Economic Quarterly— Volume 106, Number 1— First Quarter 2020— Pages 19–40

Technology Diffusion: The Case of Internet Banking

Richard Sullivan and Zhu Wang

New ideas, embodied in product and technology innovations, are fundamental driving forces for long-run growth. However, it often takes many years for an innovation to become widely adopted by the population, a process termed "diffusion." Moreover, the speed of diffusion is rarely constant. Rather, we typically observe diffusion curves that depict cumulative adoption over time to be S-shaped. To better understand the diffusion process, an extensive literature has been developed that seeks to explain how, why, and at what rate new ideas and technologies spread.

A large body of literature emphasizes the role played by communication of information (Rogers, 2003). One of the most popular theories focuses on *contagion*, or the so-called "word-of-mouth" effect, in which agents adopt innovations when they come in contact with others who have already adopted; in other words, innovations spread like epidemics. Two alternative but related theories are *social influence* and *social learning*, which attribute contagion to social forces such as conformity motive or belief updating. A common theme of these theories is that the diffusion process is driven by internal feedback effects from prior to future adopters (see, e.g. Young 2009 for an overview of the "internal diffusion" models). These models are particularly appealing for empirical uses because the internal feedback effect can be formalized as a differential equation that generates logistic diffusion curves (e.g., Griliches 1957, Mansfield 1961, Bass 1969, 2004).

In contrast, a competing view in the literature emphasizes agents' heterogeneity in terms of adoption costs and benefits (e.g., David 1969,

We thank Abigail Burns, Arantxa Jarque, Elliot Tobin, John Weinberg, and Russell Wong for helpful comments. The views expressed herein are solely those of the authors and do not necessarily reflect the views of the Federal Reserve Bank of Richmond or the Federal Reserve System.

Jovanovic and MacDonald 1994, Stoneman 2002). According to this view, diffusion lags are not necessarily explained by incomplete information. Rather, agents may have complete information and make adoption decisions based on their heterogeneous willingness to pay for the innovation. As a result, diffusion is driven mainly by *external* factors, such as price reduction or quality improvement, and diffusion curves can be S-shaped if the adoption thresholds of agents follow a positively skewed distribution.

In this paper, we incorporate and extend the ideas from the literature to study the diffusion of a recent technological innovation, internet banking. We consider that bank size follows a log-logistic distribution due to cost heterogeneity. Internet banking technology requires a fixed cost for adoption but reduces marginal cost of operation. As a result, when it is initially introduced, large banks enjoy advantages for adoption because of their size. Over time, due to external changes (e.g., demand shift, technological progress, and/or deregulation), the innovation gradually diffuses into smaller banks. This approach is consistent with the *external diffusion* view and predicts the timing of adoption by bank size that is consistent with the data. Moreover, this approach is able to generate a logistic diffusion curve that resembles those derived from the *internal diffusion* models. We test the theoretical hypothesis with an empirical study of internet banking diffusion among banks across fifty U.S. states. Using an instrument-variable approach, we identify a positive effect of average bank size on internet banking diffusion. The empirical findings also allow us to examine technological, economic, and institutional factors governing the diffusion process, and explain the variation in diffusion rates across geographic regions.

As mentioned above, our study is directly related to the literature on technology diffusion. In the banking context, several recent studies have looked at the internet and related technology adoption in the banking industry. For example, Hernández-Murillo et al. (2010) study a panel of commercial banks for 2003–2006 and show that banks adopt online banking earlier in markets where their competitors have already done so. DeYoung et al. (2007) study a sample of U.S. banks in the late 1990s. They find that branching intensity and online banking are complementary and online banking adoption positively affects the bank's future performance. Courchane et al. (2002) develop and estimate a model for early adoption of internet banking. They find that relative bank size and demographic information predictive of future demand positively influence internet banking adoption. Furst et al. (2001) estimate a logit model for internet banking adoption in a sample of national banks. They find that larger banks and banks that are younger and better-performing are more likely to adopt internet banking. However, unlike our paper, these studies focus more on individual banks' adoption decisions rather than the aggregate pattern of diffusion and bank-size distribution.[1]

The paper is organized as follows. Section 1 introduces industry background regarding the banking sector and internet banking diffusion. Section 2 describes the framework of our empirical study. Section 3 discusses our findings on internet banking diffusion among banks across fifty U.S. states. Section 4 concludes.

1. INDUSTRY BACKGROUND

In our study, internet banking is defined as a bank providing a website that allows customers to execute transactions on their accounts. In the United States, the history of internet banking can be traced back to 1995, when Wells Fargo first allowed its customers to access account balances online.[2] Since then, banks have steadily increased their online presence. Figure 1 plots the diffusion of internet banking among in-state banks from 2003 through 2007, before the start of the Great Recession.[3] In-state banks refer to commercial banks focusing on operating in a single state, which accounted for more than 90 percent of the U.S. banking population during this period.[4] The figure shows that 51.8 percent of in-state banks had adopted internet banking by 2003, and the ratio continued to rise to 81.5 percent in 2007. A similar diffusion pattern can be found if we instead consider all U.S. commercial banks. By 2003, 53 percent of all commercial banks had adopted transactional websites, and the ratio rose to 82 percent in 2007.

However, the diffusion pattern varies significantly across bank-size groups and geographic regions. First, looking across size groups, large banks appear to have an advantage over smaller ones in adopting the

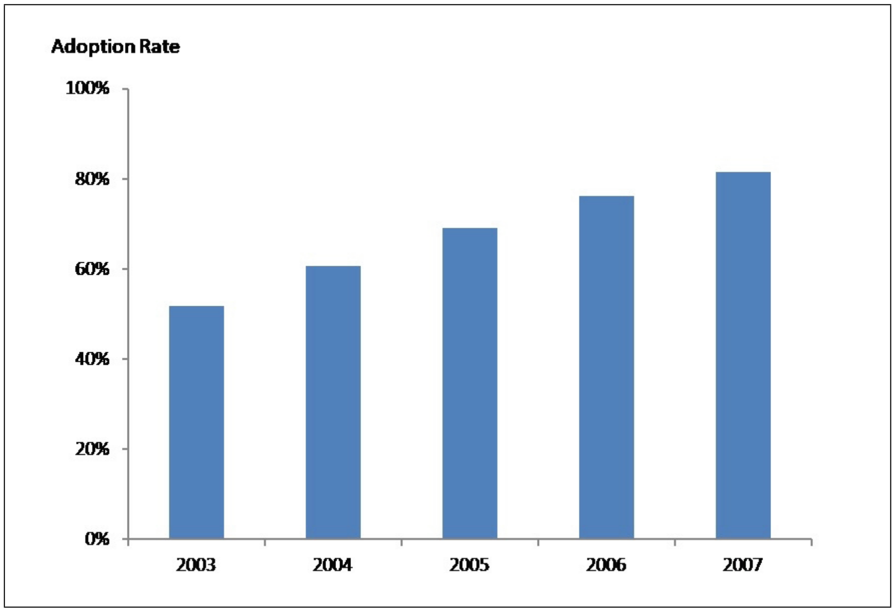
[1] Note that adoption and diffusion are two related but different terms used in the literature. Adoption typically refers to an individual process of adopting an innovation, while diffusion is a group phenomenon that refers to how an innovation spreads.

[2] Internet-only banks account for a very small fraction of the U.S. banking population (less than 0.5 percent even during the dot-com boom years). In this paper, we focus on the internet banking adoption among traditional brick-and-mortar banks. See Wang (2007) for an analysis of internet-only banks.

[3] Data source: call reports. Since 2003, depository institutions have been required to report whether their websites allow customers to execute transactions on their accounts. Our sample ends in 2007 because adoption had become almost universal by then and we also want to avoid the disruption of the Great Recession.

[4] More specifically, a bank is classified as an in-state bank if all its deposits are in the state of the bank's headquarters. As will become clear, focusing on this group of banks allows us to avoid the complications of interstate banking when measuring internet banking diffusion and bank size distribution by state. In 2003, there were 7,712 commercial banks in the United States, among which 7,183 were in-state banks (i.e., 93 percent).

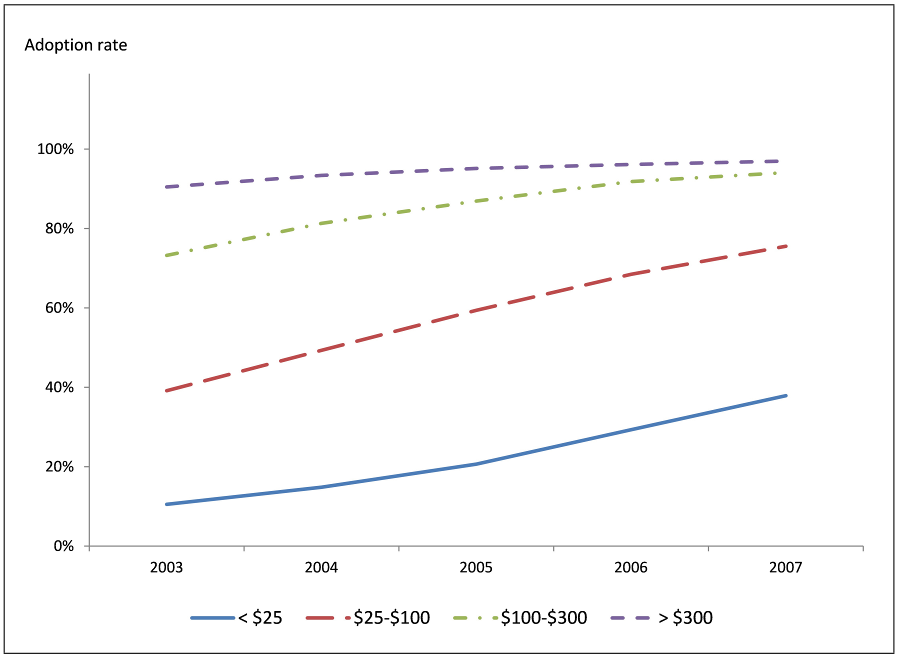
Figure 1 Internet Banking Diffusion



innovation. As shown in Figure 2, 90.5 percent of in-state banks with deposits over \$300 million reported that they had a transactional website in 2003, compared with only 10.5 percent of in-state banks with deposits under \$25 million. The variation is also striking across geographic regions. Figure 3 compares internet banking diffusion among in-state banks across U.S. states in 2003. The northeast and the west regions had the highest adoption rates (i.e., 65 percent to 85 percent in each state), while the central regions of the country had the lowest (i.e., 25 percent to 45 percent in each state). These observations raise important questions regarding technology diffusion: Why do large banks tend to be early adopters of the internet innovation? What determines the different diffusion rates across bank groups and geographic regions?

These observations and questions motivate our study. Conceptually, the benefits of internet banking can be viewed as twofold. First, it brings convenience to bank customers, allowing them to use services from banks at a distance and avoid hassles like traveling to ATMs or branches. Second, it generates substantial cost savings to banks. Most banking websites provide balance-transfer and bill-payments services, and some also process applications for deposits, loans, and credit

Figure 2 Internet Banking Adoption by Bank Size Group (Deposits in Millions)

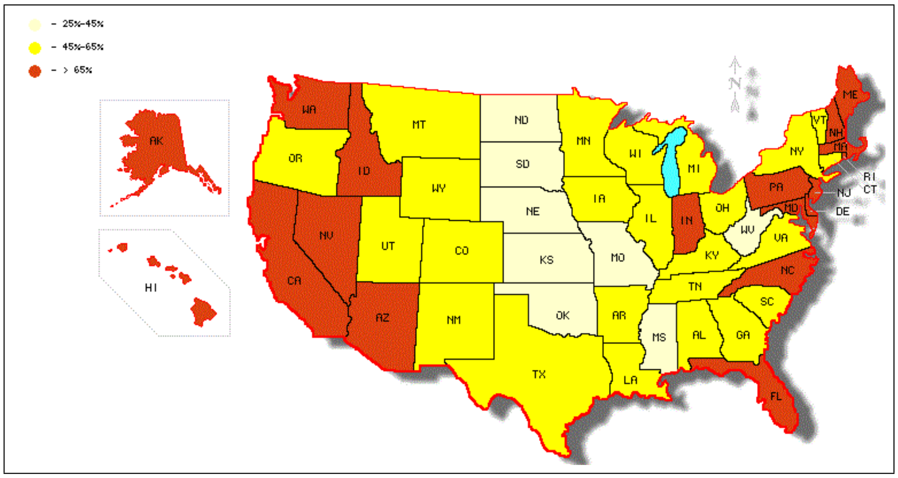


cards.[5] This allows banks to conduct standardized, low-value-added transactions through the online channel while focusing their resources on more specialized, high-value-added transactions (e.g., business lending, personal trust services, investment banking) through branches. In fact, the ratio of bank employees (and bank tellers) to deposits has been declining since the late 1990s.[6] This is consistent with continuous progress in information technology, including the increasing adoption of internet banking.

[5] For instance, a survey conducted by the Federal Reserve Bank of Kansas City shows that in the tenth Federal Reserve District, more than 70 percent of commercial bank websites provided balance-transfer and bill-payment services, and less than 20 percent allowed for online application for deposits, loans, or credit cards in 2006.

[6] From 1997 through 2007, the number of bank employees per million-dollar deposits fell from 0.44 to 0.24, and the number of bank tellers per million-dollar deposits fell from 0.14 to 0.09. (Data sources: Commercial bank employees and tellers are from the Bureau of Labor Statistics, and commercial bank deposits are from the Federal Deposit Insurance Corporation.)

Figure 3 Internet Banking Adoption by State (2003)



2. RESEARCH FRAMEWORK

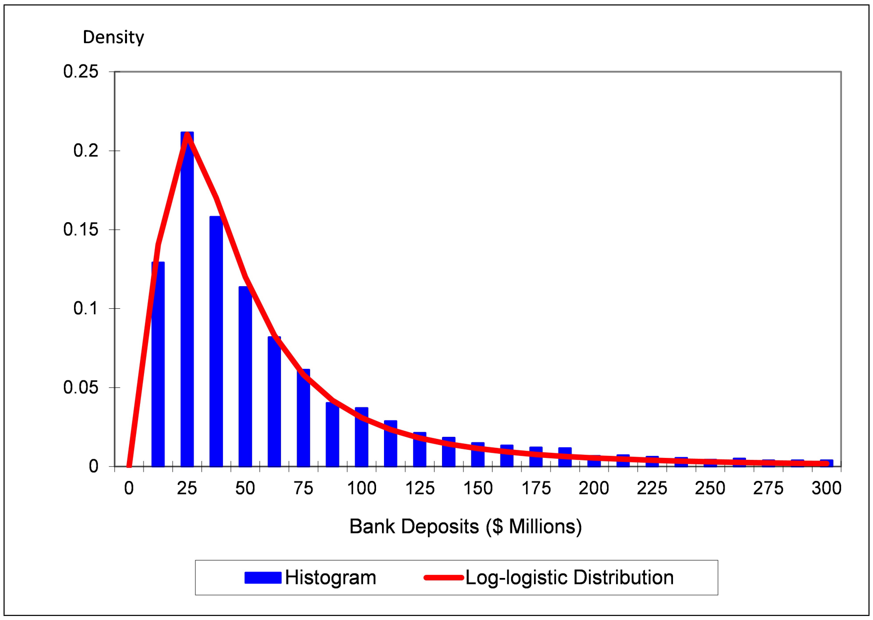
In this section, we describe the framework for our empirical study. The framework is built upon the theoretical model proposed by Sullivan and Wang (2017), which characterizes the relationship between bank-size distribution and internet banking diffusion.

Theoretical hypothesis

According to the theory of Sullivan and Wang (2017), the banking industry is composed of a continuum of banks that produce homogenous banking services and take prices as given. Banks are heterogeneous in productivity and their size follows a log-logistic distribution. As shown in Figure 4, the log-logistic distribution fits the banking industry data very well.

When internet banking technology is introduced, banks of different size need to make adoption decisions. Because the technology requires a fixed cost of adoption but reduces the marginal cost of banking operation, this pins down a threshold size of adoption. As a result, large banks have an advantage adopting the new technology. Over time, as the deep model parameters (e.g., consumer willingness to pay for banking services, average bank productivity, cost savings due to internet banking adoption, and adoption costs of internet banking) change, the technology diffuses into smaller banks. Particularly, given that the

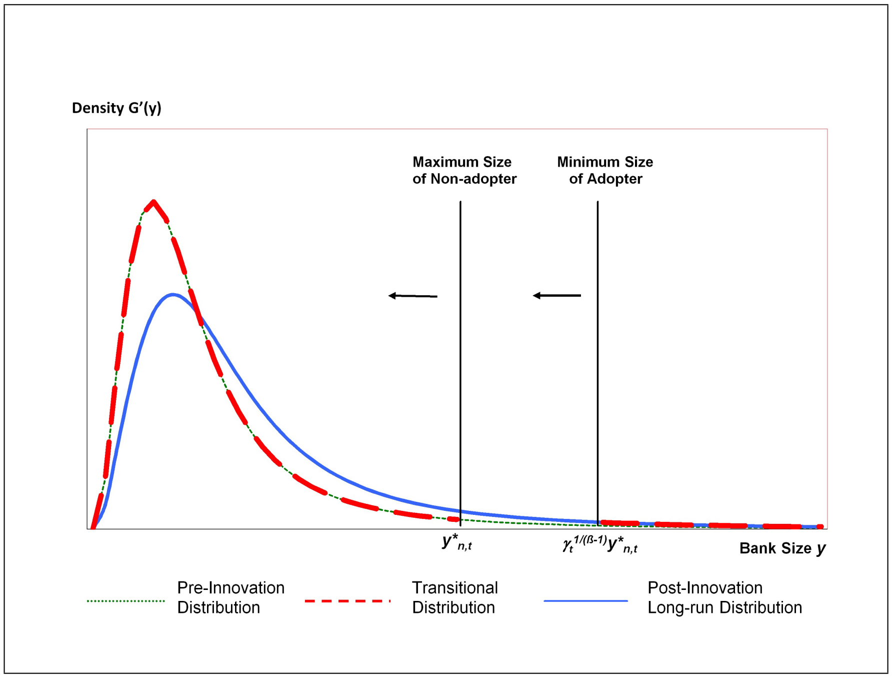
Figure 4 Bank-Size Distribution (In-State Banks 1990)



bank-size distribution follows a log-logistic distribution, as long as those deep model parameters have approximately linear time trends, the diffusion path of internet banking would follow a logistic curve, a path well documented in the technology diffusion literature (e.g., Griliches 1957, Mansfield 1961, Bass 1969, 2004).

Figure 5 illustrates the industry dynamic path. Before internet banking is introduced, the banking industry stays at a log-logistic size distribution, drawn with a dotted line. After internet banking becomes available, in the long run, the banking industry converges to a post-innovation, long-run size distribution (which again is log-logistic), drawn with a solid line. In between, the bank-size distribution is on a transitional path, drawn with a dashed line. At a given time t during the transition, a bank can always compare two options: adopting internet banking or not. Under each option, the size of the bank is denoted as $y_{a,t}$ or $y_{n,t}$. There is a size threshold $y^*_{n,t}$ at time t, which splits the pre-innovation size distribution. For banks with size $y_{n,t} \geq y^*_{n,t}$, the size distribution resembles the post-innovation, long-run distribution in the range $y_{a,t} \in [\gamma_t^{\frac{1}{\beta-1}} y^*_{n,t}, \infty)$, so $\gamma_t^{\frac{1}{\beta-1}} y^*_{n,t}$ is the minimum size of adopters (Note that, as explained in Sullivan and Wang 2017, $\gamma > 1$ is

Figure 5 Illustration of the Industry Dynamics



the cost-saving parameter associated with adopting the innovation and $1 > \beta > 0$ is the cost elasticity in banks' production function). Meanwhile, for banks with size $y_{n,t} < y^*_{n,t}$, the size distribution resembles the pre-innovation one, so $y^*_{n,t}$ is the maximum size of non-adopters. Over time, $y^*_{n,t}$ and $\gamma_t^{\frac{1}{\beta-1}} y^*_{n,t}$ fall due to external changes (e.g., demand shift, technological progress, and/or 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.

Empirical specification

The focus of this article is to test the theoretical hypothesis with an empirical study on internet banking diffusion. The sample that we consider includes all in-state banks in each of the fifty U.S. states from 2003 through 2007. Focusing on in-state banks allows us to avoid the complications of interstate banking when measuring internet banking diffusion and bank-size distribution at the state level.[7]

The theory in Sullivan and Wang (2017) shows that the diffusion of internet banking is characterized by two jointly determined endogenous variables: aggregate internet banking adoption rate and average bank size. According to the theory, using state-level data (where each state is indexed by j and each year is indexed by t), the aggregate adoption of internet banking, adjusted by the Gini coefficient of bank-size distribution, can be specified as

$$g_{j,t}\ln(\frac{F_{j,t}}{1-F_{j,t}}) = a_0 + a_1\ln(E(y)_{j,t}) + \sum_i a_i \ln(X_{i,j,t}) + \varepsilon_{j,t}, \qquad (1)$$

- F is the aggregate adoption rate of internet banking.
- g is the Gini coefficient of bank-size distribution.
- $E(y)$ is the average bank size.
- X denotes other explanatory variables.
- ε is an i.i.d. random error.

To estimate the equation, we need to collect empirical variables. Moreover, given the endogeneity of average bank size $E(y)$, we need to use instrument variables to correctly identify the effect of average bank size on internet banking diffusion. The instrument variables are supposed to only affect internet banking diffusion through average bank size.

Below is a list of the empirical variables used in our estimation. (See Tables 4 and 5 in the Appendix for the data sources and summary statistics.) For most of these variables, we take the log transformation and prefix the variables with “ln” in the notation.

The dependent variable (a measure of internet banking diffusion):

lnTRANODDS_GINI – Log odds ratio for the internet banking adoption rate adjusted by the Gini coefficient, constructed using two variables: TRANS – Adoption rate for transactional websites, and GINI – Gini coefficient for bank deposits.

An endogenous explanatory variable (a measure of average bank size):

[7] While our empirical study does not directly consider interstate banks, we include the out-of-state bank presence in the in-state banking market as a regressor to control for the demand for the services of in-state banks.

lnDEPOSITS – Log average bank size, constructed by the variable DEPOSITS – Average bank deposits.[8]

We then consider two groups of explanatory variables in X and a set of instrument variables I, listed as follows.

Variables in X that affect both internet banking diffusion and bank size:

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

LOANSPEC – Specialization of lending to consumers.[9]

OFF_DEP – Bank offices per value of deposits.

RMEDFAMINC – Real median family income in 1967 dollars.

POPDEN – Population density.

AGE – Average age of banks.

HHINET – Household internet access rate.

WAGERATIO – Ratio of computer analyst wage to teller wage.

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

DEPINT – Ratio of deposits in out-of-state banks to total deposits.

REGION and YEAR – Dummies.[10]

Variables in X that only affect internet banking diffusion:[11]

IMITATE – Years since the first bank in the state adopted a transactional website.

COMRATE – Adoption rate of high-speed internet among commercial firms in 2003, calculated as an average of urban firms' and rural firms' internet adoption using METRO to weight urban and rural location. Essentially, COMRATE measures in-state banks' exposure to other commercial firms' internet adoption in each state.

Instrument variables in I that only affect average bank size:

DEPOSITS90 – Average bank deposits in 1990.

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

Some variables in X affect both internet banking diffusion and average bank size. Take HHINET for example: if more households have access to the internet, local banks may get more cost savings from adopting internet banking. However, internet access also allows households to reach nonlocal banking services (e.g., out-of-state banks), which may then lower demand and consumer willingness to pay for local banking services. AGE is another example: established banks typically achieve

[8] Note that the empirical results would have been similar if we had used bank assets as an alternative measure of bank size.

[9] Defined by consumer loans plus 1-4 family mortgages divided by total loans.

[10] Regional dummies refer to eight geographic areas defined by the Bureau of Economic Analysis.

[11] Sullivan and Wang (2017) show that these variables can serve as instruments to estimate the effects of internet banking adoption on average bank size.

higher productivity, so they may enjoy a large size. However, established banks may also face a higher internet banking adoption cost compared to young banks given that they have to adapt internet banking to their legacy computer systems.

We also consider two variables that only directly affect internet banking diffusion but not average bank size: the number of years since the first bank in the state adopted a transactional website (IMITATE) and internet adoption rate among commercial firms in the state (COMRATE). The former variable, IMITATE, is from the *Online Banking Report*, a publication keeping track of the development of internet banking. The data suggest that the first wave of internet banking was largely driven by exogenous factors (such as entrepreneurs' risk-taking experiments) rather than cost-benefit calculations assumed in our model. In fact, the correlation between a state's first internet banking adoption (measured by IMITATE in 2003) and the average bank size in 1990 is -0.001. To some extent, this variable may capture the contagion effect suggested by the *internal diffusion* models, but we could also think that a higher value of IMITATE may reduce internet banking adoption costs by providing more local expertise on bank-specific website design and performance. The latter variable, COMRATE, is constructed based on the information provided by Forman et al. (2003). The effect of COMRATE might be ambiguous in theory. On the one hand, a higher value of COMRATE may help internet banking diffusion through an imitation effect. On the other hand, it may delay internet banking diffusion by competing away resources and pushing up local costs of internet installation and operation. Therefore, we will rely on our empirical estimation to evaluate the overall effect of COMRATE.

The two instrument variables we include in I are intuitive: a dummy variable for whether the state had intrastate branching restrictions after 1995 (INTRAREG) and average bank deposits in 1990 (DEPOSITS90). The former value is from Kroszner and Strahan (1999), and the latter is from the call reports. Both variables are expected to affect internet banking diffusion only through their effects on average bank size: INTRAREG may negatively affect the average bank size by imposing high regulation costs; DEPOSITS90 may be positively correlated with current average bank size through the persistence of underlying productivity variables.

3. EMPIRICAL FINDINGS

Our following discussions focus on the estimation results based on a 2SLS (two-stage least squares) model. In the first stage, we regress the average bank size (lnDEPOSITS) on all the exogenous variables listed in groups X and I. In the second stage, we then use the fitted value of (lnDEPOSITS) instead of the actual value to estimate equation (1). Both the first-stage and the second-stage results are reported in Tables 1 and 2. For comparison, we also include the OLS result.

Model validation

The 2SLS results suggest that the instrument variables we use are valid. In the first-stage average bank-size regression, the coefficients on INTRAREG and lnDEPOSITS90 have the expected signs and lnDEPOSITS90 is statistically significant. The relevance of the instruments is also confirmed by the F-test. As a rule of thumb, the F-statistic of a joint test where all excluded instruments are significant should be bigger than ten in case of a single endogenous regressor. As shown in Table 1, this is satisfied in our regression. Moreover, because we have two instruments for each endogenous variable, we can perform the overidentification test. This test checks whether both instruments are exogenous assuming that at least one of the instruments is exogenous. As shown in Table 1, the χ^2 statistics show that we cannot reject the null hypothesis that our instruments are exogenous.

We also test whether the 2SLS estimates are statistically different from the OLS estimates. The is done by rerunning second-stage regressions where the residuals from the first-stage regressions are included (Wooldridge 2010, Chapter 5).[12] This test is robust to heteroscedasticity given that the robust variance estimator is used. The results show that the coefficient of the first-stage residual is statistically significant, which confirms that instrumenting matters for the estimation.

Economic findings

We now turn to the economic findings based on the second-stage estimation results shown in Tables 1 and 2. The model fits the data well, with an R^2 of 0.75. Most signs of estimated coefficients, and all of those that are statistically significant, are consistent with the theoretical predictions. The findings are summarized as follows.

The coefficient on the fitted value of lnDEPOSITS is positive and statistically significant. The finding supports our theoretical hypothesis that average bank size has a positive causal effect on internet banking diffusion. Quantitatively, considering a Gini coefficient equal to

[12] An alternative is to run the Hausman test, but the Hausman test is only valid under homoscedasticity and involves the cumbersome generalized inversion of a nonsingular matrix.

Table 1 Estimation of Internet Banking Adoption (Dependent Varable: lnTRANODDS GINI)

	2SLS		**OLS**	**Reduced**
	First Stage	*Second Stage*		**Form**
lnDEPOSITS		0.5716	0.2467	
		(0.0848)***	(0.0436)***	
lnIMITATE	0.3933	0.1135	0.1915	0.3384
	(0.2848)	(0.1754)	(0.1530)	(0.1506)**
lnCOMRATE	-4.9335	-0.9002	-2.0247	-3.7200
	(1.0055)***	(0.9023)	(0.7779)***	(0.7026)***
INTRAREG	-0.1001			-0.0574
	(0.0764)			(0.0493)
lnDEPOSITS90	0.4572			0.2613
	(0.0694)***			(0.0463)***
lnMETRO	0.7520	0.1060	0.3926	0.5357
	(0.2166)***	(0.1636)	(0.1280)***	(0.1231)***
lnLOANSPEC	0.3773	-0.0837	0.0511	0.1319
	(0.2138)*	(0.1441)	(0.1205)	(0.1191)
lnRMEDFAMINC	0.2582	-0.5276	-0.4229	-0.3799
	(0.5425)	(0.3653)	(0.3247)	(0.3451)
lnPOPDEN	0.0994	-0.1059	-0.0844	-0.0490
	(0.0681)	(0.0426)**	(0.0324)***	(0.0329)
lnAGE	0.2163	-0.3449	-0.3696	-0.2213
	(0.1581)	(0.1063)***	(0.0928)***	(0.0872)**
lnHHINET	1.0941	1.6906	1.7774	2.3160
	(0.6718)	(0.3598)***	(0.3507)***	(0.3779)***
lnBHC	1.9964	0.0764	0.5697	1.2176
	(0.4520)***	(0.2211)	(0.1616)***	(0.1804)***
lnWGRATIO	-0.5468	0.0033	-0.1073	-0.3093
	(0.3983)	(0.2575)	(0.2257)	(0.2177)
lnDEPINT	-0.1557	0.0949	0.0487	0.0059
	(0.0477)***	(0.0327)***	(0.0281)*	(0.0342)
lnOFF_DEP	-0.3453	0.3009	0.1244	0.1035
	(0.1175)***	(0.0851)***	(0.0629)**	(0.0762)
Constant	-1.2171	-8.2948	-5.8434	-8.9911
	(2.3079)	(1.3169)***	(1.1062)***	(1.3336)***
Adjusted R^2	0.78	0.75	0.82	0.83
N	227	227	227	227
Weak Instrument Test: F(2,201)†	18.45			
Exogeneity of Regressors-Wald Test		-4.52***		
Overidentification Test: Chi2(1)		0.00		

0.57 (the average value in 2003), the results imply that holding everything else constant, a 10 percent increase in average bank size would

Table 2 Estimation of Internet Banking Adoption (cont'd)

	2SLS		OLS	Reduced
	First Stage	*Second Stage*		Form
d2004	-0.0636	0.1431	0.1362	0.1068
	(0.0975)	(0.0578)**	(0.0482)***	(0.0477)**
d2005	-0.0383	0.2627	0.2750	0.2408
	(0.1251)	(0.0779)***	(0.0658)***	(0.0666)***
d2006	-0.1251	0.4232	0.4246	0.3517
	(0.1502)	(0.0911)***	(0.0820)***	(0.0883)***
d2007	-0.1317	0.5446	0.5507	0.4693
	(0.1764)	(0.1061)***	(0.0980)***	(0.1030)***
Southeast	0.2575	-0.0623	0.0847	0.0849
	(0.1378)*	(0.1010)	(0.0850)	(0.0866)
Far West	0.9697	-0.4340	-0.0500	0.1203
	(0.1666)***	(0.1534)***	(0.1094)	(0.0907)
Rocky Mtn	0.3365	-0.2374	-0.1454	-0.0450
	(0.1515)**	(0.0877)***	(0.0712)**	(0.0790)
Southwest	0.3933	-0.0688	0.0829	0.1561
	(0.1335)***	(0.0898)	(0.0796)	(0.0942)*
NE	0.3811	-0.2810	0.0842	-0.0632
	(0.2509)	(0.1406)**	(0.1112)	(0.1314)
Mideast	-0.3424	0.0647	0.2995	-0.1308
	(0.2099)	(0.1527)	(0.1223)**	(0.1582)
Great Lakes	-0.3125	0.1196	0.1716	-0.0590
	(0.1332)**	(0.0871)	(0.0731)**	(0.0700)

Notes: Equations are estimated using two-stage least-squares for the time period 2003 through 2007. Robust standard errors are in parentheses. Estimated coefficients for other variables in the model equations are in Table 1. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

increase the adoption odds ratio by about 10 percent. To put things into perspective, we consider a case where the internet adoption rate is 56.4 percent and the average bank deposits are $311 million, which are mean values of the 2003 data. Therefore, based on the 2003 data, a one-standard-deviation increase of average bank deposits from the mean would increase the internet banking adoption rate from 56.4 percent to 77.1 percent.[13] The finding is in sharp contrast with the OLS regression result. Without addressing the endogeneity of regressors, the OLS results underestimate the impact of average bank size on internet banking diffusion by more than a half.

[13] This is calculated by solving F, where $0.57 \times [\ln(\frac{F}{1-F}) - \ln(\frac{0.564}{1-0.564})] = 0.5716 \times [\ln(311 + 496) - \ln(311)]$.

We also find that population density (lnPOPDEN) has a significant effect on internet banking diffusion. The effect is negative, suggesting a higher demand for internet banking in locations with higher cost of travel to bank branches. The average bank age in a state (lnAGE) shows a negative effect, which implies that as the average age of a state's banks increases, the adoption rate falls. This results is consistent with previous findings that *de novo* banks were more likely to adopt internet banking than incumbent banks (Furst et al. 2001). New banks may find it cheaper to install internet banking technology in a package with other computer facilities compared with older banks that must add internet banking to legacy computer systems. Household access to the internet (lnHHINET) is also statistically significant, and greater household access to the internet is associated with a higher adoption of internet banking. Competition from out-of-state banks (lnDEPINT) has a positive coefficient, suggesting that more deposits in out-of-state banks push more in-state banks to adopt internet banking (possibly in order to compete for business). We also find that bank offices per value of deposits (lnOFF_DEP) is statistically significant. The positive coefficient implies that banks with more offices may try to explore the synergy between branch banking and internet banking.[14]

Finally, all the year dummies are statistically significant. This suggests that after controlling for the other explanatory variables, there is a positive year trend for internet banking diffusion. In contrast, most regional dummies are not significant or have a negative sign, in comparison with the excluded Plains states, which have the lowest internet banking adoption. This suggests that the observed cross-region differences of internet banking adoption rates are mainly driven by the other explanatory variables in our model rather than the remaining regional fixed effects. We will discuss this further below.

Regional variations

Our empirical study identifies a positive effect of average bank size on internet banking diffusion. As explained by the theory, this is because large (more efficient) banks enjoy scale economies of adoption. Moreover, our empirical study can help explain the variation in internet banking diffusion across geographic regions. Particularly, why do the northeast and the west regions have the highest adoption rates, while the central regions have the lowest (see Figure 3)?

[14] This finding is consistent with optimization of branch network size that encompasses both branch-based and non-branch-based activities (Hirtle, 2007).

Table 3 Mean Values of Selected Variables by Region (Far West, Plains, and New England 2003)*

Variables	Effect on IB	Far West	Plains	New England
TRANS		0.71	0.43	0.67
GINI		0.59	0.60	0.50
DEPOSITS90	+	217.9	37.5	289.9
IMITATE	+	5.80	6.71	6.40
HHINET	+	0.61	0.55	0.60
METRO	+	0.95	0.51	0.79
BHC	+	0.66	0.87	0.62
COMRATE	−	0.90	0.90	0.88
AGE	−	25.6	81.6	68.1

*Far West includes AK, CA, HI, NV, OR, and WA; Plains includes IA, KS, MN, MO, NE, ND, and SD; New England includes CT, MA, ME, NH, RI, and VT.

In order to answer the question, we run a reduced-from regression in which the dependent variable (lnTRANODDS_GINI) is regressed on all the exogenous variables listed in groups X and I. In doing so, we bypass the endogenous variable of average bank size, and measure the overall effect of each exogenous variable on internet banking diffusion (i.e., by taking into account their direct effects on internet banking diffusion and indirect effects through average bank size). The results are also reported in Tables 1 and 2. In Table 3, we present regional averages of variables that are found to significantly affect internet banking diffusion in the reduced-form regression. Far West, Plains, and New England are used to represent the west, central and northeast regions respectively. As shown, the Plains region had a similar Gini coefficient of bank size in 2003 as the Far West and New England, but the internet banking adoption rate was much lower. Compared with the other two regions, we find that the Plains region has smaller initial bank size, lower household internet access, fewer banks in metro markets, and older bank vintages. Based on the coefficients (marginal effects) that we uncovered from the reduced-form regression, we conclude that these are the factors that have contributed to slow diffusion of internet banking in the Plains region. On the other hand, our findings reject several alternative hypotheses that may have seemed appealing, including imitation of early adopters, internet adoption of commercial firms, and bank holding company membership. In fact, some of those would have been the Plains region's advantages for adoption.

We also rule out several other factors that are only found to significantly affect internet banking diffusion in the second stage of our 2SLS regression, such as deposits held in out-of-state banks, population density, and bank offices per value of deposits. This is because those factors have opposite effects on the average bank size (see Sullivan and Wang, 2017). Therefore, their overall effects on internet banking diffusion become insignificant in the reduced-form regression where the interaction effects between internet banking diffusion and average bank size are taken into account.

Internal *versus* external diffusion

Our empirical analysis sheds light on the debate regarding internal and external diffusion models. The classic internal diffusion models (e.g., Griliches 1957, Mansfield 1961, Bass 1969, 2004) typically assume that the hazard rate of adoption increases with cumulative adoption due to contagion or the "word-of-mouth" effect:

$$\frac{dF_t/dt}{1-F_t} = vF_t,$$

where F_t is the fraction of potential adopters who have adopted the innovation at time t, and v is a constant contagion parameter. Solving this first-order differential equation yields the logistic function

$$F_t = \frac{1}{1+(\frac{1}{F_0}-1)e^{-vt}},$$

which implies that one could use our state-level internet banking diffusion data to estimate a simple log-linear equation:

$$\ln(\frac{F_{j,t}}{1-F_{j,t}}) = a_j + v_j t, \tag{2}$$

where $a_j = \ln(\frac{F_{j,0}}{1-F_{j,0}})$.

Comparing with the regression model (1) used above, model (2) suggests that the diffusion process in a state j can now be explained by two state-specific parameters: the initial condition a_j and the contagion rate v_j. Such a model predicts an S-shaped logistic diffusion curve, which could serve as a convenient tool for data fitting or forecasting. However, it is difficult to explore deeper economic questions beyond that, for example, why the contagion rate, or the "word-of-mouth" effect, differs across regions, and why large banks rather than small banks tend to be the early adopters.

In contrast, the external-diffusion approach we take in this paper provides a better micro-founded explanation. By modeling explicitly the size heterogeneity of banks, we keep the appealing feature of S-shaped logistic diffusion curves but connect them to more meaningful economic factors. Our empirical findings, besides providing good fitting of the data, offer several additional insights:

- First, employing instrument variables in the estimation confirms the causal effect of firm-size distribution on technology diffusion, which justifies the external-diffusion approach we take.

- Second, the variation in diffusion rates across regions can be well explained by underlying technological, economic, and institutional factors. We find that, after controlling for those variables in the regressions, regional dummies are left with little explanatory power.

- Finally, technology diffusion and firm-size distribution are jointly determined, so they should not be treated exogenously to each other. As our results show, without addressing the endogeneity problem, the OLS regression results can be significantly biased.

4. CONCLUSION

Taking internet banking as an example, we study diffusion of cost-saving technological innovations. When such an innovation is initially introduced, large firms enjoy adoption advantages. Over time, due to external changes (e.g., demand shift, technological progress, and/or deregulation), the innovation gradually diffuses into smaller firms. As a result, the firm-size distribution shifts, and the technology diffusion follows an S-shaped logistic curve.

We test the theoretical hypothesis with an empirical study of internet banking diffusion among banks across fifty U.S. states. Using an instrument variable approach, we identify a positive effect of average bank size on internet banking diffusion. The empirical findings also allow us to examine technological, economic, and institutional factors governing the diffusion process and explain the variation in diffusion rates across geographic regions.

REFERENCES

Bass, Frank M. 1969. "A New Product Growth for Model Consumer Durables." *Management Science* 15 (January): 215–227.

Bass, Frank M. 2004. "Comments on 'A New Product Growth for Model Consumer Durables The Bass Model.'" *Management Science* 50 (December): 1833–40.

Courchane, Marsha, David Nickerson, and Richard J. Sullivan. 2002. "Investment in Internet Banking as a Real Option: Theory and Tests." *Journal of Multinational Financial Management* 12 (October-December): 347–63.

David, Paul A. 1969. "A Contribution to the Theory of Diffusion." Stanford University Research Center in Economic Growth Memorandum 71.

DeYoung, Robert, William W. Lang, and Daniel L. Nolle. 2007. "How the Internet Affects Output and Performance at Community Banks." *Journal of Banking and Finance* 31 (April): 1033–60.

Forman, Chris, Avi Goldfarb, and Shane Greenstein. 2003. "The Geographic Dispersion of Commercial Internet Use." In *Rethinking Rights and Regulations: Institutional Responses to New Communication Technologies*, edited by Lorrie Faith Cranor and Steven S. Wildman. Cambridge, Mass.: MIT Press, 113–45.

Furst, Karen, William W. Lang, and Daniel E. Nolle. 2001. "Internet Banking in the U.S.: Landscape, Prospects, and Industry Implications." *Capco Institute Journal of Financial Transformation* 2 (July): 45–52.

Griliches, Zvi. 1957. "Hybrid Corn: An Exploration in the Economics of Technological Change." *Econometrica* 25 (October): 501–22.

Hernández-Murillo, Rubén, Gerard Llobet, and Roberto Fuentes. 2010. "Strategic Online Banking Adoption." *Journal of Banking and Finance* 34 (July): 1650–63.

Hirtle, Beverly. 2007. "The Impact of Network Size on Bank Branch Performance." *Journal of Banking and Finance* 31 (December): 3782–805.

Jovanovic, Boyan, and Glenn M. MacDonald. 1994. "Competitive Diffusion." *Journal of Political Economy* 102 (February): 24–52.

Kroszner, Randall S., and Philip E. Strahan. 1999. "What Drives Deregulation? Economics and Politics of the Relaxation of

Banking Branching Restrictions." *Quarterly Journal of Economics* 114 (November): 1437–67.

Mansfield, Edwin. 1961. "Technical Change and the Rate of Innovation." *Econometrica* 29 (October): 741–66.

Rogers, Everett M. 2003. *Diffusion of Innovations*, 5th ed. New York: Free Press.

Stoneman, Paul. 2002. *The Economics of Technological Diffusion.* Oxford, England: Blackwell Publishers.

Sullivan, Richard, and Zhu Wang. 2017. "Internet Banking: An Exploration in Technology Diffusion and Impact," Federal Reserve Bank of Richmond Working Paper No. 13-10R, revised November 2017.

Wang, Zhu. 2007. "Technological Innovation and Market Turbulence: The Dot-com Experience." *Review of Economic Dynamics* 10 (January): 78–105.

Wooldridge, Jeffrey M. 2010. *Econometric Analysis of Cross Section and Panel Data*, 2nd ed. Cambridge, Mass.: MIT Press.

Young, H. Peyton. 2009. "Innovation Diffusion in Heterogeneous Populations: Contagion, Social Influence, and Social Learning." *American Economic Review* 99 (December): 1899–1924.

APPENDIX

Table 4 Summary Statistics

	2003				2005				2007			
VARIABLE	*Mean*	*S. D.*	*Min*	*Max*	*Mean*	*S. D.*	*Min*	*Max*	*Mean*	*S. D.*	*Min*	*Max*
TRANS	0.564	0.136	0.263	0.852	0.729	0.121	0.456	0.949	0.830	0.095	0.624	0.978
TRANODDS	1.588	1.063	0.357	5.750	3.880	3.474	0.837	18.501	7.888	7.930	1.659	44.004
GINI	0.574	0.122	0.338	0.847	0.568	0.119	0.325	0.862	0.583	0.117	0.305	0.908
DEPOSITS*	$311	$496	$65	$3,307	$406	$783	$67	$4,028	$486	$970	$71	$5,057
METRO	0.741	0.187	0.295	1.000	0.741	0.184	0.300	1.000	0.737	0.185	0.298	1.000
LOANSPEC	0.373	0.121	0.144	0.608	0.351	0.122	0.137	0.581	0.333	0.124	0.102	0.574
OFF_DEP	0.023	0.008	0.003	0.037	0.021	0.008	0.003	0.034	0.020	0.008	0.003	0.031
RMEDFAMINC**	$93.5	$13.9	$70.0	$126.9	$93.6	$13.9	$70.0	$129.2	$95.3	$12.6	$72.1	$131.1
POPDEN	148.0	179.6	1.1	821.4	153.4	181.5	5.2	820.6	148.9	175.8	5.4	822.7
IMITATE	6.745	1.132	4.000	9.000	8.783	1.114	6.000	11.000	10.791	1.103	8.000	13.000
AGE	58.7	23.2	6.7	111.7	59.2	23.9	7.4	112.5	60.4	25.6	5.8	121.5
HHINET	54.4	6.2	38.9	67.6	57.6	6.1	42.4	70.1	60.7	6.2	46.0	71.6
WGRATIO	3.035	0.238	2.417	3.396	3.056	0.218	2.689	3.497	3.049	0.268	2.230	3.572
INTRAREG	0.234	0.428	0.000	1.000	0.239	0.431	0.000	1.000	0.256	0.441	0.000	1.000
BHC	0.776	0.118	0.444	0.931	0.792	0.121	0.429	0.937	0.808	0.110	0.579	0.940
DEPINT	0.283	0.185	0.002	0.741	0.351	0.197	0.005	0.843	0.341	0.192	0.020	0.831
COMRATE	0.889	0.026	0.778	0.921	0.889	0.026	0.777	0.922	0.889	0.027	0.776	0.922
DEPOSITS90*	$207	$365	$26	$2.393	$207	$369	$26	$2,393	$209	$382	$26	$2,393
SE	0.255	0.441	0	1	0.261	0.444	0	1	0.279	0.454	0	1
FARWEST	0.106	0.312	0	1	0.087	0.285	0	1	0.093	0.294	0	1
ROCKYMTN	0.106	0.312	0	1	0.109	0.315	0	1	0.093	0.294	0	1
SW	0.085	0.282	0	1	0.087	0.285	0	1	0.093	0.294	0	1
NWENGLND	0.106	0.312	0	1	0.109	0.315	0	1	0.093	0.294	0	1
MIDEAST	0.085	0.282	0	1	0.087	0.285	0	1	0.070	0.258	0	1
GRTLAKE	0.106	0.312	0	1	0.109	0.315	0	1	0.116	0.324	0	1
PLAINS	0.149	0.360	0	1	0.152	0.363	0	1	0.163	0.374	0	1

Notes: Sample population includes the fifty states in the U.S. and the District of Columbia. The sample size varies from year to year because the transactional website adoption rate reached 100 percent for some observations and TRANODDS cannot be calculated. The actual sample size in 2003, 2005, and 2007 is 47, 46, and 43, respectively. See Table 1 for variable definitions and sources. *In millions. **In thousands

Table 5 Empirical Variable Definitions and Sources

Variable	Definition	Source
TRANS	Adoption rate for transactional websites	Call reports
TRANODDS	Odds ratio for adoption of transactional websites	Call reports
GINI	Gini coefficient for bank deposits	Call reports
DEPOSITS	Average bank deposits	Call reports
METRO	Ratio of banks in metropolitan areas to all banks	Call reports
LOANSPEC	Specialization of lending to consumers (consumer loans plus 1-4 family mortgages divided by total loans)	Call reports
OFF_DEP	Bank offices per value of deposits	Call reports; FDIC *Summary of Deposits*
RMEDFAMINC	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 reports
HHINET	Household access rate for internet	*Statistical Abstract of the United States*
WGRATIO	Ratio of computer analyst wage to teller wage	BLS
INTRAREG	Indicator variable for whether the state had branching restrictions after 1995	Kroszner and Strahan (1999)
BHC	Ratio of banks in bank holding companies to total banks	Call reports
DEPINT	Ratio of deposits in out-of-state banks to total deposits	FDIC *Summary of Deposits*
COMRATE	Adoption rate of high-speed internet among commercial firms	Forman et al., 2003
DEPOSITS90	Average bank deposits in 1990	Call reports

Regional Dummy Variables from the BLS are as follows:
(SE): AL, AR, FL, GA, KY, LA, MS, NC, SC, TN, VA, WV.
(FARWEST): AK, CA, HI, NV, OR, WA. (ROCKYMTN): CO, ID, MT, UT, WY.
(PLAINS): IA, KS, MN, MO, NE ,ND, SD. (SW): AZ, NM, OK, TX.
(GRTLAKE): IL, IN, MI, OH, WI. (MIDEAST): DC, DE, MD, NJ, NY, PA.
(NWENGLND): CT, MA, ME, NH, RI, VT.

Notes: Data are for individual states. Variables for banks are unweighted averages for those located in individual states. Selected banks are full-service, retail commercial banks. Data for adoption of high-speed internet among commercial firms is for 2003. COMRATE is an average of urban firms' and rural firms' internet adoption, using METRO to weight urban and rural location. BEA Regions are a set of geographic areas that are aggregations of the states. 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. For a brief description of the regional classification of states used by BEA, see U.S. Census Bureau, Geographic Areas Reference Manual, Washington, D.C., U.S. Government Printing Office, November 1994, pp. 6–19.