneous-equation regressions, we are able to disentangle quantitatively the complex relationship between IB adoption and growth of average bank size, and explain the variation of IB diffusion rates across geographic regions. We find that the factors significantly affecting IB adoption include mean bank size, per capita income, household access to Internet, average bank age, bank loan specialization, imitation of early adopters, percentage of BHC membership, competition from out-of-state banks and population density. In particular, it is the first four factors that are primarily responsible for the slower diffusion of Internet Banking in the Central region than the West and Northeast regions.

The theoretical and empirical approach that we develop in the paper goes far beyond the Internet Banking. It indeed provides a general framework to study the joint evolution of technology adoption and firm size distribution, and can be readily applied to other case studies of technology diffusion and industry dynamics.

References

[1] Axtell, Robert L. (2000). "Zipf Distribution of U.S. Firm Sizes," *Science,* 293: 1818-1820.

[2] Berger, Allen and Robert DeYoung (2002). "Technological Progress and the Geographic Expansion of the Banking Industry," *Finance and Economics Discussion Series*, 2002-31, Federal Reserve Board.

[3] Berger, Allen and Loretta Mester (2003). "Explaining the Dramatic Changes of Performance of U.S. Banks: Technological Change, Deregulation and Dynamic Changes in Competition," *Journal of Financial Intermediation*, Vol. 12(1), pp 57-95.

[4] Comin, D. and Hohijn B., (2004). "Cross-Country Technological Adoption: Making the Theories Face the Facts," *Journal of Monetary Economics*, January 2004, pp. 39-83.

[5] Courchane, Marsha, David Nickerson and Richard J. Sullivan, (2002). "Investment in Internet Banking as a Real Option: Theory and Tests." *The Journal of Multinational Financial Management*, 12 (4-5), Oct.-Dec., pp. 347-63.

[6] David, Paul, (1969). "A Contribution to the Theory of Diffusion," mimeo.

[7] Davies, Stephen. (1979). *The Diffusion of Process Innovations,* Cambridge University Press.

[8] Furst, Karen, William Lang, and Daniel Nolle (2001). "Internet Banking in the U.S.: Landscape, Prospects, and Industry Implications," *Journal of Financial Transformation*, The Capco institute, 2, pp 45-52.

[9] Fisk, Peter R., (1961). "The Graduation of Income Distributions," *Econometrica*, 29, 2, 171-185.

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

[11] Harker, Patrick and Baba Prasad (1997). "Examining the Contribution of Information Technology Toward Productivity and Profitability in U.S. Retail Banking," *Working paper* 97-09, Wharton Financial Institutions Center, The Wharton School.

[12] Hopenhayn, H. A. (1992). "Entry, Exit, and Firm Dynamics in Long Run Equilibrium," *Econometrica*, 60(2): 1127-1150.

[13] Jovanovic, Boyan and G. M. MacDonald, (1994). "The Life Cycle of a Competitive Industry," *Journal of Political Economy*, 102 (Apr.), 322-347.

[14] Klepper, Steven, (1996). "Entry, Exit, Growth, and Innovation over the Product Life Cycle," *American Economic Review*, 86 (June), 562-583.

[15] Lucas, Robert E., (1978). "On the Size Distribution of Business Firms," *The Bell Journal of Economics*, 9, 2, 508-523.

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

[17] Mansfield, Edwin, (1962). "Entry, Gibrat's Law, Innovation, and the Growth of Firms," *American Economic Review*, 52 (Dec.), 1023-51.

[18] Manuelli, Rodolfo and Ananth Seshadri, (2003). "Frictionless Technology Diffusion: The Case of Tractors," *NBER Working Papers* 9604.

[19] Olmstead, Alan and Paul Rhode, (2001). "Reshaping the Landscape: The Impact and Diffusion of the Tractor in American Agriculture, 1910-1960," *The Journal of Economic History*, Vol. 61, No. 3. p663-698.

[20] Rogers, Everett (1995). *Diffusion of Innovations*, 4th Edition. Free Press, New York.

[21] Stiroh, Kevin (2002). "Information Technology and the U. S. Productivity Revival: What do the Industry Data Say?" *American Economic Review*, Vol. 92(5), pp 1559-1576.

[22] Sullivan, Richard, (2004). "Payment Services and the Evolution of Internet Banking," *Payments System Reserch Briefing*, (Aug.), Federal Reserve Bank of Kansas City.

[23] Sullivan, Richard, (2000). "How Has the Adoption of Internet Banking Affected Performance and Risk in Banks? A Look at Internet Banking in the Tenth Federal Reserve District," *Financial Industry Perspective*, Federal Reserve Bank of Kansas City.

[24] Sutton, John, (1997). "Gibrat's Legacy," *Journal of Economic Literature*, 35(1), pp. 40-59.

[25] Wang, Zhu. (2005) "Technology Innovation and Market Turbulence: A Dotcom Example," *Working Paper*, Payments System Research Department, Federal Reserve Bank of Kansas City.

[26] Wang, Zhu. (2004) "Learning, Diffusion and Industry Life Cycle," *Ph.D. Dissertation*, Department of Economics, University of Chicago.

Table 1
Empirical Variable Definitions and Sources

Variable name	Definition	Source
TRANSAVE	Adoption rate for transactional Web sites	Call Report
TRANODDS	Odds ratio for adoption of transactional Web sites	Call Report
WEBAVE	Adoption rate information and transactional Web sites	Call Report
WEBODDS	Odds ratio for adoption of information and transactional Web sites	Call Report
GINIASST	Gini coefficient for bank assets	Call Report
ASSTAVE	Bank assets	Call Report
METROAVE	Ratio of banks in metropolitan areas to all banks in state	Call Report
LNSPAVE	Specialization of lending to consumers (consumer loans plus 1-4 family mortgages / total loans)	Call Report
RPCY	Per capita income/CPI	*Statistical Abstract of the United States*
POPDEN	Population density	*Statistical Abstract of the United States*
IMITATE	Years since the first bank in the state adopted a transactional Web site	*Online Banking Report*
AGEAVE	Age of banks	Call Report
INETADOPT	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	FDIC
BHCAVE	Ratio of banks in bank holding companies to total banks	Call Report
DEPINTST	Ratio of deposits in out-of-state banks to total deposits	FDIC *Summary of Deposits*
ASST90	Bank assets in 1990	Call Report
YEAR	Year	Call Report
SE	Indicator variable for states located in the Southeast (AL, AR, FL, GA, KY, LA, MS, NC, SC, TN)	Bureau of Economic Analysis
FARWEST	Indicator variable for states located in the Far Western region (AK, CA, HI, NV, OR, WA)	Bureau of Economic Analysis
ROCKYMTN	Indicator variable for states located in the Rocky Mountain region (CO, ID, MT, UT, WY)	Bureau of Economic Analysis
SW	Indicator variable for states located in the Southwest (AZ, NM, OK TX)	Bureau of Economic Analysis
NWENGLND	Indicator variable for states located in New England (CT, MA, NH, RI, VA)	Bureau of Economic Analysis
MIDEAST	Indicator variable for states located Middle Eastern region (DC, DE, MD, NJ, NY, PA)	Bureau of Economic Analysis
GRTLAKE	Indicator variable for states located in the Great Lakes region (IL, IN MI, OH, WI)	Bureau of Economic Analysis

Notes: data are for individual states. Data for banks are unweighted averages for those located in individual states. Selected banks were state-chartered, full-service, retail commercial banks.

Table 2
Summary Statistics

	2003				2004				2005			
VARIABLE	Mean	Std. Dev.	Min	Max	Mean	Std. Dev.	Min	Max	Mean	Std. Dev.	Min	Max
TRANSAVE	0.573	0.166	0.277	1	0.671	0.169	0.353	1	0.745	0.152	0.429	1
TRANODDS	1.596	1.248	0.382	7.0	2.565	2.293	0.546	11.0	4.166	4.241	0.752	23.00
WEBAVE	0.757	0.162	0.443	1	0.813	0.153	0.471	1	0.840	0.133	0.542	1
WEBODDS	4.334	4.342	0.794	22.00	6.374	6.357	0.892	26.50	8.382	8.130	1.184	34.00
GINIASST	0.618	0.153	0.298	0.922	0.620	0.153	0.307	0.914	0.624	0.164	0.150	0.911
ASSTAVE*	838	1648	78	9486	800	1293	85	6024	918	1615	93	8609
METROAVE	0.759	0.190	0.264	1	0.763	0.190	0.264	1	0.764	0.188	0.277	1
LNSPAVE	0.365	0.120	0.130	0.609	0.355	0.120	0.124	0.591	0.342	0.120	0.116	0.587
RPCY	55	8	42	77	57	8	43	80	57	8	42	82
POPDEN	187	256	1	1165	188	257	1	1171	189	258	1	1175
IMITATE	6.7	1.111	4	9	7.7	1.11	5	10	8.7	1.11	6	11
AGEAVE	56.6	23.3	5.1	95.7	56.7	23.7	5.9	96.7	57.1	24.3	6.3	102.0
INETADPT	58.0	5.9	43.5	69.4	64.0	5.6	50.7	73.5	69.5	5.2	55.9	77.6
WAGERATIO	3.04	0.25	2.42	3.60	3.06	0.25	2.52	3.70	3.06	0.23	2.69	3.58
INTRAREG	0.24	0.431	0	1	0.24	0.431	0	1	0.24	0.431	0	1
BHCAVE	0.772	0.139	0.308	1	0.780	0.136	0.333	1	0.783	0.138	0.385	1
DEPINTST	0.278	0.187	0.002	0.741	0.328	0.201	0.003	0.840	0.351	0.198	0.005	0.843
ASST90*	292	504	30	2451	292	504	30	2451	292	504	30	2451
YEAR	2003	0	2003	2003	2004	0	2004	2004	2005	0	2005	2005
SE	0.240	0.431	0	1	0.240	0.431	0	1	0.240	0.431	0	1
FARWEST	0.120	0.328	0	1	0.120	0.328	0	1	0.120	0.328	0	1
ROCKYMTN	0.100	0.303	0	1	0.100	0.303	0	1	0.100	0.303	0	1
SW	0.080	0.274	0	1	0.080	0.274	0	1	0.080	0.274	0	1
NWENGLND	0.120	0.328	0	1	0.120	0.328	0	1	0.120	0.328	0	1
MIDEAST	0.100	0.303	0	1	0.100	0.303	0	1	0.100	0.303	0	1
GRTLAKE	0.100	0.303	0	1	0.100	0.303	0	1	0.100	0.303	0	1

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

Table 3
Single Equation Models of Adoption of Transactional Websites and Average Bank Assets
Ordinary Least Squares Estimates

Dependent variable:	lnTRANODDS*GINIAVE	lnASSTAVE
lnASSTAVE	0.1554***	
	(0.0450)	
lnTRANODDS*GINIAVE		0.6342***
		(0.1629)
lnIMITATE	0.4298**	
	(0.1908)	
lnWAGERATIO	0.0546	
	(0.3689)	
INTRAREG		-0.0230
		(0.1549)
lnASST90		0.6267***
		(0.1268)
lnBHCAVE		0.6816
		(0.4808)
lnDEPINTST		-0.1862***
		(0.0566)
lnMETROAVE	0.2951*	-0.1196
	(0.1630)	(0.3201)
lnLNSPECAVE	0.3557**	-0.6273**
	(0.1469)	(0.3074)
lnAGEAVE	-0.4230***	0.7216***
	(0.1006)	(0.1710)
lnRPCY	-0.2366	1.9704***
	(0.3473)	(0.6703)
lnPOPDEN	-0.1733***	0.3160***
	(0.0559)	(0.1052)
lnINETADPT	1.9214***	-3.8726***
	(0.4774)	(0.9691)
SE	0.1975	0.5768**
	(0.1400)	(0.2441)
FARWEST	0.5176***	0.7191***
	(0.1436)	(0.2175)
ROCKYMTN	-0.1010	1.0015***
	(0.1197)	(0.2329)
SW	0.0464	0.1189
	(0.1128)	(0.1906)
NWENGLND	-0.1567	0.4602
	(0.1489)	(0.3172)
MIDEAST	0.4013**	-0.3890
	(0.1885)	(0.3331)
GRTLAKE	0.2610**	0.0690
	(0.1165)	(0.2124)
YEAR	0.0409	0.2302**
	(0.0599)	(0.1046)
Constant	-88.7221	-453.4880**
	(119.2062)	(208.2705)
Observations	137	138
R-squared	0.75	0.79

Robust standard errors in parentheses. See Table 1 for variable definitions and sources.
* significant at 10%; ** significant at 5%; *** significant at 1%.

Table 4
Simultaneous Equation Model of Adoption of Transactional Websites and Average Bank Assets
Instrumental Variables Estimates

	Reduced Forms		Structural Equations	
Dependent variable:	lnTRANODDS*GINIAVE	lnASSTAVE	lnTRANODDS*GINIAVE	lnASSTAVE
lnASSTAVE (fitted)			0.1499**	
			(0.0623)	
lnTRANODDS*GINIAVE (fitted)				0.7601
				(0.7688)
lnIMITATE	0.5691***	0.2683	0.4292**	
	(0.1878)	(0.3992)	(0.1906)	
lnWAGERATIO	0.4512	1.9074**	0.0603	
	(0.3225)	(0.8517)	(0.3722)	
INTRAREG	0.0140	0.0457		-0.0242
	(0.0846)	(0.1615)		(0.1558)
lnASST90	0.1268	0.7361***		0.6144***
	(0.0767)	(0.1095)		(0.1465)
lnBHCAVE	0.8926***	1.2545**		0.5727
	(0.2205)	(0.4988)		(0.8107)
lnDEPINTST	0.0709**	-0.1429***		-0.1939**
	(0.0331)	(0.0533)		(0.0777)
lnMETROAVE	0.3291	0.1274	0.2996*	-0.1567
	(0.2054)	(0.3231)	(0.1665)	(0.4123)
lnLNSPECAVE	0.2499**	-0.4371	0.3520**	-0.6381**
	(0.1199)	(0.3487)	(0.1540)	(0.3100)
lnAGEAVE	-0.4106***	0.4466**	-0.4206***	0.7599***
	(0.1095)	(0.1814)	(0.1046)	(0.2866)
lnRPCY	-0.0812	1.9245***	-0.2299	1.9616***
	(0.3141)	(0.6797)	(0.3509)	(0.6611)
lnPOPDEN	-0.1125**	0.2316*	-0.1724***	0.3239***
	(0.0552)	(0.1249)	(0.0570)	(0.1006)
lnINETADPT	1.4573***	-3.2846***	1.9068***	-4.0536**
	(0.4733)	(0.9660)	(0.4833)	(1.6379)
SE	0.2725**	0.7267***	0.2044	0.5283
	(0.1318)	(0.2090)	(0.1563)	(0.3557)
FARWEST	0.6416***	1.1421***	0.5245***	0.6386
	(0.1367)	(0.2247)	(0.1569)	(0.4589)
ROCKYMTN	0.0204	1.0344***	-0.0965	0.9788***
	(0.1131)	(0.2606)	(0.1295)	(0.2461)
SW	-0.0250	0.0399	0.0475	0.1065
	(0.1162)	(0.1778)	(0.1144)	(0.2018)
NWENGLND	0.1041	0.5731*	-0.1494	0.4406
	(0.1703)	(0.3147)	(0.1636)	(0.3308)
MIDEAST	0.4388*	-0.2877	0.4100**	-0.4587
	(0.2295)	(0.3182)	(0.1942)	(0.4785)
GRTLAKE	0.2481**	0.1757	0.2666**	0.0224
	(0.1177)	(0.2124)	(0.1276)	(0.2974)
YEAR	0.0539	0.3055***	0.0425	0.2126*
	(0.0575)	(0.1080)	(0.0590)	(0.1255)
CONSTANT	-113.8324	-608.4542***	-91.8547	-417.5535
	(114.3936)	(214.5147)	(117.5792)	(252.7620)
Observations	137	137	137	137
R-squared	0.78	0.78	0.75	0.79

Robust standard errors in parentheses. See Table 1 for variable definitions and sources.
* significant at 10%; ** significant at 5%; *** significant at 1%.

Table 5

Single Equation Models of Adoption of Informational or Transactional Websites and Average Bank Assets

Ordinary Least Squares Estimates

Dependent variable:	lnWEBODDS*GINIAVE	lnASSTAVE
lnASSTAVE	0.3176***	
	(0.0632)	
lnWEBODDS*GINIAVE		0.6586***
		(0.0998)
lnIMITATE	0.3656	
	(0.2493)	
lnWAGERATIO	-0.0433	
	(0.3962)	
INTRAREG		0.0121
		(0.1189)
lnASST90		0.5145***
		(0.1202)
lnBHCAVE		-0.1752
		(0.4224)
lnDEPINTST		-0.1635***
		(0.0481)
lnMETROAVE	0.2153	-0.3235
	(0.1766)	(0.2735)
lnLNSPECAVE	0.2114	-0.1926
	(0.1714)	(0.2670)
lnAGEAVE	-0.3524**	0.1527
	(0.1677)	(0.2213)
lnRPCY	0.0092	1.2796**
	(0.4201)	(0.5988)
lnPOPDEN	-0.1293	0.1669*
	(0.0818)	(0.0848)
lnINETADPT	2.7495***	-3.8629***
	(0.6342)	(0.9659)
SE	0.4403***	0.1568
	(0.1578)	(0.2342)
FARWEST	0.4849**	0.2797
	(0.2134)	(0.2128)
ROCKYMTN	-0.0234	0.4769**
	(0.2019)	(0.1931)
SW	0.1805	-0.0715
	(0.1159)	(0.1595)
NWENGLND	0.6787*	0.8381**
	(0.3813)	(0.3550)
MIDEAST	0.6095***	-0.4723*
	(0.1962)	(0.2401)
GRTLAKE	0.3729***	0.1407
	(0.1275)	(0.1765)
YEAR	-0.1354*	0.3147***
	(0.0730)	(0.0913)
Constant	258.0096*	-615.7636***
	(145.0315)	(181.2335)
Observations	122	123
R-squared	0.83	0.88

Robust standard errors in parentheses. See Table 1 for variable definitions and sources.

* significant at 10%; ** significant at 5%; *** significant at 1%.

Table 6
Simultaneous Equation Model of Adoption of Informational or Transactional Websites and Average Bank Assets
Instrumental Variables Estimates

	Reduced Forms		Structural Equations	
Dependent variable:	lnWEBODDS*GINIAVE	lnASSTAVE	lnWEBODDS*GINIAVE	lnASSTAVE
lnASSTAVE (fitted)			0.2835***	
			(0.0852)	
lnWEBODDS*GINIAVE (fitted)				1.1752**
				(0.5702)
lnIMITATE	0.7306**	0.6199	0.3799	
	(0.3024)	(0.4459)	(0.2525)	
lnWAGERATIO	0.7146	2.1615**	0.0202	
	(0.4388)	(0.9995)	(0.4048)	
INTRAREG	0.0528	0.1105		-0.0028
	(0.1053)	(0.1459)		(0.1226)
lnASST90	0.3923***	0.7929***		0.3254
	(0.0811)	(0.1171)		(0.2320)
lnBHCAVE	0.4866	0.1939		-0.3527
	(0.3697)	(0.4529)		(0.5018)
lnDEPINTST	0.0887**	-0.1079**		-0.2056***
	(0.0383)	(0.0477)		(0.0746)
lnMETROAVE	0.0577	-0.2376	0.2320	-0.3987
	(0.2372)	(0.2909)	(0.1777)	(0.3095)
lnLNSPECAVE	0.3817*	0.1854	0.2018	-0.2564
	(0.1942)	(0.3073)	(0.1716)	(0.2774)
lnAGEAVE	-0.5802***	-0.3161	-0.3548**	0.3250
	(0.2108)	(0.2647)	(0.1669)	(0.3011)
lnRPCY	-0.0622	1.0936	0.0312	1.0674*
	(0.4689)	(0.6781)	(0.4302)	(0.6263)
lnPOPDEN	-0.1724*	-0.0118	-0.1282	0.2102**
	(0.0915)	(0.1103)	(0.0825)	(0.1005)
lnINETADPT	1.9766***	-2.7084***	2.6939***	-4.7932***
	(0.6397)	(0.9898)	(0.6656)	(1.4949)
SE	0.3423**	0.3687	0.4805***	-0.0818
	(0.1564)	(0.2232)	(0.1769)	(0.3314)
FARWEST	0.5650**	0.7443***	0.5217**	0.0246
	(0.2228)	(0.2259)	(0.2388)	(0.3834)
ROCKYMTN	-0.0879	0.3902	-0.0047	0.4621**
	(0.2289)	(0.2397)	(0.2144)	(0.2157)
SW	-0.0489	-0.1901	0.1841	-0.1004
	(0.1303)	(0.1602)	(0.1175)	(0.1791)
NWENGLND	1.0037***	1.7359***	0.7982*	0.4175
	(0.3418)	(0.3501)	(0.4350)	(0.6767)
MIDEAST	0.3655	-0.3026	0.6682***	-0.6455*
	(0.2706)	(0.2483)	(0.2221)	(0.3719)
GRTLAKE	0.3959***	0.3828**	0.4117***	-0.0896
	(0.1212)	(0.1848)	(0.1466)	(0.3081)
YEAR	-0.0910	0.2578**	-0.1301*	0.3134***
	(0.0793)	(0.1074)	(0.0757)	(0.0981)
CONSTANT	172.0133	-509.0216**	247.8406	-607.6061***
	(157.8712)	(213.1903)	(150.2518)	(194.4208)
Observations	122	122	122	122
R-squared	0.81	0.86	0.83	0.86

Robust standard errors in parentheses. See Table 1 for variable definitions and sources.
* significant at 10%; ** significant at 5%; *** significant at 1%.

Table 7a
Mean Values of Selected Variables by Region
(2003)

VARIABLE	New England	Mideast	Southeast	Great Lakes	Plains	Rocky Mountain	Southwest	Far West	United States
TRANSAVE	0.695	0.686	0.522	0.533	0.399	0.559	0.485	0.768	0.573
TRANODDS	2.180	2.518	1.214	1.242	0.712	1.407	1.131	3.160	1.596
WEBAVE	0.967	0.894	0.718	0.722	0.539	0.749	0.640	0.882	0.757
WEBODDS	13.749	9.782	3.003	3.040	1.319	3.386	3.241	5.982	4.334
GINIASST	0.536	0.691	0.677	0.765	0.567	0.529	0.572	0.561	0.618
ASSTAVE*	1,563	2,537	569	559	107	175	145	1,337	838
METROAVE	0.857	0.958	0.690	0.782	0.510	0.688	0.766	0.958	0.759
LNSPAVE	0.430	0.422	0.446	0.451	0.287	0.290	0.307	0.208	0.365
RPCY	62.9	64.8	49.2	56.2	54.6	52.1	49.0	57.8	55.2
POPDEN	470	566	132	192	39	20	50	95	187
IMITATE	6.3	7.2	7.0	7.8	6.7	6.0	6.5	5.8	6.7
AGEAVE	57.5	53.8	55.1	76.4	80.2	44.1	45.0	34.9	56.6
INETADPT	62.9	60.8	52.1	56.4	58.8	61.3	53.1	63.5	58.0
WAGERATIO	2.85	3.29	3.02	3.18	3.13	2.90	3.07	2.94	3.04
INTRAREG	0.00	0.20	0.25	0.00	0.57	0.60	0.25	0.00	0.24
BHCAVE	0.599	0.701	0.785	0.850	0.867	0.820	0.743	0.780	0.772
DEPINTST	0.294	0.274	0.313	0.184	0.164	0.305	0.379	0.319	0.278
ASST90*	325	1,080	137	138	43	73	195	579	292
n	6	5	12	5	7	5	4	6	50

Notes: See Table 1 for variable definitions and sources.
*In $ millions.