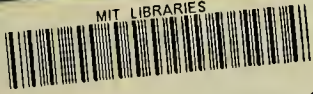



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ADOPTION OF TECHNOLOGIES WITH NETWORK
EFFECTS: An Empirical Examination of the
Adoption of Automated Teller Machines

Garth Saloner
and
Andrea Shepard

No. 577

April 1991

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An Empirical Examination of the Adoption of Automated Teller Machines***

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Current Version: April 9, 1991

ABSTRACT

The literature on networks suggests that the value of a network is positively affected by the number of geographically dispersed locations it serves (the “network effect”) and the number of its users (the “production scale effect”). We show that as a result a firm’s expected time until adoption of technologies with network effects declines in both users and locations. We provide empirical evidence on the adoption of automated teller machines by banks that is consistent with this prediction. Using standard duration models, we find that a bank’s date of adoption is decreasing in the number of its branches (a proxy for the number of locations and hence for the network effect) and the value of its deposits (a proxy for number of users and hence for production scale economies). The network effect is the larger of the two effects.

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1. Introduction

With the proliferation of information technology over the past several decades, networks have become increasingly important. Examples include banks' automated teller machines, airlines' customer reservation systems, and the growing network of facsimile machines. In such networks, the value to each individual or firm of participating increases with network size. Network effects, and demand-side economies of scale more generally, have been shown in theory to have implications for a variety of important economic activities including technology adoption, predatory pricing, and product preannouncements.¹ There have not, however, been any attempts to test econometrically for the effects of networks on these phenomena.² In this paper we construct and apply a test for network effects on the adoption by banks of automated teller machines (ATMs).

For telephone systems, which are perhaps the best known example of a technology with important network effects, there are two types of effects. First, the benefit of the technology to an individual user increases in the number of telephones, *i.e.*, in the number of locations from which the system can be accessed. This size effect also exists, for example, in retail distribution networks where consumer benefit increases in the number of outlets at which the good is available. Second, the benefit increases in the number of people who are on the system: as the number of people who make and receive calls increases, each individual can communicate with more people. This second effect is the source of network externalities because each new user confers a benefit on all other users.

In the case of ATMs the network effect is of the first type. A cardholder is better off the larger the number of geographically dispersed ATMs from which she can access her account. The convenience of access to one's account wherever one happens to be means that the value of the ATM network increases in the number of ATM locations it includes. A bank can increase its network size by adding more ATMs to its proprietary system and by linking its network with the networks of

¹ See, for example, Katz and Shapiro (1986) and Farrell and Saloner (1985,1986).

² Several case studies have been conducted to confirm the relevance of the theories. For example, David (1985) argues that demand-side economies explain the dominance of the QWERTY typewriter keyboard.

other banks. In the early days of ATM adoption studied here, interbank networks were quite rare for a variety of technical and institutional reasons. As a result the value of the network to depositors was increasing in the number of ATM locations in their bank's network.

Because differences in banks' post-adoption network size would generate different valuations to their depositors, the value of adopting an ATM system would be higher for banks expecting to have larger proprietary networks in equilibrium, all else equal. Because new technologies diffuse gradually through an industry, it is common and reasonable to expect those firms that value the technology more to adopt earlier. If either the cost of adopting an ATM network of a given size falls over time (because banks and/or suppliers have a learning curve) or the benefit rises over time (because depositors learn about the value of ATMs or ATMs perform more functions), then banks with a relatively higher valuation of the technology at any point in time will adopt relatively early.

A reasonable version of the network effects hypothesis, therefore, is that banks expecting to have a larger number of locations in equilibrium will adopt sooner. To test this hypothesis we proxy unobservable expected network size by the number of branches a bank has. Branches are a good proxy for expected network size because they are the most common location for ATMs, they are the lowest-cost locations, and because legal restrictions limited placement outside branches during the sample period. Further, commentary in the trade press and casual empiricism suggest that banks eventually place ATMs in most, if not all, branches. Accordingly we focus on the likelihood that banks adopt as a function of the number of branches they have.

The net value of an ATM system to a bank also will be affected by the number of its depositors to whom ATMs are valuable. Because there are fixed costs of adoption, economies of scale in production mean that a bank's propensity to adopt will increase in the number of these depositors. Indeed, earlier studies of ATM adoption by Hannan and McDowell (1984, 1987) find that bank size, as measured by total assets, is an important determinant of time of adoption. We confirm these results by including a measure of size more directly related to the number of depositors. By including measures of both network size and number of depositors

we are able to separate the network effect from the scale economies effect.

Controlling for variation in the number of depositors and other heterogeneity, we find that increasing network size increases the probability of early adoption. When evaluated at the sample mean, the estimated probability that a bank would have adopted in the first nine years ATMs were available is 17.1 percent. Adding a single branch increases this probability by at least 5.7 percent (to 18.1 percent) and perhaps by as much as 10 percent. In comparison, adding enough depositors to equal an average sized branch increases the adoption probability by 4.3 percent. The strong network effect is robust to specification and to removing large outliers.

In section 2, we discuss the determinants of ATM adoption and develop a test for network effects. In Section 3 we briefly discuss the statistical models used. The data used to implement these models are discussed in Section 4, and in Section 5 we present our results. Section 6 provides some concluding comments.

2. Network Effects and ATM Adoption

In this section we develop a framework for considering a bank's adoption decision. While this discussion does not identify structural parameters, it does provide insight into the relationship between network size and a bank's propensity to adopt ATMs that guides the empirical analysis. In particular, we focus on distinguishing the effect of network size from the effect of the number of end-users.

In our context, end-users are the bank's depositors and the relevant measure of network size is the number of physical locations at which any given depositor can carry out a transaction. While each user is largely unaffected by the number of other users of the same network, each user is better off the greater the number of outlets from which she can access the network. Feasible locations for ATMs include the bank's branches and may also include some non-branch locations.³ To simplify the analysis and be consistent with the data available for empirical work, we assume that if a bank decides to adopt ATMs it will be optimal for it to install ATMs in all feasible locations and make the system accessible to all its depositors.

³ As discussed in a subsequent section, placing ATMs outside of existing branches is constrained by regulatory agencies.

We start with banks endowed with a set of characteristics including its depositors and feasible ATM locations. Throughout the analysis, we treat these characteristics as predetermined, focusing on the adoption decision conditional on bank characteristics. With the number of depositors and potential network size predetermined, a bank decides whether to adopt an ATM system of a fixed size to serve a fixed number of depositors and, if so, when.

The bank's decision, depends on the flow of benefits and costs from adoption. We begin by considering the "benefit side", and in particular, the benefits to an individual user. In the theoretical literature on network effects, an end-user's per period benefits are frequently represented by $a + b(N)$, where a represents the "stand-alone" benefit from the technology and $b(N)$ represents the network effect.⁴ The "stand-alone" or "network independent" component of the user's benefit is that which the user obtains regardless of the size of the network. Thus, a might represent the utility that a depositor receives from having an ATM installed at the branch she "usually" uses: the depositor may get superior service simply by substituting the automated teller for the human one during normal business hours, and will be able to lengthen the period during which she can transact at that branch by substituting an after-hours ATM for a daytime teller.

The network effect term, $b(N)$, increases in N which measures the size of the network ($N > 1$). The variable N then represents the number of other locations from which a depositor is able to access her account from an ATM. If those ATMs are located at existing branches the benefits they provide are of two kinds. First, they provide the benefits discussed above of substituting machines for tellers and after-hours use for daytime use. Second, by standardizing depositor identification and account access procedures the existence of an ATM in branches other than the one at which the user has an account may make it easier for the user to transact at those branches. If the ATMs are not located at existing branches, they effectively increase the number of branches (for the subset of transactions that can be performed by an ATM).⁵

⁴ See Farrell and Saloner (1986) for example.

⁵ In this setting a probably depends on N . The value of having an ATM at one's "usual" branch might be lower if the network of ATMs is larger. However, it is useful

The aggregate per period value of the ATM network to a bank's depositors if there are n of them is $n[a + b(N)]$. In general one might expect the per period benefits to increase with calendar time as the number of services which ATMs provide increase. In what follows we suppose that benefits have growth factor g , where $g \geq 1$. The flow of benefits that the bank's users derive from an ATM during period t is therefore $[a + b(N)]g^t$. Assuming that the per-period increase in revenues to the bank is proportional to the per-period benefits to the depositors (in particular if the bank's revenues are λ times the benefit to depositors where $\lambda \leq 1$), then the present value of the bank's revenues (evaluated at time T) from adopting an ATM at time T are:

$$\sum_{t=0}^{\infty} \lambda n[a + b(N)]\delta^t g^{T+t} \quad (1)$$

where δ is the discount factor. Note that these benefits are increasing in both n and N .⁶

We turn now to the "cost" side of the analysis. In making its adoption decision, the bank must consider both variable and fixed costs. The variable costs are mainly supplies (such as film) that are incurred with each transaction. Because we assume that each depositor makes the same number of transactions, the variable costs are proportional to the number of depositors. For simplicity, we assume that the variable costs are incorporated in λ so that $\lambda n[a + b(N)]g^t$ represents the benefit net of variable cost in period t to a bank that has adopted an ATM.

The fixed costs include the cost of making alterations to branches to accommodate ATMs, expenses related to adapting the bank's computer software to the ATMs, the cost of purchasing or leasing the ATMs themselves, the cost of service

to maintain the distinction between stand-alone effects and the network effect of additional locations in what follows. For simplicity we suppress the dependence of a on N in the notation. If this effect is important it will reduce the network effect measured in the empirical work.

⁶ For reasons discussed at length later (principally that banks did not share ATM networks in the 1970s), we assume that bank A 's depositors are unable to use bank B 's ATMs. Therefore N represents only the bank's own ATM locations. If such networks were shared and if a bank thereby obtained some benefits from the adoption of ATMs by other banks, there might be an externality in banks' adoption decisions. In our case, where each bank's network benefits are independent of other banks' actions, no externality is involved. Hence the term "network effect".

and the cost of marketing. Many of these costs, such as the cost of purchasing or leasing ATMs or of installing them, depend on N . Others, such as software or marketing costs, are “system costs” and are arguably independent of N . We denote the present value of the cost of adopting an ATM system in N locations at time T as $C(N, T) = S(T) + Nc(T)$, where $S(T)$ represents the system costs and $c(T)$ represents the cost per location. A typical assumption in the literature on the adoption of technology, and one which we make as well, is that the fixed cost of adopting the technology, $C(N, T)$, declines over time as the suppliers’ and/or the banks’ experience with the technology accumulates. The net present value of a bank’s profits from adopting ATMs at time T is therefore:

$$\Pi = \sum_{t=0}^{\infty} \lambda n[a + b(N)]\delta^t g^{T+t} - C(N, T).$$

A bank with n depositors and N locations earns higher profits from adopting at time T than from waiting until time $T + 1$ if:

$$\frac{\lambda g^T n[a + b(N)]}{1 - \delta g} - C(N, T) > \delta \left(\frac{\lambda g^{T+1} n[a + b(N)]}{1 - \delta g} - C(N, T + 1) \right),$$

$$\text{i.e., if } \frac{\lambda n[a + b(N)](g^T - \delta g^{T+1})}{1 - \delta g} > C(N, T) - \delta C(N, T + 1),$$

$$\text{i.e., if } \lambda n[a + b(N)]g^T > C(N, T) - \delta C(N, T + 1). \quad (2)$$

The assumptions that variable profits grow and the cost of adoption declines over time implies that every bank eventually finds it profitable to adopt ATMs. This allows us to focus on when, rather than whether, adoption takes place. Provided the rate of decline of the cost of adopting decreases over time, the smallest T that satisfies Equation (2) is the optimal time to adopt.⁷

There are two interesting polar cases of Equation (2). The first is where $C(N, T)$ is constant over time so that growth is the only factor in the timing of adoption. In that case Equation (2) reduces to:

$$\frac{\lambda n[a + b(N)]g^T}{1 - \delta} > C(N),$$

⁷ A similar model of the optimal adoption time (but without network effects) is contained in David and Olsen (1986).

i.e., the bank adopts as soon as the net present value of variable profits assuming no further growth exceeds the cost of adoption. Since costs do not decline with time in this case there is no point to waiting: future per-period profits will be higher than today's, and if adoption would be profitable with a stream of profits equal to this period's, the bank should adopt.

The second polar case is where there is no growth ($g = 1$) and the only temporal effect is the declining cost of adoption over time. Then Equation (2) becomes $\lambda n[a + b(N)] > C(N, T) - \delta C(N, T + 1)$. The right-hand-side of this expression is the cost-saving from delaying adoption by one period, and the bank adopts as soon as that cost saving is less than the (constant) per-period variable profit.

The general case (Equation (2)) is a combination of these two effects. The bank adopts when the per-period variable profits exceed the cost-saving of waiting an additional period. Each period adoption becomes more tempting both because per-period variable profits are higher and because the cost of adoption is lower.

In this model n enters on the left-hand-side of (2) only, *i.e.*, it increases the benefits (net of variable costs) and does not affect fixed costs. As is apparent by dividing (2) by n , the bank's net benefit per depositor is constant, but total costs decline in n ; there are production side economies of scale in ATM systems. As a result of these scale economies, the bank's profit from an ATM system is increasing in n .⁸ Therefore, adoption occurs earlier the larger the number of depositors.

In the empirical work, we are interested primarily in testing for a network effect and assessing its magnitude. This requires separating the effect of variation in network size from the effect of variation in number of depositors. One simple test for network effects is to estimate the effect of variation in N holding n constant. However correctly interpreting the result is complicated by the cost-side effects. The overall effect of N on the timing of adoption is ambiguous since it affects both the left- and right-hand-sides of (2). The left-hand-side of (2) is increasing in N because of the network effect. However, the right-hand-side also increases

⁸ The assumption that fixed costs are not a function of n is violated if usage levels vary across locations, particularly if banks respond to usage variation by varying the number of ATMs across locations. Multiple ATMs per location was perhaps less common in the early days of ATM adoption studied here than it is now. If fixed costs increase in n , the sign of the overall effect of n is, in principle, ambiguous.

with N . To see this recall that $C(N, T) = S(T) + Nc(T)$, so that the right-hand-side of (2) is $[S(T) - S(T + 1)] + N[c(T) - c(T + 1)]$. Two banks with different numbers of locations enjoy the same benefits in terms of reduction in the system costs if they wait; however the bank with more locations reaps the reduction in the location specific costs at more locations. Thus, holding n constant, banks with more locations will adopt earlier only if the network effect outweighs this cost effect. Consequently a test that measures the effect of N on adoption propensities, holding n constant, is immune to false positives, but will tend to *understate* the network effect and may yield a false negative.

An alternative way to get at the network effect is to hold $n/N \equiv \nu$ constant rather than n , that is, to hold constant the number of depositors per location and increase the number of locations. Dividing (2) by n gives:

$$\lambda[a + b(N)] > \frac{[S(T) - S(T + 1)]}{n} + \frac{[c(T) - \delta c(T + 1)]}{\nu}.$$

Holding ν constant removes the downward bias from the additional location-specific cost. However, because increasing N while holding ν constant adds both a location and ν depositors to the network, an upward bias is introduced. The term involving S is now decreasing in n because system costs are spread over more depositors. Thus if banks with more locations (holding ν constant) are found to have a higher propensity to adopt this could simply be due to increasing returns to scale in system costs and not due to the network effect. This test, then, will *overstate* the network effect and can yield false positives but not false negatives.

In summary, examining the propensity to adopt holding n constant understates the impact of the network effect, while holding n/N constant overstates it. As described in Section 5, we test for the presence of a network effect by holding n constant, then use these two assessments to bound the magnitude of the impact of the network effect. The size of the network effect will be closer to the upper bound estimate if location-specific costs are more important than system costs.

We have assumed thus far that there is no variation in the valuation of an ATM network among banks with the same number of depositors and ATM locations. In practice, however, this is unlikely to be the case. For example, some banks might face higher labor costs so that substituting ATMs for tellers is more attractive.

Alternatively, the benefits of after-hour banking might be greater for some banks, such as those situated in the suburbs, than for others. In this case, among the banks with a given number of depositors and locations, the banks for whom such idiosyncratic benefits are the greatest will adopt earliest while the others wait.

To take account of such differences among banks, let ϵ_i ($E(\epsilon_i) = 0$) represent the deviation of the per period profits of bank i from the mean profit of banks with the same number of depositors and locations. In this case the net present value of a bank's profit from adopting at time T is:

$$\Pi_i = \frac{\lambda g^T n [a + b(N)]}{1 - \delta g} - C(N, T) + \frac{\epsilon_i}{1 - \delta},$$

and Equation (2) becomes:

$$\epsilon_i > C(N, T) - \delta C(N, T + 1) - \lambda n [a + b(N)] g^T, \quad (3)$$

i.e., banks with idiosyncratically large net benefits adopt early while others wait. The smallest $T_i = T(n, N, \epsilon_i)$ that satisfies (3) is the optimal adoption date for the i th bank.

In general the rate of adoption may change over time. This depends on how the cost or benefits of adoption change over time and on how ϵ_i is distributed. To see this, use Equation (3) to define:

$$\epsilon_i^*(n, N, T) \equiv C(N, T) - \delta C(N, T + 1) - \lambda n [a + b(N)] g^T. \quad (4)$$

Then $\epsilon_i^*(n, N, T)$ is the ϵ_i of the bank with n depositor and N locations that is just indifferent between adopting and not adopting at time T . Then the probability that a bank with n depositors and N locations adopts in period T (i.e., the hazard rate at period T) is:

$$\frac{H[\epsilon_i^*(n, N, T + 1)] - H[\epsilon_i^*(n, N, T)]}{1 - H[\epsilon_i^*(n, N, T)]}, \quad (5)$$

where $H(\cdot)$ is the cumulative distribution function for ϵ . If, as assumed above, the benefits of adopting relative to costs increase over time, the right-hand-side of equation (4) decreases with T . Therefore even if ϵ is uniformly distributed so that the numerator of (5) is constant over time, the denominator declines in T . As

a result, more banks find it profitable to adopt each period than did the period before. Moreover, if ϵ_i is normally distributed, say, then in the early periods when the Normal density is an increasing function even more banks find it profitable to adopt each period than the period before so that this tendency is reinforced. For both of these reasons we expect to find positive duration dependence in the hazard rate.

3. Estimation Models

Equation (4) implies that adoption time, conditional on a bank's observable characteristics, is a random variable. The choice of an estimation model involves choosing a distribution for adoption dates. In addition, because our observations of adoption times are right-censored, the estimation model must accommodate censoring. The strategy we follow is to estimate standard duration models. These models easily incorporate censored observations and yield readily interpretable reduced form parameters.⁹ The duration model which is the main focus of our analysis assumes that the time until adoption for bank i conditional on its characteristics follows a Weibull distribution. Let x_i be the vector of observed characteristics for bank i and β be the unknown coefficients. Then the probability that bank i adopts before time T is given by:

$$F(x_i'\beta, T, \gamma) = 1 - e^{-\psi(x_i'\beta)T^{1/\gamma}}.$$

For convenience, we make the standard assumption that $\psi(x_i'\beta)$ can be written as $e^{x_i'\beta}$.

An attractive feature of the Weibull distribution is that the computation of the effects of the covariates on adoption probabilities from parameter estimates is relatively simple. The hazard rate is $(1/\gamma)\psi(x_i'\beta)t^{-1/\gamma}$. Under the assumption that $\psi(x_i'\beta) = e^{x_i'\beta}$, the estimated coefficients are simply the effect of x on the \log of the hazard rate. The Weibull distribution allows the hazard rate for a given bank to change monotonically over time. This probability increases, declines, or is

⁹ For a discussion of duration models in general, see Kiefer (1988), and for an overview of applying these techniques to technology diffusion, see Rose and Joskow (1990).

constant as γ is less than, greater than, or equal to one.¹⁰ For reasons discussed in Section 2, we expect to find $\gamma < 1$.

The Weibull, however, constrains the hazard rate in two potentially important ways. First, it requires that duration dependence be monotonic. A standard empirical regularity in diffusion studies is an initially increasing then declining hazard rate. Since we have data on only the early years of the diffusion process for ATMs, it seems likely that a functional form that allows a monotonically increasing rate will be adequate. Nonetheless, a more general functional form is a useful check on the Weibull results. Second, the Weibull (in common with the other members of the family of proportional hazard models) constrains the relative hazard rates of any two banks to be constant over time. For example, the ratio of the hazard rate of a bank with many depositors and many locations to the hazard rate of a bank with many depositors and one location is assumed to be time invariant. Suppose, however, that the date of adoption conditional on bank characteristics is Normally distributed. Then this ratio might be relatively large early on and decline over time. This could happen because, with a Normal distribution, the density function of the many-location bank can be declining while the density function for the single-location bank is increasing.

To test the results for sensitivity to the constraints imposed by the Weibull, we estimate a duration model in which the underlying adoption date distribution is assumed to be log-logistic. The log-logistic distribution allows a non-monotonic hazard rate and allows relative hazard rates to change over time. It approximates a model in which the log of adoption dates is Normally distributed. For the log-logistic, the probability that bank i has an adoption date earlier than T is given by:

$$1 - \left[\frac{1}{1 + T^{1/\gamma} \psi(x_i; \beta)} \right],$$

¹⁰ The Weibull is a generalization of the exponential distribution used in the Hannan and McDowell (1984, 1987) analysis. It collapses to the exponential when $\gamma = 1$. Although they assume a time invariant underlying hazard rate, Hannan and McDowell use time varying covariates so that the hazard rate can change as bank characteristics change over time. We have chosen an alternative approach of allowing the hazard rate to be a function of t directly and using each bank's 1971 characteristics. With this approach, bank characteristics are necessarily exogenous.

where we assume again that $\psi(x'_i\beta) = \exp(x'_i\beta)$. The hazard rate is

$$\frac{(1/\gamma)\psi(x'_i\beta)t^{1-1/\gamma}}{1 + \psi(x'_i\beta)t^{1/\gamma}}.$$

For γ less than 1, this functional form has an underlying hazard function that initially increases and then decreases over time. If γ is greater than or equal to one, the underlying hazard function has negative duration dependence.

For both distributions, the likelihood function for observations on m banks is:

$$\prod_{i=1}^m f(x'_i\beta, T, \gamma)^{d_i} [1 - F(x'_i\beta, T, \gamma)]^{1-d_i}$$

where d is an indicator variable equal to one if the firm adopts and $f(\cdot)$ ($F(\cdot)$) is the density function (cumulative distribution function) for the Weibull or log-logistic distribution. The first term is the contribution to the likelihood of a firm observed to adopt at time T ; the second term is the contribution of a firm failing to adopt prior to time T after which it is no longer observed.

Both these models assume a distribution for adoption times conditional on bank characteristics. If these parameterizations fit the data badly, the coefficient estimates may be adversely affected. We therefore compare these parametric estimates to results from a nonparametric (Cox) partial-likelihood estimator. This estimator makes no assumption about the underlying distribution of adoption times, but instead uses the proportional hazard model assumption that the ratios of hazard rates for any two banks are time invariant and estimates the relative probabilities.

4. Data

Testing the hypothesis that network size matters given the number of depositors requires variables that capture network size, number of depositors, and date of adoption. This section describes these variables as well as variables used to control for other bank characteristics that might affect adoption probabilities and be correlated with the variables of interest. Descriptive statistics for the variables used in the analysis appear in Table 1.

The data base includes information on adoption dates, bank characteristics and state regulations. Because adoption is presumptively more likely in urban areas,

the sample was restricted to commercial banks operating in a county that was part of an SMSA or had a population center of at least 25,000 in 1972. This subset of all commercial banks in operation between 1971 and 1979 was further restricted to conform to the available adoption data and to capture variation in network size. The final sample includes all commercial banks that satisfied the geographic criterion in 1971 and that existed throughout the 1971-1979 sample period.

The adoption data come from surveys of all commercial banks conducted by the Federal Deposit Insurance Corporation in 1976 and 1979. The 1976 survey asks the year the bank first installed at least one ATM. The 1979 survey asks whether the bank has installed an ATM by the 1979 sample date. Combining these surveys gives a date of first adoption for banks adopting prior to 1977 and identifies banks adopting between 1976 and 1979. Year of adoption for these later adopters was collected by a supplementary survey conducted by Hannan and McDowell (1987).¹¹ The date of adoption is the year the bank first installed at least one ATM. Because the surveys cover only banks existing at the survey dates, consistency requires that our sample be restricted to banks existing in 1976 and 1979. Since we use 1971 characteristics data, the sample also is restricted to banks in existence by 1971.

The adoption data were merged with data on firm characteristics maintained by the Federal Reserve Board in the Report of Condition and Income and the Summary of Deposits. These sources have detailed balance sheet and other summary information on all commercial banks operating in the United States. In particular, they contain the best available information on number of depositors and network size as well as information used to control for other dimensions of bank heterogeneity.

In the 1990s ATMs are commonly linked in regional and national networks. For at least some ATM transactions then, the relevant network size is now the size of the interbank network. In the 1970s, however, interbank connections were un-

¹¹ The raw survey data and the supplementary information on later adopters were generously given to us by Hannan and McDowell. Our sample has been constructed to be roughly consistent with theirs. Despite their efforts, adoption dates are not available for 87 banks known to have adopted and otherwise consistent with the sample definition. Except where otherwise noted, these banks have been dropped from the sample.

common. Many of the early machines were independent units; they were not fully connected with the bank's data system, let alone an interbank system. Further, in the early seventies ATM producers had not yet achieved a technological standard that would make machines compatible. Legal issues with respect to shared ATMs also slowed the development of interbank networks. Interstate banking was not permitted in this period and many state's regulated the number and location of bank branches. Allowing interbank networks would clearly affect the existing regulatory regimes, and sharing was delayed while regulators decided how it should be managed. State and federal rulings on interbank networks have reflected both a concern that large, single bank systems might reinforce the market dominance of banks already large and a countervailing concern that cooperative arrangements among banks might create collusive pricing.¹² The combination of potential or actual legal constraints and the rudimentary state of the new technology meant that interbank networks were not important in the 1970s. As a result, the network size relevant to a cardholder was the size of her bank's proprietary network.¹³

For these single bank networks, the relevant network size is the number of ATM locations the firm expected to have in equilibrium when making the adoption decision. This number, however, is inherently unobservable. Even if the data reported the number of ATM locations for each bank in each year, these numbers would not necessarily include the planned equilibrium number.¹⁴ We therefore use the number of branches a bank has (BRANCH) as a proxy for expected network size. BRANCH

¹² For a review of the law on interbank networks, see Felgran (1984).

¹³ If banks anticipated that ATM networks would ultimately be interlinked, this would of course affect their estimates of the net present value of benefits in Equation (1). However, provided that in the 1970s banks believed that such interlinking would not occur until the 1980s, such benefits would be irrelevant to the timing of adoption decision represented by Equation (2). However the analysis in Section 2 ignores possible competitive advantages that might accrue to banks that adopt early. For example, if firms that pioneer interbank networks are able to extract some of the rents from the creation of such networks, and if banks with many branches who adopt early are well-positioned in the competition to form interbank networks, those banks would have an added incentive to adopt early. We hope to consider such competitive incentives to adopt, which are largely ignored in this paper, in future work.

¹⁴ In fact, the data do not report the number of ATM locations. Nor is the number of ATMs installed systematically available.

is an excellent proxy if banks typically place at least one ATM in each branch and place relatively few or no ATMs elsewhere.

Banks tend to place ATMs in branches for several reasons. Installing and maintaining ATMs on the premises of existing branches may be less expensive than at off-premise locations. Consumers also may – at least in the early days of ATM use covered in this study – have felt more comfortable using machines located where they could get assistance with usage problems. Further, the legal status of off-premise placement was unresolved for a substantial portion of the sample period. State regulatory agencies and legislatures control whether off-premise placement is allowed for state chartered banks. For national banks, off-premise placement is controlled by the Comptroller of the Currency. In 1979, the Comptroller ruled that off-premise placement by national banks would be allowed.¹⁵ Some state authorities acted to allow off-premise placement prior to the Federal ruling and some tied state regulations to the Federal standard. Still others had not yet issued regulations for off-premise placement by 1979.¹⁶ Until off-premise placement was authorized, the number of branches was a clear upper bound on network size. Even when off-premise placement was allowed, on-premise placement was more common. Commentary in the trade press during this period suggests that banks eventually place ATMs in most branches so that the number of branches is also a good lower bound.

Because states regulate branching, the distribution of branches per bank will vary across states. In some states, branching is not allowed; banks can have no more than a single banking office. Because there is no variation in network size in these states, banks in these states are not included in the sample.¹⁷ As a result, the 2293 banks in the sample are distributed over the 37 states in which multiple branches were allowed in 1971. Among these states, 19 placed no restrictions on

¹⁵ This ruling meant that the Federal government no longer had an interest in regulating ATMs. As a result, national data on ATMs were not collected after 1979.

¹⁶ Most states regulate off-premise placement in some fashion even where it is allowed. For example, banks may be required to get approval for each off-premise location or to share off-premise locations with rival banks.

¹⁷ In principle, these single branch banks can be included in the analysis to provide additional information on the effect of variation in the number of depositors on adoption probabilities. But including them does not substantively affect the parameter estimates.

the number or location of branches. We refer to these states as “unrestricted”. The remaining 18 states had some limitation on the number or location of branches. Banks in these “limited” states may be required to restrict branching to, say, a single county or to refrain from placing a branch in a small community already served by a competitor.¹⁸

Ideally, the n in Equation (1) would be implemented as the number of depositors for whom ATM transactions have value. A close proxy might be the number of depositors with personal checking accounts. However, there are no data available on the number of accounts of any type.¹⁹ The next best proxy is total deposits by customers who would use an ATM. This proxy might be affected by variation in the size of accounts across banks. The closest available proxy is “demand deposits by individuals, partnerships, and corporations” (DEPOSITS). DEPOSITS specifically excludes time and savings deposits (certificates of deposits and savings accounts, for example) and other less liquid holdings, as well as deposits held for other banks or the public sector, but includes commercial demand accounts even though these accounts probably do not generate ATM demand. The extent to which DEPOSITS is a good proxy for n depends on how much variation there is in the proportion of individual accounts in DEPOSITS across banks.

Four additional variables are used to control for other factors that might affect adoption: wage in the area (WAGE), labor expense per employee (WB/L), the average number of branches per bank in the state (PROPBR), and product mix (PRODMIX). The wage variable is included to control for variations in ATM value arising from variations in labor cost. If tellers are more expensive, technology that can substitute for tellers should be more attractive. In this case, higher wages should promote ATM adoption. On the other hand, the wage, as a measure of average income in the bank’s area, may also be correlated with the average size

¹⁸ The data used to classify states with respect to branching regulations were provided by the Conference of State Bank Supervisors. Two states changed from limited to unrestricted regulation during the sample period. Because substantive changes in branching regulations might change adoption behavior, observations for banks in these states are treated as censored at the date of change.

¹⁹ The only data on number of accounts come from the Functional Cost Analysis reports. These data are not publicly available in disaggregate form and cover only a very small, nonrandom sample of banks.

of checking accounts. If people with higher income typically hold larger demand deposits, the WAGE variable may pick up some variation in the relationship between DEPOSITS and the number of customers for whom ATMs are of value. The wage used is the average manufacturing wage for 1977.²⁰

The bank's labor expense per employee is total expenditures on salaries and benefits divided by the number of employees. There is some evidence that this variable is high in concentrated markets, presumably because of rent sharing with employees (Rhoades 1980). In that case, banks with high values of WB/L may be more likely to adopt because they can extract a larger share of the resulting consumer value (i.e., they have higher λ s in Equation (1) than banks in less concentrated markets). On the other hand, WB/L might capture variation in the mix of banks' employees. It is possible, for example, that a bank with a relatively high value for WB/L has fewer relatively low-wage tellers and more relatively high-wage commercial account managers or investment advisors. A high value of WB/L might therefore indicate a low proportion of individual depositors and, therefore, a low propensity to adopt.

The variable PROPBR is included to absorb variation in state branching regulations. Within the limit category there is substantial variation in the severity of the branching restrictions. As a result, the average number of branches per bank in limit states varies from less than 2 to more than 8.²¹

Increasingly restrictive branching regulations suggest that the stand-alone value of adoption (a in Equation (1)) might be higher. The reason for this is that a depositor at a bank with, say, a single branch has no substitute for visiting that bank's single location during normal business hours. By contrast, a depositor at a multi-branch bank may at least be able to substitute a transaction during normal

²⁰ As reported in the *City and County Data Book*.

²¹ Wisconsin banks average less than 1.5 branches per bank, and branching is allowed only within the same county as the bank's main office and then only if there is no other bank operating in that municipality or within three miles of the proposed branch. New York, in contrast, has more than eight branches per bank and allows statewide branching except that a bank cannot branch in a town with a population of 50,000 or less in which another bank has its main office. The number of branches per bank is a statewide average based on all the banks in the state, not just those in our sample.

hours at another branch for a transaction at her usual branch. Or, more generally, banks whose depositors would feel constrained if they could only bank at their usual branch during daytime hours might find it in their interests to open additional branches. Since restricted banks are unable to open as many branches as they would like, they might more readily turn to ATMs as a way to relieve a tightly binding constraint. As a result, since a lower value of PROPBR indicates a more restrictive regulatory environment, PROPBR should have a negative effect on adoption. There is, however, a potentially offsetting competitive effect. If a bank operates in a state in which there are many multi-branch competitors, competition may push a bank to adopt earlier than it would if it faced a less competitive environment. In that case, PROPBR might be positively correlated with adoption. In unrestricted states the regulatory effect should be absent so that PROPBR should reflect the competitive effect. We therefore expect a positive coefficient there. In the limited states, however, both effects might be present. If the regulatory effect outweighs the competitive effect in those states, the coefficient will be negative.

Finally, following Hannan and McDowell (1984) we include a product mix variable, PRODMIX, which we measure as the ratio of DEPOSITS to the sum of all deposits. The denominator, therefore, includes all time and savings deposits and deposits held for the public sector as well as the commercial and individual demand deposits appearing in the numerator.²² Since in the 1970s ATMs were used mainly for transactions involving checking accounts, banks whose total deposits include a larger share of individual and commercial demand deposits might have a higher demand for ATM services. In that case PRODMIX would have a positive coefficient.

Table 1 presents summary statistics for the entire sample of banks in multi-branching states and for the limited and unrestricted subsamples. The average bank has over \$36 million in DEPOSITS. As might be expected, banks in states that do not restrict branching are larger on average than those in states with limited branching. As a result, there are many more banks in the 18 limited states than in the 19 unrestricted states. The size distribution of banks is skewed to the right: the

²² Alternative product mix ratios were used in unreported regressions, including the ratio of DEPOSITS to the bank's total assets. The results were substantively unaffected.

largest banks have DEPOSITS over \$5,000 million, but only 22 banks have deposits over \$500 million, and 75 percent of the banks have DEPOSITS under \$16 million.

While the average bank across both regulatory regimes has slightly more than six branches, the average unrestricted bank has three times as many branches as the average limited bank. This variation is also reflected in the PROPBR variable that reports the average number of branches for all banks in the state. The PROPBR values are somewhat lower than the sample averages for BRANCH because PROPBR includes banks operating only in less densely populated areas excluded from the sample. Like DEPOSITS, BRANCH is skewed to the right: the bank with the most branches (Wells Fargo in California) has 1013 branches, but the next highest number is 443, and 75 percent of the banks have fewer than five branches. Because the DEPOSITS and BRANCH variables have similarly skewed distributions, there is much less variation in the average for DEPOSITS per BRANCH across regimes. The limited branching states have banks that average \$5 million per branch versus \$3.6 million in unrestricted branching states.

The adoption rate during the sample period is 17-19 percent and is higher in unrestricted states. Among adopting banks, the average time until adoption is 5.5 years with unrestricted banks adopting earlier than limited banks (4.7 versus 5.7).

5. Results

In this section we present the empirical evidence for a network effect on adoption rates. To develop the argument, we focus initially on the relationship between the number of depositors, as proxied by DEPOSITS, and the propensity to adopt early. Next, the main results are presented by introducing the number of branches as a proxy for expected network size. These results are first presented as estimates from a Weibull specification. To test for robustness to functional form, the Weibull results are then compared to estimates based on the Cox partial-likelihood and log-logistic forms. Finally, the possibility that the observed relationship between number of branches and propensity to adopt is simply an order statistic effect is addressed.

Weibull estimates of the relationship between adoption and number of depositors are reported in Table 2. Pooled estimates for banks in all states permitting multiple branches and separate estimates for banks in limited and unrestricted states

are reported. The results are consistent with the findings of Hannan and McDowell: the coefficients imply that the *log* of the hazard rate is an increasing, concave function of DEPOSITS. The estimates are precise, and the pattern is consistent across regulatory regimes. As reported at the bottom of the table, these estimates imply that increasing DEPOSITS by \$1 million above the sample mean leads to about an 0.5 percent increase in the hazard rate in the pooled regression. The increase is more marked in limited than unrestricted states, perhaps because banks in limited states have much smaller DEPOSITS on average and the *log* of the hazard rate is concave in DEPOSITS.²³

When BRANCH is included in the regressions it is entered as a quadratic to allow it to have a curvature independent of DEPOSITS. As suggested by the model in Section 2, we also include DEPOSITS/BRANCH to account for location-specific costs of installing ATMs. The sign on DEPOSITS/BRANCH should be positive, and if location-specific costs are high relative to the system fixed costs, this coefficient might capture a large share of the effect of DEPOSITS.

For the pooled regression, the coefficients on the BRANCH terms imply that adding a branch has – at best – no effect on the adoption rate. The derivative of the *log* of the hazard rate with respect to branch is negative with a large standard error. The estimates for banks in unrestricted states, however, tell a very different story. The branch derivative is positive in this regime. But, including the BRANCH variables changes the sign of the DEPOSITS derivative: the apparent effect of an increase in DEPOSITS holding number of branches constant is to reduce the adoption rate. This counterintuitive result and the poor showing of BRANCH in the pooled regression appear to be the results of near colinearity of DEPOSITS and BRANCH in the unrestricted states.

The correlation coefficient between BRANCH and DEPOSITS for banks in unrestricted states is .98. Apparently, when branching is unrestricted, banks add depositors by adding branches. The effect of near colinearity is reflected in the large increase in the standard errors on the DEPOSITS coefficients when BRANCH is added. In (unreported) regressions including only linear DEPOSITS and BRANCH

²³ All reported derivatives are evaluated at the sample means for the observations included in the associated regression.

terms, the estimates display the classic near colinearity pattern: the estimated coefficients are opposite in sign, have a large covariance and sum approximately to the size of the coefficient on DEPOSITS in a regression including only DEPOSITS. This correlation makes the coefficient estimates in the unrestricted states unreliable and may well contaminate the pooled results as well.

In contrast, colinearity does not appear to be a problem in the limited branching states. Perhaps because branching regulations disrupt the natural growth pattern of banks, the correlation coefficient is smaller (0.77) and including branches does not have much effect on the standard errors for the DEPOSITS coefficients. To avoid the colinearity problem, our analysis of the branching effect is restricted to banks in limited branching states.²⁴

The results for the limited branching states are consistent with the hypothesis that ATM adoption is affected by network benefits. In these states, both adding an additional branch and increasing the value of DEPOSITS are associated with an increase in the adoption rate. Adding a branch (an ATM location) to the average bank, while holding DEPOSITS constant, increases the hazard rate by 6.3 percent, adding 0.97 percentage points to the nine year cumulative adoption probability. The effect of adding enough in DEPOSITS to equal an average size branch, but holding the number of branches constant, increases the hazard rate by 4.5 percent. Adding a “branch worth” of people increases the cumulative probability of adoption over the sample period by 0.79 percentage points.

The effect of the size of deposits appears to come through the DEPOSITS/BRANCH ratio rather than through DEPOSITS, implying that there are important location-specific costs and that system fixed costs are not particularly important. This is consistent with the early state of the technology. As late as 1975, 50 percent of the stock of ATMs in place and 30 percent of the machines on order were not on-line machines.²⁵ The primary system cost for off-line machines is the planning and acquisition process. There is little research and development or applications

²⁴ The eighteen limit branching states are: Alabama, Georgia, Indiana, Iowa, Kentucky, Louisiana, Massachusetts, Michigan, New Hampshire, New Jersey, New Mexico, New York, Ohio, Pennsylvania, Tennessee, Virginia and Wisconsin.

²⁵ *Computerworld*, April 16, 1975, p.35.

software for the system and most software was supplied by the vendor.²⁶

As discussed in Section 2, the above estimate of the effect of adding a branch understates the network effect. Holding DEPOSITS constant while increasing BRANCH necessarily reduces depositors per branch. If location-specific costs are important, as suggested by the DEPOSITS/BRANCH coefficient, this will increase unit costs, partially offsetting the network effect.

Recall, however, that the analysis in Section 2 suggests another calculation that overstates the network effect and therefore gives us an upper bound on its magnitude. The thought experiment is to add a branch (an ATM location) with enough new depositors to keep depositors per branch constant. Doing so increases the hazard rate by 11.3 percent and increases the nine year cumulative probability of adoption by 1.76 percentage points. Combining this result with that above, we can conclude that the effect on the adoption rate of increasing network size by one location is between 0.97 and 1.8 percentage points. This translates to a 5.7 to 10.3 percent increase in the adoption probability for the average bank.

The coefficients on the other variables have plausible signs and magnitudes. In all the regressions, γ is well below unity, implying positive duration dependence as expected. This is consistent with the net benefits of adoption increasing over time at an increasing rate during this early phase of ATM diffusion. The sign of the PROPBR variable in the limited states is consistent with restrictive branching regulation increasing the stand-alone benefit to adoption. Although the standard error is fairly large in the unrestricted states, the positive coefficient there is consistent with competition creating a race to adopt when there are several many-branch banks.²⁷

Consistent with incentives for substituting ATMs for tellers, the WAGE coefficient is always positive, although its standard error is quite large. The coefficient is

²⁶ The positive coefficient on DEPOSITS/BRANCH also suggests that fixed costs are not substantively affected by the number of depositors, an assumption built into Equation 2. If costs per location increased in n , this coefficient would be small and perhaps even negative

²⁷ To test for bias introduced by other state-specific effects, the regressions were also run using state fixed effects. The coefficient estimates on the BRANCH and DEPOSITS terms were substantively unchanged.

economically and statistically more significant in unrestricted states than in limited states. This is consistent with the notion that in limited states ATM adoption is in large part an attempt to relax the effects of the regulatory branching constraints that the banks face by, for example, adding after-hours banking possibilities, rather than to substitute automated transactions for human ones. This would lead the sensitivity to WAGE in limited states to be smaller than in unrestricted states.

When it is significantly different from zero, the coefficient on WB/L is positive. This is consistent with the hypothesis that a bank earning positive rents will adopt sooner because it is better able to extract the resulting surplus.²⁸ Finally, the PRODMIX coefficient is positive as expected.

As noted in section two, the Weibull imposes a structure on the adoption process that may affect the coefficient estimates. In Table 3, the Weibull results are presented again along with the results from a nonparametric (Cox) partial likelihood and a duration model that allows the underlying hazard to have a log-logistic distribution. The results are clearly robust across these functional forms. The similarity of the Cox and Weibull estimates argues that imposing the additional structure for the Weibull has not substantively affected the estimates. The Weibull and log-logistic estimates are also very close. Apparently the time invariance of relative probabilities imposed by the Weibull has not adversely affected the coefficient estimates. The estimate of gamma for the log-logistic implies a hazard rate that increases initially. Although this functional form implies that the hazard will decrease as t gets large, the hazard is increasing at mean values throughout the sample period. This suggests that the simpler, monotonic Weibull hazard is an adequate characterization of the time path of adoption over the sample period.

The network effect results were also tested for sensitivity to having omitted the observations for 87 banks known to have adopted but for whom adoption dates are not available. For this purpose, banks known to have adopted by 1976, but for whom adoption dates are not available were treated as 1976 adopters. Banks without adoption dates but known to adopt between 1976 and 1980 were assigned

²⁸ The WAGE and WB/L results are not an artifact of colinearity. The correlation coefficient for these variables is .03 and dropping one of the variables from the regression has no substantive effect on the coefficient of the other.

an adoption date of 1978. Repeating the estimation for limit banks confirms the reported results. If anything, the effect of adding a branch is increased by including this additional information. As expected, duration dependence increases.

Another robustness issue is raised by the very skewed BRANCH and DEPOSITS distributions. Given these distributions, it is possible that the results are heavily influenced by outliers. To check for outlier effects, the limited state regressions were run on a sample trimmed to eliminate the banks with more than \$1.2 billion in DEPOSITS or more than 84 branches.²⁹ This eliminates the six largest banks with respect to DEPOSITS and the six largest banks with respect to BRANCH for a total of eight banks. The effect on the distribution of banks is dramatic. In the untrimmed sample, the maximum values were \$5.2 billion in DEPOSITS and 201 branches. Trimming reduces the standard deviation for DEPOSITS by more than one-half and the standard deviation for BRANCH by approximately one-quarter. However, trimming has little effect on the estimated derivatives. The BRANCH derivative is slightly larger than in the full sample and the DEPOSIT derivative is essentially unchanged.

The regressions summarized in Tables 2 and 3 support the hypothesis that the number of branches increases the propensity to adopt early when controlling for number of depositors. We have interpreted these results as evidence that banks with more potential ATM locations will adopt relatively early because they benefit from a network effect. An alternative interpretation is that the relationship between BRANCH and time of adoption is only an order statistic effect. If there is no network effect and if, as argued above, system fixed costs are relatively small, banks could make the decision to adopt on a branch by branch basis where the decision to adopt at any one of its branches is independent of the decision to adopt at any other of its branches. In this case, a bank with many branches will adopt earlier because its observed adoption date is simply the minimum of the adoption dates of all of its branches.

If the observed relationship between branches and adoption dates is an order statistic effect, the adoption of an ATM at one branch of a bank should have no effect

²⁹ The trimming criteria are arbitrary and several variations were implemented without changing the basic results.

on the adoption decision at another of its branches. A simple test of this independence assumption would compare the expected number of of adopting branches at banks where at least one branch has adopted with the number of branches adopting at banks with at least one adopting branch. Data for a test of this sort are presented in Table 4.

The first row of Table 4 reports the adoption rates over the sample period observed in the data for banks with two, five, ten and fifteen branches. As expected, these rates increase in the number of branches. Under the order statistic hypothesis, these frequencies are the probabilities that at least one branch has adopted by 1979. Abstracting from the distribution of adoption dates over time, this means that these are the probabilities of at least one success in N draws where N is the number of branches and the adoption distribution is binomial. For example, .455 is the probability that a bank with ten branches will have at least one adopting branch. Let these probabilities be denoted by q . The second row calculates the probability that any single branch adopts (p) that is consistent with the observed q . That is, p satisfies the expression $q = 1 - (1 - p)^N$ where $(1 - p)^N$ is the probability of no successes in N draws from a binomial with parameter p . If a bank with 10 branches has a .455 probability of at least one success, for example, then each of its ten branches must have a .059 probability of adoption. Given p one can then calculate the expected number of adopting branches for banks that do adopt ($N_0 = pN/q$). These numbers are reported in the the third row of the table. Thus, the order statistic effect and the observed adoption rates imply that a ten branch bank that adopts has, on average, 1.294 adopting branches.

The number of adopting branches are not in the data set. However, the 1979 survey does contain information on the number of ATMs installed by each bank by 1979. The average number of ATMs at adopting banks is recorded in the fourth row of Table 4. If banks typically place one ATM in a branch, the average number of adopting branches for ten branch banks is 6.778, for example, well above the 1.294 expected under the order statistic hypothesis. This pattern is consistent across all branch categories and holds even if banks are assumed to install two ATMs per branch on average. The number of adopting branches is too high to be consistent with the order statistic hypothesis.

6. Concluding Comments

The main finding of this paper is that banks with many branches adopt ATMs earlier than banks with fewer branches, adjusting for the number of depositors. This is consistent with the presence of a network effect. An ATM network is more valuable to depositors when it has many geographically dispersed ATMs because of the convenience it provides. If banks are able to extract some of the benefits to depositors, banks that will have many ATM locations are likely to adopt first. Since banks with many branches are likely to have large networks, it is they whom we expect to adopt early.

The theoretical framework developed here suggests two thought experiments for providing bounds on the magnitude of the network effect. The first, which provides a lower bound, is to add an additional branch while holding the number of depositors constant. Doing this necessarily lowers the average number of depositors per branch. Because the location-specific costs of adopting ATMs mitigate against adoption when depositors per branch falls, this understates the value of adding a branch. Nonetheless, this thought experiment yields the result that adding a branch increases the hazard rate by 6.3 percent, adding almost one percentage point to the estimated nine year cumulative adoption probability (which is 17.1 percent for the average bank).

The second though experiment involves adding a branch while keeping the size per branch constant. This therefore involves adding some depositors at the same time as the branch is added and therefore overstates the network effect. Performing this calculation yields the result that adding a branch increases the hazard rate by 11.3 percent, adding 1.8 percentage points to the nine year cumulative probability of adoption. Therefore the effect of adding a single additional location adds between 0.97 and 1.8 percentage points to the cumulative probability of adoption.

We can contrast this result with the effect of increasing the number of depositors, holding the number of branches constant to isolate the effect of production scale economies. Adding enough in depositors to equal an average size branch increases the hazard rate by 4.5 percent. The effect of this is to increase the nine year cumulative probability of adoption by 0.79 percentage points. The network effect is larger than the scale effect documented in previous studies.

There are two open issues not addressed here which relate to the effect of competition on adoption. The first relates to the incentives for banks to use the adoption of ATMs to gain competitive advantage. In particular, are banks that have a dominant position in terms of number of branches able to exploit network effects to gain market share over their rivals by adopting ATMs? The second issue is whether this potential for exploiting network effects leads to races to adopt among equally well-positioned rivals, and how this is affected by market structure. We hope to address these issues in future work.

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TABLE 1: DESCRIPTIVE STATISTICS

	MULTIPLE BRANCHING	UNRESTRICTED BRANCHING	LIMITED BRANCHING
DEPOSITS (millions)	36.495 (218.39)	69.520 (338.13)	28.763 (178.412)
BRANCH	6.260 (27.230)	13.789 (58.062)	4.497 (10.529)
PRODMIX	0.334 (0.110)	0.387 (0.122)	0.321 (0.103)
WAGE	6.013 (1.062)	5.708 (0.852)	6.084 (1.093)
WB/L	7.580 (2.181)	7.649 (3.624)	7.564 (1.674)
DEPOSITS/ BRANCH	4.704 (12.542)	3.552 (4.255)	4.973 (13.768)
PROPBR	4.934 (4.206)	10.407 (6.302)	3.653 (1.974)
ADOPTION (%)	17.750	19.080	17.438
ADOPTION TIME	5.509 (2.441)	4.651 (2.506)	5.728 (2.379)
NUMBER OF OBSERVATIONS	2293	435	1858

Standard deviations in parentheses

TABLE 2: WEIBULL ESTIMATES FOR MULTI-BRANCHING STATES

	ALL MULTI-BRANCH		UNRESTRICTED		LIMITED	
CONSTANT	-7.181 (0.406)	-7.074 (0.413)	-7.862 (1.149)	-7.936 (1.147)	-6.179 (0.493)	-6.253 (0.512)
DEPOSITS	4.7 E-3 (4.6 E-4)	3.7 E-3 (1.2 E-3)	2.3 E-3 (4.4 E-4)	-7.1 E-3 (-2.7 E-3)	0.011 (1.2 E-3)	2.4 E-3 (1.6 E-3)
BRANCH		0.011 (7.2 E-3)		0.054 (0.016)		0.112 (0.018)
DEPOSITS ²	-1.4 E-6 (1.9 E-7)	-3.3 E-6 (5.6 E-7)	-3.9 E-7 (1.2 E-7)	4.4 E-6 (1.9 E-6)	-7.4 E-6 (1.7 E-6)	-3.2 E-6 (6.7 E-7)
BRANCH ²		5.7 E-5 (1.8 E-5)		-1.5 E-4 (6.2 E-5)		-1.1 E-3 (2.4 E-4)
DEPOSITS/ BRANCH		0.027 (3.4 E-3)		0.079 (0.017)		0.036 (4.4 E-3)
PRODMIX	1.848 (0.431)	1.466 (0.445)	2.148 (0.873)	1.647 (0.907)	1.373 (0.539)	0.870 (0.580)
WAGE	0.088 (0.048)	0.073 (0.048)	0.292 (0.149)	0.245 (0.150)	0.047 (0.052)	0.050 (0.052)
WB/L	0.045 (0.015)	0.039 (0.018)	0.045 (0.013)	0.053 (0.013)	-0.034 (0.036)	-0.051 (0.039)
PROPBR	-0.025 (0.013)	-0.028 (0.014)	0.021 (0.018)	0.020 (0.018)	-0.166 (0.039)	-0.222 (0.042)
GAMMA	0.540 (0.025)	0.541 (0.025)	0.750 (0.079)	0.716 (0.075)	0.500 (0.026)	0.493 (0.027)
NO. OF OBS.	2293	2293	435	435	1858	1858
Loglikelihood	-1181.38	-1151.81	-250.21	-240.68	-884.35	-842.66
$\frac{d \log(\text{HAZARD})}{d(\text{DEPOSITS})}$	0.005 (4.6 E-3)	7.8 E-3 (1.1 E-3)	2.2 E-3 (4.4 E-4)	-7.9 E-4 (1.9 E-3)	0.011 (1.2 E-3)	0.010 (1.5 E-3)
$\frac{d \log(\text{HAZARD})}{d(\text{BRANCH})}$		-8.9 E-3 (6.6 E-3)		0.030 (0.012)		0.063 (0.015)

Standard errors in parentheses

TABLE 3: ALTERNATIVE FUNCTIONAL FORMS FOR LIMITED BRANCHING BANKS

	WEIBULL	COX	LOG-LOGISTIC
CONSTANT	-6.253 (0.512)		-6.719 (0.588)
DEPOSITS	2.4 E-3 (1.6 E-3)	2.2 E-3 (1.6 E-3)	3.2 E-3 (2.4 E-3)
BRANCH	0.112 (0.018)	0.110 (0.017)	0.148 (0.021)
DEPOSIT ²	-3.2 E-6 (6.7 E-7)	-3.2 E-6 (6.7 E-7)	-4.6 E-6 (1.0 E-6)
BRANCH ²	-1.1 E-3 (2.4 E-4)	-0.001 (2.2 E-3)	-1.2 E-3 (2.5 E-4)
DEPOSITS/ BRANCH	0.036 (4.4 E-3)	0.035 (0.004)	0.050 (7.7 E-3)
PRODMIX	0.870 (0.580)	0.870 (0.580)	1.089 (0.679)
WAGE	0.050 (0.052)	0.053 (0.052)	0.051 (0.060)
WB/L	-0.051 (0.039)	-0.054 (0.039)	-0.070 (0.046)
PROPBR	-0.222 (0.042)	-0.234 (0.039)	-0.271 (0.050)
GAMMA	0.493 (0.027)		0.437 (0.022)
NUMBER OF OBSERVATIONS	1858	1858	1858
LOGLIKELIHOOD	-842.66	-2267.90	-832.24

Standard errors in parentheses

**TABLE 4: ORDER STATISTIC TEST
(LIMITED BRANCHING BANKS)**

	TWO BRANCHES	FIVE BRANCHES	TEN BRANCHES	FIFTEEN BRANCHES
BANK ADOPTION RATE (q)	0.157	0.166	0.455	0.545
BRANCH ADOPTION RATE (p)	0.081	0.036	0.059	0.052
EXPECTED ADOPTING BRANCHES PER ADOPTING BANK (N_0)	1.043 (0.957)	1.074 (1.036)	1.294 (1.218)	1.408 (1.336)
AVERAGE ATMS PER ADOPTING BANK	2.390	4.167	6.778	10.000
NO. OF OBS.	274	78	22	11

Standard errors in parentheses

1367 037

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