THE ADOPTION OF INTERORGANIZATIONAL SYSTEMS AND NETWORK EXTERNALITIES: AN ANALYTICAL AND EMPIRICAL STUDY

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ABSTRACT

Recent work in the information systems literature has argued that network externalities, the value of a network created as a by-product of an existing installed base, are a determinant of interorganizational systems (IOSs) adoption. However, almost no empirical studies have reported the impact of network externalities on the adoption of IOSs. As a result, little is known about the extent to which network externalities may influence the adoption and diffusion of IOSs. Using electronic banking as a context, an analytical framework is developed to model the business value of a shared network to a bank that is considering whether to become involved. We show that network externalities, proxied by expected shared network size, as well as the size of banking firms, are major elements of the perceived value of the network. To empirically assess the impact of these elements on the timing of network adoption and validate our analytical model, we estimate a hazard model (also known as duration or failure time model) using the adoption data for Yankee 24, the largest shared electronic banking network in New England. The hazard model approach that explicitly incorporates covariates in the specification of time to adopt is employed to accommodate *right-censoring* of our observations of adoption times. We find that banks in markets that can generate a larger effective network size and have more depositors served per branch tend to adopt early, while the size of a bank's own branch network decreases the probability of early adoption.

1. INTRODUCTION

The rate at which technologies are adopted by firms is a fundamental aspect of the process of technological change. Accordingly, investigation of the firm-specific and market-specific characteristics which influence decisions to adopt technologies has long been recognized as an important area of study. With the advent of modern telecommunications capabilities, a particularly interesting technology, interorganizational systems (**IOSs**), is rapidly becoming a competitive necessity in a wide variety of industries.

IOSs are automated information systems shared by two or more companies (Cash and Konsynski, 1985). Several studies report on successful applications of IOSs, including regionally shared electronic banking networks in the middle Atlantic United States (Banker and Kauffman, 1990; Clemons, 1990), the CIRRUS and PLUS nationally shared electronic banking networks (Kauffman and Wang, 1992), airline computerized reservation systems (**CRS**) (Copeland and McKenney, 1988), and wholesale distribution systems (Clemons and Row, 1988). Other well known IOSs include credit card switching and transaction confirmation systems (Steiner and Teixeira, 1990), and the Society for Worldwide Interbank Financial Telecommunications (**SWIFT**) that has traditionally provided telecommunications links between international commercial banks to permit the exchange of payment information. Keen (1991) suggests that firms not able to adopt IOSs in time may be locked out of a wide range of services and the market.

Like telephone networks, IOSs are subject to significant *network externalities* in that the value of an IOS to a given subscriber is affected by the number of others joining the same network. The literature suggests that network externalities have a number of strategic implications for technology adoption and yields a conclusion that technologies subject to network externalities have characteristics not shared by many other traditional technological innovations (Cabral, 1990; Dybvig and Spatt, 1983; Farrell and Saloner, 1985 and 1986; Katz and Shapiro, 1985, 1986a and 1986b; Oren and Smith, 1981; Rohlfs, 1974). In the information systems (**IS**) literature, there have been some theoretical analyses or frameworks to guide the study of IOSs (e.g., Bakos, 1991; Gurbaxani and Whang, 1991; Johnston and Vitale, 1988; Malone, Yates, and Benjamin, 1987). However, there has been little empirical research on the determinants of IOS adoption, and almost no empirical studies have reported the impact of network externalities on the adoption of IOSs. As a result, little is known about the extent to which network externalities and other factors may influence the adoption and diffusion of IOSs.

This paper first develops an analytical model to examine the impact of key variables influencing the perceived network business value in the context of a shared electronic banking network, a subset of IOSs that exhibited rapid growth throughout the U.S. in the 1980s. Network externalities in this context are significant because the participation of new member banks not only brings in additional automated teller machines (**ATMs**) that can enhance locational convenience and service coverage for depositors of existing members, but also more card holders that enable additional *interchange revenues* -- access fees earned by a bank if the card holders of other member banks access their accounts using the bank's ATMs. Thus, the value of a shared network to depositors as well as member banks increases as the network grows.

We model the perceived business value of a shared network to a potential adopting bank in terms of the benefits and costs of adoption. We proxy network externalities using the expected shared network size and show that demand side network externalities contribute positively to the perceived network business value. In addition, the number of depositors served per network ATM location is shown to have a positive impact on network value, while the effect of the number of depositors and ATMs on a bank is ambiguous.

To gauge the extent of network externalities and test the impact of various other factors on network adoption decisions, we examine the adoption and diffusion of Yankee 24, the largest regionally shared network in the northeast region of the U.S. Because Yankee 24 started in Connecticut in 1984 and banks in other New England states were allowed to join the network only after 1987, we include only Connecticut-based banks in our sample. Although we are limited in our ability to generalize on the basis of the results obtained in the study of a single network, our choice has two advantages. First, examining the adoption of a single technology in a single industry avoids the difficulties encountered in previous research in controlling for differences across innovations in capital costs or potential profitability (Rose and Joskow, 1990). Second, because the founding members of Yankee 24 were a significant group of banks in Connecticut, no other networks were likely to enter the market and thus our sample had little uncertainty regarding the ultimate success of Yankee 24. This unique aspect of Yankee 24 allows us to focus on the determinants of high level externalities rather than on the question of the success of Yankee 24.

We employ a *hazard model* (also known as duration or failure time model) approach which addresses a series of assumptions and modeling concerns that made subsequent empirical analysis possible and overcomes some of the limitations of previous work on technology adoption using cross-sectional models. We specify a hazard model that explicitly incorporates explanatory variables in the specification of banks' probabilities to adopt. The model is estimated using a data set that includes the adoption dates, a proxy for network externalities, banking firm characteristics, and market structure variables. We find that banks in markets that are expected to have a larger effective network size and have more depositors served per branch tend to adopt early. The number of a bank's depositors also contributes to early adoption, while the size of a bank's own branch network decreases the probability of network adoption. The results indicate that network externalities play an important role in determining the timing of network membership.

2. NETWORK EXTERNALITIES AND SHARED NETWORK VALUATION

In this section, we review relevant literature and develop an analytical model that represents the decision problem faced by a potential adopting bank when it evaluates the perceived business value of a shared electronic banking network. We assume that a bank's decision to participate in a shared electronic banking network is a rational economic decision, which reflects the present and future benefit and cost flows associated with network adoption. The analytical model yields a number of implications and hypotheses to guide an empirical test that we will discuss in Sections 3 and 4.

2.1. Network Externalities as a Determinant of Shared Network Adoption

First recognized in the context of communications networks, the concept of positive network consumption externalities is based on the observation that the value of a network to a subscriber increases with the number of adopters of the network. Accordingly, the demand for network membership depends on the size of the network, and as the network grows, it becomes more attractive to non-subscribers, inducing some of them to join the network. Farrell and Saloner (1986) present models that yield the following conclusions: because of economies of scale and positive externalities, network goods have a greater tendency towards monopoly (or greater concentration) than services that do not generate externalities; the strength of the network externalities created as a by-product of an existing installed base may lead to a *bandwagon effect* and result in choices of inferior network technologies. In addition, they show that the existence of network externalities has strategic implications for a variety of important economic activities, including technology adoption, predatory pricing, and product preannouncements.

Katz and Shapiro (1986a) argue that, because of scale economies and network externalities, the dynamics of network goods are fundamentally different from those of conventional innovations. In the presence of network externalities, the total benefits derived from the network depends, in part, on the number of consumers who adopt compatible products in the future. Thus, a consumer in the market today also cares about the future success of the products. Tirole (1988) also suggests that firms must anticipate which technology will be widely used by others since they are afraid of being stranded if another network becomes the standard. In some cases, however, there may be benefits to early adoption of what later becomes an industry-wide standard -- the first-mover advantage. This line of theoretical research suggests that network externalities have economic value and strategic impacts on the structure of markets, industries, and organizations. Network externalities, hence, should be a major element in the valuation of network goods.

In the financial services industry, shared electronic banking networks generate significant network business value externalities. As new member banks join the network and bring in ATMs, depositors of all existing member banks value more highly their ATM cards and would pay a certain share of their network privileges because of more convenient locations for account access. In addition, participation of new member banks brings to the network more card holders that may access their accounts using the ATMs of existing members, and thus increases the potential for some deployers of ATMs to earn more interchange revenues. As a result, banks value the shared network more highly as it grows, and late entrants at some point in time find that they must join the network in order to avoid competitive disadvantage.

2.2. Analytical Framework for Shared Electronic Banking Network Valuation

Saloner and Shepard (1991) employ an econometric model to test the impact of explanatory variables on the timing of ATM adoption among banking firms in the U.S. They find that a bank's date of adoption is earlier the larger the number of its branches (a proxy for the proprietary network benefits to the bank in adopting ATM) and the larger the value of its deposits base (a proxy for the number of users). Because there was little sharing of ATMs at the time of their study, the focus of their study was the benefits of ATM adoption in the presence of network effects in the proprietary ATM networks. The analytical framework they developed, however, can be extended to model the value of a shared network for considering a bank's adoption decision. Specifically, the model of technology adoption they present gives rise to a network effect, but each bank's network benefits are independent of other banks' actions. In other words, the adoption decisions were self-contained, and no network externalities were involved. In the context of shared electronic banking network, a bank must evaluate the expected adoption behavior of other banks.

2.2.1. The Benefit Dimensions

McAndrews and Kauffman (1993) model the perceived business value of a shared electronic banking network to a bank's depositors per period as $a+b(N)$, where a represents the "stand-alone" or "network independent" benefit from the ATM technology and b(N) represents the network externalities effect. Note that b(N) monotonically increases in the size of the network, N, which represents the number of locations from which a depositor is able to access his or her account. In our context, N is the unique equilibrium number of participating banks in Connecticut given the sure viability of Yankee 24, and is known to all potential members in our sample because the equilibrium adoption of Yankee 24 membership was foreseen. We assume that the per period increase in revenues to the bank is proportional to the per period value to the depositors, and let the parameter $\lambda < 1$ denote the proportion. Then, the bank's per period revenues can be formulated as in Equation 1, where n is the number of the bank's depositors. For simplicity, we will assume that λ remains constant throughout the study period and that it is known to a bank's managers.

$$\lambda n[a+b(N)] \tag{1}$$

We extend the above formulation to incorporate the impact of time varying network externalities on interchange revenues that was significant in the context of shared networks. Because banks in our sample were able to observe a group of banks in their market that founded and adopted Yankee 24 in Connecticut and there was no significant statewide competition with Yankee 24, they could foresee that Yankee 24 would be a viable and successful venture. Hence, there was little uncertainty regarding the desirability of Yankee 24 membership.

To facilitate the discussion and analysis of the increase in revenues associated with network adoption in the remaining section, we define three types of ATM transactions. *Us-on-us* refers to the use of a bank's ATM by its card holders. *Others-on-us* refers to the use of a bank's ATM by card holders from another bank. *Us-on-others* refers to the use by a bank's card holders of another bank's ATM. Of these three types of transactions, the first two give rise to benefits and the last one gives rise to a cost. Us-on-us provides a bank's ATM service benefit for which customers are willing to pay. Us-on-others and others-on-us require interchange. For each interchange transaction, an *interchange fee* is paid to the owner of an ATM by a network member whenever that member's card holders use an ATM. Thus, us-on-others requires a bank to pay out on transactions that other banks service for its customers, while others-on-us enables it to earn interchange revenues.

Because the participation of other member banks brings in additional ATMs that can enhance the locational convenience and service coverage for depositors, adopting a shared electronic banking network creates an us-on-us benefit. Let n_i represent the number of depositors of bank i, and N_t the installed base of the shared network at time t. The present value of bank i's decision to adopt a shared network due to the network effect, evaluated at time t=0, is expressed in Equation 2. $\lambda_1 < 1$ denotes the proportion of the per period value to the depositors that a bank can capture. $\delta < 1$ is the discount factor.

$$\sum_{t=0}^{\infty}[\lambda_1 n_i(a+b(N_t))]\delta^t \tag{2}$$

By adopting a shared network, banks have opportunities to obtain additional benefits through interchange revenues, when other banks' customers' ATM transactions are captured. Because the more banks in the shared network, the greater the number of card holders are available that are likely to initiate others-on-us transactions and thus contribute to the benefit, we express the present value of bank i's interchange revenues earned through network membership in Equation 3.

$$\sum_{t=0}^{\infty}[p_1 f_1(n_t-n_i)\frac{N_i}{N_t}]\delta^t \tag{3}$$

In this expression, n_t is the total number of card holders that can access the shared network at time t. N_i is the number of ATMs that bank i has deployed. N_i/N_T represents the likelihood that bank i's ATMs will be used by other banks' card holders. n_t-n_i is the number of card holders that may initiate others-on-us transactions, f_1 represents a permissible fee schedule, and p_1 represents the proportion of those card holders that will do so. For simplicity, we will assume N_i, n_i, p_1, f_1 and λ_1 are predetermined and fixed over the study period. These reflect pieces of information that should be available to bank managers either through market research, forecasts or directly from the electronic banking network.

As more ATM locations become available, the depositors of a bank are also likely to access their bank accounts using the ATMs of other competing banks. Because the competitor is able to charge interchange revenues, in the absence of a policy to pass these costs onto a bank's customers, they must be absorbed as a cost of network participation. As a result, bankers often talk about "favorable" and "unfavorable" interchange ratios: in order to generate net revenues, others-on-us transactions must exceed us-on-others. Thus, we also include in our model a term to reflect this reduction to network interchange revenues, expressed as Equation 4.

$$-\sum_{t=0}^{\infty}[p_2 f_2 n_i \frac{N_t - N_i}{N_t}]\delta^t \tag{4}$$

In this expression, f_2 is a parameter that reflects the transaction fees earned by the bank's competitors for us-on-others interchange, which results in a direct cost to the bank. p_2 denotes the proportion of the bank's card holders that will initiate such transactions. Similar to our earlier assumptions with respect to model parameters, we again presume f_2 and p_2 to be predetermined and fixed over the study period. The negative sign that precedes Equation 4 reflects that this is a revenue benefit that accrues to a competitor, resulting in a cost for the potential network adopter. Taken together, Equations 3 and Equation 4 reflect the net interchange benefits. As expected, the net interchange benefits are greater, the larger the values for n_t and N_i, and the smaller the values for N_t and n_i. Taking into account the benefit due to the network effect expressed in Equation 2, Equation 5 represents the total benefits associated with network adoption, which is equal to the sum of Equation 2, 3, and 4. Only N_i and n_t, however, have an unambiguous and positive impact on the benefit side of shared network adoption.

$$\sum_{t=T}^{\infty}[\lambda_1 n_i(a+b(N_t))]\delta^t + \sum_{t=T}^{\infty}[p_1 f_1 (n_t - n_i)\frac{N_i}{N_t}]\delta^t - \sum_{t=T}^{\infty}[p_2 f_2 n_i \frac{N_t - N_i}{N_t}]\delta^t \tag{5}$$

2.2.2. The Cost Dimensions

Having analyzed the benefits side, we now turn to the costs of adopting a shared network. We envision two kinds of opportunity costs. First, there is an opportunity cost of adoption for banks that have already deployed proprietary networks. These costs are likely to be proportional to N_i , but negatively related to N_t, as reflected in the first element of Equation 6. Second, an opportunity cost may also develop out of per period revenue losses that the bank will incur if it does not participate in the network. This opportunity cost should be proportional to the per period value that bank customers place on their ability to access other banks' ATMs, which is expressed as the second element in Equation 6.

$$\sum_{t=0}^{\infty}[\lambda_2 n_i(a+b(N_i))]\delta^t - \sum_{t=0}^{\infty}[\lambda_3 n_i(a+b(N_t - N_i))]\delta^t \tag{6}$$

λ_2 and λ_3 in this expression are parameters denoting the respective proportions, and N_t - N_i is the resulting shared network size should the bank decide not to adopt the shared network.

Thus, for banks that are small in terms of N_i relative to N_t, the opportunity costs will be low. But, for banks that have deployed ATMs to a large number of locations, the opportunity costs will very be high, especially in markets where the network effects are significant. Overall, however, the opportunity cost for a bank declines over time.

In addition to opportunity costs, there are other variable costs and fixed costs associated with network adoption. Assuming that each depositor makes the same number of transactions, the variable costs are proportional to the number of transactions. Without loss of generality, we can incorporate the variable costs in the parameters λ_1 and p_1, or p_2, depending on the type of transactions.

The fixed costs may 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 ATMs themselves, the cost of service and marketing (Saloner and Shepard, 1991). In the context of shared networks, the shared network organizations typically are responsible for marketing and promotional activities. Thus, the fixed costs include hardware and software investments, membership fees, and terminal hook-up fees. The terminal hook-up fees are proportional to N_i, and thus can be incorporated into the parameter f_1, without loss of generality. The hardware and software investment costs are usually too high for small banks to justify. With the help of third-party vendors who deliver outsourced electronic banking services, however, smaller banks are more likely to be able to derive the economic benefits of network participation. Again, without loss of generality, we can treat the hardware and software costs as part of the variable transaction costs. As a result, the fixed cost of adoption are minimal, which presumably is the one-time membership fee assessed at the time of adoption, denoted by C_T.

2.2.3. Net Benefits and Decision Model

Taking the elements of benefits (Equation 5) and costs (Equation 6 and $C_T\delta^T$) together, π_T in Equation 7 denotes the present value of bank i's net benefits of shared network adoption at time T.

$$\Pi_T=\sum_{t=T}^{\infty}[\lambda_1 n_i(a+b(N_t))]\delta^t+\sum_{t=T}^{\infty}[p_1 f_1(n_t-n_i)\frac{N_i}{N_t}]\delta^t-\sum_{t=T}^{\infty}[p_2 f_2 n_i\frac{N_t-N_i}{N_t}]\delta^t$$
$$-\sum_{t=T}^{\infty}[\lambda_2 n_i(a+b(N_i))]\delta^t+\sum_{t=T}^{\infty}[\lambda_3 n_i(a+b(N_t-N_i))]\delta^t-C_T\delta^T \tag{7}$$

A bank earns greater benefits from adopting at time T than from waiting until time T+1 if $\pi_T > \pi_{T+1}$. Given that the potential adopting bank's decision depends on the flow of benefits and costs from adoption, bank i will adopt at time T if $\pi_T - \pi_{T+1}$ in Equation 8 is greater than 0. Thus, the smallest T that satisfies $\pi_T > \pi_{T+1}$, or equivalently, Equation 9, is the optimal time for bank i to adopt.

$$\Pi_T - \Pi_{T+1} = [\lambda_1 n_i (a + b(N_T))]\delta^T + [p_1 f_1 (n_T - n_i)\frac{N_i}{N_T}]\delta^T - [p_2 f_2 n_i \frac{N_T - N_i}{N_T}]\delta^T$$
$$-[\lambda_2 n_i (a + b(N_i))]\delta^T + [\lambda_3 n_i (a + b(N_T - N_i))]\delta^T - C_T\delta^T + C_{T+1}\delta^{T+1} \quad (8)$$

$$\lambda_1 n_i [a + b(N_T)] + p_1 f_1 (n_T - n_i)\frac{N_i}{N_T} - p_2 f_2 n_i \frac{(N_T - N_i)}{N_T} - \lambda_2 n_i [a + b(N_i)]$$
$$+ \lambda_3 n_i [a + b(N_T - N_i)] > C_T - \delta C_{T+1} \quad (9)$$

To simplify, we can assume that the fixed cost function, C_T, is constant over time. Thus, the right hand side in Equation 9 becomes $C_T(1-\delta)$. With the help of third party processors, smaller banks can now have low investment costs and the same opportunity to adopt as the larger ones. The one-time membership fee is relatively low and almost fixed, and is in the range of a nominal fee to several thousand dollars, in general. Thus, C_T is not likely to be a dominant factor, and hence, we can leave out $C_T(1-\delta)$ without loss of generality. As a result, the condition in Equation 9 reduces to Equation 10.

$$\lambda_1 n_i [a + b(N_T)] + p_1 f_1 (n_T - n_i)\frac{N_i}{N_T} - p_2 f_2 n_i \frac{(N_T - N_i)}{N_T} - \lambda_2 n_i [a + b(N_i)] + \lambda_3 n_i [a + b(N_T - N_i)] > 0 \quad (10)$$

Another assumption we make is that banks do not generate net revenues if the total number of others-on-us transactions equals us-on-others transactions, i.e., $p_1 f_1 = p_2 f_2$. As described, f_1 and f_2 are parameters representing the interchange fee schedules. Because the interchange fee is mandated by the shared network organization, presumably it is the same for all network members. Thus, the assumption boils down to $p_1 = p_2$. This is equivalent to saying that banks do not differ in the proportion of their card holders that will initiate interchange transactions, and all customers, irrespective of which services they use, act the same when they initiate interchange transactions. In other words, we assume that others-on-us customers react to the environment in the same way that us-on-others customers do. Although we recognize that many ATM value platform features, such as ATM location design choices, depth of ATM services, and environment features may shift the balance of interchange (Kauffman and Lally, 1993), and thus may affect the net interchange revenues, these variables are beyond the scope of our analytical model and empirical test. This assumption allows us to focus on the major variables of interest, and as a result, Equation 10 can be further reduced to Equation 11.

$$\lambda_1 n_i [a + b(N_T)] + p_1 f_1 N_i \frac{n_T}{N_T} + \lambda_3 n_i [a + b(N_T - N_i)] > \lambda_2 n_i [a + b(N_i)] + p_1 f_1 n_i \quad (11)$$

The adoption decisions that are determined by Equation 11 are consistent with our assumption of equilibrium in the adoption of Yankee 24 membership in that given N_T, the adoption evolves according to the expected equilibrium adoption path. In other words, given the equilibrium size of Yankee 24, N_T, for each period t, adding up the locations deployed by the adopters according to Equation 11 above sums up to the equilibrium size N_T. For example, suppose $N_{T-1}=50$ and $N_T=65$. In period T-1, each banking firm adopts or fails to adopt according to Equation 11 (with the base value $N_{T-1}=50$). In this case, we could have 5 adopting banks each adding 3 locations for a total of 15 locations, yielding a new base of $N_{T-1}=65$, which was the expected equilibrium level of the base in period T. We assume that the equilibrium adoption path was unique at a high level of participation, given the significant group of founding members of Yankee 24.

2.3. Implications and Hypotheses

Analytical Model Implications. The analytical framework developed in the previous section, Equation 11 in particular, yields several implications. First, the shared network installed base at decision period T, N_T, appears on the left hand side of Equation 11. It contributes to early adoption by a bank if n_T grows with N_T (i.e., the increase in N_T is offset by that in n_T) or if the network effect is strong. Second, the number of customers served per network location, n_T/N_T, leads to early adoption. This result is intuitive in the sense that n_T/N_T is a measure of network service coverage as perceived by bank i, and the larger the value of the ratio n_T/N_T, the greater the opportunity for the bank to earn interchange revenue. Note that the impact of n_T, the total number of depositors of all member banks, is subtle because N_T grows as it grows. However, it contributes to early adoption if we hold N_T constant. Third, the number of a bank's depositors, n_i, has an ambiguous impact on early adoption. However, it appears that the impact of n_i is positive if the network effect is strong and the shared network installed base is much larger than the size of a bank's ATM network (i.e., $N_T > N_i$).

Fourth, the overall effect of N_i, the size of a bank's ATM network, is also ambiguous. In particular, its impact depends, in part, on the network effect, i.e., the function b(N). If the network effect is strong, N_i is more likely to have a negative impact because of high opportunity costs. In general, however, banks which have deployed a small number of ATMs are very likely to adopt early, because they have very low opportunity costs relative to the potential benefits. On the other hand, although banks with large ATM networks have a better chance of earning more interchange revenues, they also have high opportunity costs, especially in the early stages of network growth in which network installed base is relatively small. In other words, banks which have deployed a larger number of ATMs may find it advantageous to wait for the shared network to grow to an extent to break even. As a result, they are likely to be later adopters.

Generally speaking, the benefits grow and the opportunity costs of adoption decline over time. In other words, the left hand side in Equation 11 increases as the shared network continues to grow, which implies that every bank may eventually find it profitable to adopt the shared network. In cases when the market potential for the shared network is limited, however, banks with very large own ATM networks or a strong competitive position may never adopt. (Consider, for example, how long Citibank held up from participating in any sharing agreement whatsoever; it was not until 1992 that Citibank decided to join the CIRRUS national shared electronic banking network.)

Hypotheses. For the purpose of performing an empirical test to gauge the strength of network externalities and other key variables influencing the adoption of Yankee 24, we next discuss a series of hypotheses that follow directly from the analytical model presented above. The hypotheses employ the concept of "effective network size" in the local markets in which banks operate, recognizing the importance of network growth expected by potential adopters in their adoption decisions. Thus, our proxies for theoretical variables rely on an implicit hypothesis that network externalities are significant and measurable at the local market level. This enables us to test them using relevant data that adequately describe electronic banking network growth and banking firm competitive interactions in a realistic applied setting. Each of the hypotheses reflects a prediction about the conditions which lead to earlier adoption.

H.1 Banks in markets that are expected to generate a larger network installed base have higher adoption probabilities.

H.2 Banks in markets that have more card holders served per branch office have higher adoption probabilities.

H.1 applies the general assertion that firms which have the opportunity to adopt networked technologies will do so especially when the network is well established. Because differences in banks' post-adoption effective network size may be different depending on the local markets in which the banks operate, a shared network may generate different valuations for different banks. In other words, H.1 suggests that the value of adopting a shared network would be higher for banks in markets expected to have a larger network installed base in equilibrium, all else equal.

H.2 is an alternative to the hypothesis that the number of network card holders served per network ATM location has a positive impact on network valuation and the probability of adoption. The reason for having this alternative is that we cannot observe ATM placement, but we can observe branch placement from publicly available data. As we discussed earlier, banks in a market that has more customers served per branch office have lower customer service coverage and a greater opportunity to earn interchange revenue, and hence, higher adoption probabilities. Instead of adding costly new branches, those banks can also enhance their customer service coverage by joining shared electronic banking networks.

For banks operating in the same local market, however, heterogeneity in banks' characteristics may play a role in determining the likelihood of earlier adoption, e.g., the number of ATM locations and the number of card holders. These observations suggest the following hypotheses:

H.3 The larger the number of a bank's ATM locations, the lower the probability of adoption.

H.4 Banks with more card holders will register higher adoption probabilities.

The effect of the size of a bank's ATM network on adoption probability is ambiguous in the analytical model, however, banks with small ATM networks are likely to adopt early, and banks with large ATM networks are likely to adopt later for reasons discussed earlier. In the presence of a strong network effect, the number of a bank's ATM locations will have a negative impact on adoption probabilities because of high opportunity costs. H.4 derives directly from our analytical model: the number of depositors has an unambiguous and positive impact on network value and hence on the probability of early adoption.

Two additional variables, wage rate and market structure, have been shown to influence ATM adoption (Hannan and McDowell, 1984 & 1987; Saloner and Shepard, 1991). Although we do not incorporate them in our analytical model, we include them in our development of hypotheses and empirical test for control purposes. Mansfield (1968) and Romeo (1977) reported evidence supporting the hypothesis that the more competitive the market the greater rate of innovation diffusion. Kamien and Schwartz (1982) reviewed the empirical evidence and noted that diffusion does indeed tend to be faster in non-concentrated industries, i.e., diffusion should be faster the fewer firms there are in the region and the smaller the size inequalities between firms. Market structure and other industry characteristics have been hypothesized to influence innovation adoption and diffusion by many other studies, however, the results are inconclusive. Hannan and McDowell (1984) find that banks operating in concentrated markets were likely to adopt ATM technology earlier. H.5 follows the finding by Hannan and McDowell (1984).

H.5 Banks that are located in more concentrated markets have a higher probability of adoption.

Hannan and McDowell (1984) find support for their hypothesis that the higher the prevailing wage rate in the market in which the bank operates the more attractive the adoption of ATM to the bank. The findings by Saloner and Shepard (1991) also suggest that, consistent with the incentive for substituting ATMs for tellers, the wage rate contributes positively to early adoption. Because ATMs are labor saving, we expect this hypothesis, H.6, to hold for the adoption of shared electronic banking networks.

H.6 The higher the wage rate in the market in which the bank operates the higher the probability of early adoption.

3. MODELING APPROACH AND PRELIMINARIES

In this section we provide an overview of the econometric analysis approach used to investigate the impact of explanatory variables on the adoption probabilities. We also review studies of technology adoption that employed similar econometric techniques, as a means to contrast elements of our approach.

3.1. Rationale for Using Hazard Model

This study uses adoption data indicating the point in time that each of a large number of banking firms joined the shared electronic banking network. Thus, the statistical model to be employed should be able to assess the dependence of adoption time on explanatory variables, whose relationships are structured by our analytic model. In addition, because our observations of adoption times are *right-censored* -- by the end of some observation period, some firms have adopted during the period of observation, while some firms may not have done so -- the estimation model must accommodate censoring. Hazard models developed in the statistics and econometrics literature, which attempt to assess the impact of covariates on the duration of an event, are readily applicable for the purpose of this study. Hazard models can explicitly incorporate covariates in the specification of time or probabilities to adopt, so that the population is heterogeneous in timing of adoption. As suggested by Mahajan, Muller, and Bass (1990), hazard models are particularly important in studying the innovation diffusion process.

Note that hazard models are also known as duration models and failure time models. We use the term hazard models throughout this paper. Interested readers can refer to (Kalbfleisch and Prentice, 1980) which offers a thorough discussion of the statistics of failure time data. Peterson (1991) describes the use of hazard rate models when analyzing event histories. Kiefer (1988) also provides a discussion of duration models in general.

The impact of explanatory variables on the timing of adoption constitutes the hazard modeling tradition of innovation diffusion models at the individual level. Hannan and McDowell (1984) were the first to employ the hazard model to investigate the impact of covariates, mainly market structure and firm size, on the timing of adoption of ATMs. Levin, Levin, and Meisel (1987), and Rose and Joskow (1990) applied similar techniques to study technology adoption. These studies have essentially explored the impact of market structure and the positive influence of firm size on the process of technology diffusion.

3.2. Formulation of the Hazard Model

To test the hypotheses derived from our analytical model and to gauge the strength of various variables on the probability of network adoption, the general strategy is to construct and estimate a hazard model, which assumes that the time until adoption for a banking firm is conditional on the explanatory variables and follows some distribution, the exponential or the Weibull distribution, for example. We next introduce the terminology and summarize the statistical model used in the study.

In this application, *failure time* denotes the elapsed time from the start of observation until the date on which the event of interest -- the adoption of shared electronic banking network -- occurs or the observation period ends. There are several ways to describe the distribution of observed failure times for an event:

(1) the cumulative *failure time probability distribution function* $F(t) = Pr(T<t)$, which specifies the probability that the random variable T is less than some value t;
(2) the corresponding *probability density function*, $f(t) = dF(t)/dt$;
(3) the *survivor function*, $S(t) = 1 - F(t) = Pr(T \geq t)$, defined as the probability that the firm will not have adopted the network by the end of period t; and
(4) the *hazard function*, $h(t) = f(t)/S(t)$.

Although each of the four functions above can be used to derive the others, we choose to focus on the hazard function, which is a particularly convenient and useful function. Specifically, if T is a non-negative random variable representing the failure time of an individual banking firm from a population of n independent banking firms, the hazard function, $h_i(t)$, specifies the conditional probability that banking firm i will join the shared network at time t, given that it has not done so by t-1.

Because the adoption time conditional on a firm's observable characteristics is assumed to be a random variable, we consider a subset of parametric hazard models, which embody specific assumptions about the distribution of failure time. The choice of an estimation model involves choosing a distribution for adoption dates. The *exponential distribution* is commonly used as a model for failure time data. With that distributional assumption, $h(t) = \gamma$ and $S(t) = \exp(-\gamma t)$, where $\gamma > 0$ (we use the notation exp( ) for convenience, for example, $\exp(-\gamma t)$ is equivalent to $e^{-\gamma t}$). This model assumes a time invariant underlying hazard. Using time varying explanatory variables in the model, however, the hazard rate can change as explanatory variables change over time. For example, Hannan and McDowell (1984) incorporated the effect of time varying covariates, X_{it}, on the hazard function by writing $h_i(t) = \gamma = \exp(\beta X_{it})$. In their expression, X_{it} is a vector of observed explanatory variables relevant to period t adoption for firm i, and β is a column vector of unknown parameters that may be interpreted in terms of the relationship between explanatory variables and the conditional probability of adoption. As a result, the relative probabilities of adoption across firms change through time.

The probability that banking firm i will adopt during a period T_i, prior to the end of the study period, can be shown to be $S_i(T_{i-1}) - S_i(T_i)$. Hence, the likelihood of adoption is also a function of the explanatory variables prevailing in each period up to the end of the study period or the time of adoption, whichever comes first. The estimation procedure will yield parameter estimates for β that maximize a likelihood function composed of the above probabilities. The likelihood function is expressed in Equation 12.

$$L=\prod_{i=1}^{n_1}[S_i(T_{i-1})-S_i(T_i)]\prod_{j=1}^{n_2}[S_i(T^*)] \tag{12}$$

In this expression, T^* is the end of observation period, and n_1 and n_2 denote the number of firms that adopted by T^*, and did not adopt by T^*, respectively .

An alternative approach is to allow the hazard rate to be a function of time directly. We employ the *Weibull distribution*, a functional form that has been widely used in modeling technology diffusion (e.g., Rose and Joskow, 1990 and Saloner and Shepard, 1991). With the assumption of this functional form, $h(t) = \gamma\alpha t^{\alpha-1}$ and $S(t) = \exp(-\gamma t^{\alpha})$ ($\gamma > 0$ and $\alpha > 0$). Note that the Weibull distribution is a simple generalization of the exponential distribution, which is obtained by setting $\alpha = 1$. The effect of explanatory variables on the hazard function can be also incorporated by letting $\gamma = \exp(-\beta X_i)$, a standard assumption (Saloner and Shepard, 1991). X_i is a vector of fixed explanatory variables for firm i, and β is a column vector of unknown coefficients. One of the attractive features of the Weibull distribution is that the computation of the effects of the covariates on adoption probabilities from parameter estimates is relatively simple. Here the covariates are assumed to be constant throughout the observation period.

Other functional forms include the *normal distribution* and *logistic distribution*. Because the choice of a particular parameterization depends, in part, on empirical considerations (Sinha and Chandrashekaran, 1992), we estimate several hazard models with different distributions to justify the specific choice for this study empirically.

4. MEASURES AND DATA COLLECTION

We briefly describe the diffusion of Yankee 24, and the measures and data set used to examine the impact of various variables influencing Yankee 24 membership.

4.1. Yankee 24

New England Network Inc. is the Connecticut-based owner of Yankee 24, which was officially organized in August 1983 by nine banks in Connecticut. The network organization was then called Connecticut Switch Inc., and it was owned by the founders. In July 1984, the network went into operation, and began to seek other banking firm members. Because regulatory policies toward shared ATM networks in Connecticut at the time ruled that ATM sharing was *mandatory*, membership was open to all depository institutions in Connecticut and all members shared the ownership of the non-profit network organization. Potential entrants could, thus, become actual members by requesting to join Yankee 24. Out-of-state banks, however, were prohibited from establishing or using ATMs within the state at that time. Each participating bank paid a one-time membership fee of $5,000, a terminal hook-up fee of $300 per ATM, and an ongoing monthly fee of $35 per ATM. Services offered by the network included withdrawal, deposits, transfers, and cash advances. For each interchange transaction, an interchange fee set by Yankee 24 was paid to the owner of an ATM by a network member whenever that member's card holders used an ATM.

In 1985, Yankee 24 became the largest shared electronic banking network in New England in terms of number of ATMs shared and interbank ATM transactions. By 1987, Yankee 24 had over 700 ATMs, and a great majority of banks in Connecticut had joined

Yankee 24. Around that time, banking firms in other New England states were allowed to join the shared network organization, and the network's marketing staff began to actively solicit new members in those states, based on prior approval by the network's board of directors. By April 1991, Yankee 24 had grown to be the dominant shared electronic banking network in New England. Today, it has more than 700 network members and some 4,000 ATMs accessible to all members' ATM card holders, including 223 members in Connecticut with 1306 ATMs.

The founding members of Yankee 24 basically achieved a minimum viable scale that deterred further entry into Connecticut. Thus, for every bank a local market, the decision was whether to join the statewide network. When Yankee 24 entered the Massachusetts market in 1987, its largest competitor was BayBanks, particularly in the Boston area. The other competing network was the New York Cash Exchange (NYCE), owned by a consortium of many New York City banks around mid 1970s. However, it was not until mid-1987 that NYCE began to establish a significant presence outside its New York home market. Thus, competition from other networks was not an important factor in Connecticut prior to 1987.

4.2. Scope of Study and Description of Measures

The Scope of Study and Rationale. For the reasons discussed below, the scope of the empirical study is restricted to Connecticut-based banks. First, banking firms in other New England states were allowed to join the shared network organization only after the second quarter of 1987, and a great majority of Connecticut-based banking firms had signed up with Yankee 24 by that time. Therefore, the network installed base and the number of network card holders was large enough such that many banks would obtain positive net benefits from adoption once Yankee 24 opened up to them. As a result, the variables of interest in this study may not be able to explain Yankee 24 outside of Connecticut due to differences in state environments.

Second, because larger banks with more card holders and ATMs were more valuable to the shared network organization, it is likely that there were member solicitation and coalition formation activities prior to the date Yankee 24 was officially opened to all banking firms in other New England states. Third, there was no competition in Connecticut in the time frame of our study, whereas outside of the state, several competing networks began to operate (e.g., BayBanks and NYCE). The presence of those competing networks would require us to model the perceived business value of network membership differently.

Thus, to focus on the variables of interest, we limit our sample to include only Connecticut-based banks. The sample was further restricted to commercial banks and savings banks because of two reasons: (1) credit unions are very different organizations from savings and commercial banks; and (2) savings and loans are not under the supervision of Federal Reserve Bank, and hence their data are difficult to get.

Definition of Variables. In the hazard model we employ, the time to adoption is grouped into quarterly intervals. T is set to 1 for banks that joined Yankee 24 by the end of the fourth quarter of 1984, and the value of T for each other bank is determined by the elapsed time in quarters until adoption. Banks that had not joined Yankee 24 by the end of the first quarter of 1987 are right-censored with a T value of 10.

Following the market research tradition in the banking industry, we break Connecticut into 18 banking markets where Yankee 24 is offered. A market is either a Standard Metropolitan Statistical Area (SMSA) or a county that has been judged to approximate a local banking market. Explanatory variables of network adoption and the measures used in this study are:

1. NETWORK_BASE: A weighted average of market bank branches, a proxy for the unobservable expected size of the network installed base in the local banking markets. Because data on the number of ATM locations are not available, we use the number of bank branches as a proxy; branch offices are the most common and lowest cost locations for ATMs (Saloner and Shepard, 1991). For banks that have branch offices covering more than one market, a weighted average is used. Because banks in markets that are expected to have a larger network installed base are likely to adopt early, we expect that large values of NETWORK_BASE will have a positive impact on the hazard rate.

2. SERVICE_COV: The number of residents per branch office in the local market, which is a proxy for the number of card holders per branch. We expect that the lower the level of service coverage (the higher the value for SERVICE_COV), the higher the adoption probability.

3. BRANCH: The total number of branch offices operated by a bank. This is a proxy for the size of a bank's ATM network, for which data were not available for non-Yankee 24 members. This variable contributes to the opportunity costs of joining Yankee 24 as discussed in Section 2.

4. LOG_DEPOSIT: The *log* of total demand deposits, a proxy for the number of bank card holders, for which data is not available. The logarithm is used because the distribution of deposits is skewed.

5. CR4: market concentration, measured as the proportion of total market deposits accounted for by the largest four banking firms in the local market.

6. SALARY_EMP: Salary expenses per employee, defined as salary expenses and employee benefits over full-time equivalent employees. This a proxy for wage rate.

For control purposes, we also include BHC, a dummy indicating ownership of a bank by a bank holding company. Descriptive statistics for the variables used in the hazard model appear in Table 1.

Table 1. Descriptive Statistics

Variables	Mean	Standard Deviation
NETWORK_BASE	108.72	68.91
SERVICE_COV	2880.50	642.79
BRANCH	11.17	24.62
LOG_DEPOSIT	8.43	2.16
CR4	37.21	11.92
SALARY_EMP	10.17	1.54

4.3. Data Sources

To determine the impact of the explanatory variables on network adoption in the Yankee 24, we put together a data set that includes network adoption dates, bank characteristics and local market structure variables. Membership adoption data were obtained from New England Network Inc. Local banking market and population data were obtained from the statistics presented in the 1980 U.S. Census of Population.

Banking firm characteristics were obtained from periodic reports, including the Report of Condition and Income (referred to in the banking industry as a "call report") and the Summary of Deposits (SUMD) maintained by the Federal Reserve Board. The call and SUMD reports detailed balance sheet and other summary information on banks, which provided the basis for some of the explanatory variables. Additional information related to bank branches and locations was obtained from Polk's Bank Directory (1987).

A list of commercial banks and a list of savings banks that operated in Connecticut were obtained from the Federal Reserve Bank of Philadelphia and the Federal Reserve Bank of Boston, respectively. These two lists were combined for a total of 104 Connecticut-based commercial banks and savings banks, which define the universe of commercial banks and savings banks in Connecticut.[1] However, only 85 out of those 104 were found to have filed call and SUMD reports with the Federal Reserve Board in June 1984. Thus, 19 banking firms were eliminated from the sample, presumably because of bankruptcy, merger and consolidation, or missing data during the sample period. To focus on the adoption and diffusion of Yankee 24 after it was established, we excluded the founding members from the estimation of hazard model, yielding a final sample of 78 banking firms.

[1]This number is very realistic. As of June 1987, there were a total of 120 commercial and savings bank in Connecticut reported by Polk's Bank Directory.

Of the 78 banking firms in the sample, 61 had adopted by the second quarter of 1987, an adoption rate of 78%. Table 2 presents a sample frequency distribution of the Yankee 24 network members by bank type.

Table 2. Sample Distribution by Bank Type

Bank Type	Yankee 24	Non-Yankee 24	Total
Commercial Banks	22	8	30
Savings Banks	39	9	48
Total	61	17	78

5. RESULTS AND DISCUSSION

This section summarizes the results and major findings of the hazard model estimations. In particular, we present the empirical evidence for network externalities on Yankee 24 adoption. In our model of perceived network business value, the adoption benefits grow and the opportunity costs of adoption decline over time, which implies that every bank may eventually find it profitable to adopt the shared network. Thus, our empirical model focuses on *when* Connecticut-based banks would adopt Yankee 24, instead of *whether* they would adopt.

To test the hypotheses derived from our analytical model and to gauge the strength of various variables on the probability of network adoption, we estimated four hazard models, with exponential, Weibull, normal, and logistic distributional forms, respectively, using Yankee 24 adoption data. Econometric estimation of the hazard function model was performed using LIMDEP 6.0, an econometric package developed by Greene (1992). The Weibull model performed better than the other three via maximum likelihood estimation in terms of log-likelihoods, although not statistically significant with likelihood ratio tests. As a matter of fact, all four models yielded qualitatively similar results -- the estimation results from all four models were very close in terms of the sign and significance of the coefficients. Although the parameter estimations were found to be relatively robust across various assumptions of distributional functional forms with our data set, we report the results based on Weibull hazard model estimation in this study.

The parameter estimates and the significance level are shown in Table 3. The coefficients for BRANCH and CR4 variables are positive, and those for LOG_DEPOSIT, SALARY_EMP, SERVICE_COV, NETWORK_BASE, and BHC are negative. All coefficients, except the one for CR4, are significant at the 5 percent level.

The hazard function is increasing in time with $\alpha > 1$, which suggests a hazard rate that is generally increasing over time. In other words, the probability of adoption for banks

Table 3. Maximum Likelihood Estimates for Weibull Hazard Model

Variables	Coefficient[2] (Standard error)	t-ratio
NETWORK_BASE	-.279 (.0012)	-2.29*
SERVICE_COV	-.453 (.0001)	-3.19**
BRANCH	.022 (.0072)	3.04**
LOG_DEPOSIT	-.180 (.0519)	-3.46**
CR4	.012 (.0103)	1.20
SALARY_EMP	-.125 (.0548)	-2.30*
BHC	-1.261 (.540)	-2.34*
Constant	5.829 (.935)	6.24**
α	1.729 (.198)	8.71**
Log-likelihood	-80.31	

* $p < .05$
** $p < .01$

with mean values on explanatory variables increases over time, given that they have not adopted the shared network. This result is consistent with the prediction by the analytical model. Our analytical model indicates that the benefits of network adoption grow and the opportunity cost of adoption declines over time. Thus, as the network grows, the value of the shared network increases, and it may be that over time an increasing percentage of those who haven't adopted the shared network finds it profitable to do so.

The variable NETWORK_BASE has a significant and negative coefficient, which implies that the hazard rate is an increasing function of the expected network installed base, a proxy for the extent of network externalities. This confirms our hypothesis that banks in

[2]Given our formulation of the Weibull model, a positive coefficient implies a negative impact on the hazard and therefore a positive impact on the mean time to adoption. Elsewhere, the interpretation of the sign of parameters and variable coefficients may be different.

markets that are expected to generate greater extent of network externalities have higher adoption probabilities. In other words, because differences in banks' post-adoption effective network size may be different depending on the local markets in which the banks operate, banks in markets expected to have larger network installed base value highly the shared network. Note that although this result is consistent with our analytical model, which indicates that the shared network installed base in general contributes to early adoption, the empirical result implies that the impact of network installed base may be in the local markets. In other words, our finding suggests the importance of the concept of expected effective shared network size, which lies in the local market in which a bank operates.

The variable measuring customer service coverage, SERVICE_COV, has a significant and negative coefficient, which shows that banks in markets that have more customers served per bank branch have higher adoption probabilities. Thus, the lower the level of network service coverage in the market as perceived by the bank, the earlier the adoption. The result can be interpreted as follows: banks in the markets that have more customers served per ATM have a better chance to earn interchange revenues. The empirical result indicates that the impact of service coverage for a bank is in the local market in which the bank competes. Although this corresponds with our assumption that the local market is important, it does not rule out the possibility that some benefits, which are very difficult to measure, are enjoyed across the markets. In that case, the network externalities would be underestimated.

The positive coefficient for BRANCH indicates that the more branch offices a bank operates, the more likely the bank will wait longer until adoption. Because BRANCH is a proxy for the size of a bank's ATM network, it suggests that the smaller the size of a bank in terms of its branch network, the higher the probability of adoption, given that the bank has not yet done so. Alternatively, banks with large own branch networks are not willing to join the shared network early and share their facilities with other members. Thus, the result is contrary to the finding by Saloner and Shepard (1991), and clearly distinguishes the effect of network externalities from the proprietary network effect. Our analytical model suggests that the effect of the size of a bank's ATM network depends, in part, on the network effect. If the network effect is strong, a negative impact is more likely because of high opportunity costs. Thus, the result can also be interpreted as evidence of strong network effect and that banks with large ATM networks waited longer for the shared network to grow to a break even point.

With a negative estimated coefficient, LOG_DEPOSIT registers a positive impact on the adoption probability. The result is consistent with that reported by Saloner and Shepard (1991): a bank's date of adoption is earlier the larger the value of its deposit base. Because total demand deposits proxy for the number of a bank's customers, the result indicates that banks with more customers are more likely to join shared networks early. Presumably, the benefits of network membership for them are greater. As discussed earlier, the reasons can be that the network effect is strong or that the initial (start-up) shared network installed base is much larger than the size of most bank's ATM networks.

The coefficient for CR4 is insignificant although positive. Hence, in the context of shared network, we did not find support for the finding reported by Hannan and McDowell (1984) that banks operating in concentrated markets were likely to adopt earlier. The coefficient for SALARY_EMP is negative, indicating that the salary expenses per employee paid by a bank have a positive impact on the adoption probability. This result confirms our hypothesis that shared networks are labor-saving, and that shared network membership can substitute for labor expenses. A negative coefficient was obtained for BHC, indicating that ownership by a bank holding company leads to early adoption.

6. CONCLUSIONS AND FUTURE RESEARCH

This section presents the conclusions of this research, followed by its limitations and possible extensions for future research.

6.1. Conclusions

This paper goes beyond the widely applied classical diffusion model which stresses the innovativeness of potential adopters with an assumption that everyone has an equal opportunity to adopt. We examine instead the attributes of technology, organization and market as well as network externalities that channel shared network technologies to potential adopters.

The analytical model incorporates major variables that are likely to affect the net benefits of adoption. It can be used to assess the impact of network externalities or other important variables on the perceived business values of adoption analytically. In particular, it can be used to develop realistic study hypotheses that can be tested with real data and available statistical tools, and guide the empirical analysis. Although some of our variables in our analytical model do not have an unambiguous impact on the perceived network business value, we view that as a positive aspect because in its general form we can investigate the various conditions under which perceived network value varies.

The empirical results tend to support the hypotheses derived from the analytical model. We find that banks in markets that are expected to have larger shared network installed base have higher adoption probabilities. We also find that banks in markets that have more customers served per branch office (lower in the level of branch service coverage, or higher in unfulfilled demand for service coverage) tend to join shared network earlier. Thus, we conclude that, all else equal, banks in markets that can generate larger network externalities and higher network value have higher probabilities of adopting a shared network. In terms of bank characteristics, we find that the size of branch network a bank operates decreases the probability of early shared network adoption. In addition, a bank adopts sooner, the larger the value of its deposits. The salary expenses per employee paid by a bank increase the adoption probability, indicating that shared networks are labor saving. Ownership structure by a bank holding company may exert some influence on the adoption decision.

This paper is one of the few attempts to assess the impact of network externalities on the perceived business value of the network, and thus on the timing of adoption. We find evidence to support the assertion that network externalities are a determinant of shared network adoption. The results also suggest the importance of the concept of expected effective network size as a measure of network externalities. Network owners can look into the local markets for potential adopting firms and identify the effective network size that is likely to affect the perceived network business value and adoption decisions. Investigation of the conditions under which early adoption is encouraged will also be very fruitful. Finding answers to important questions such as what are the factors likely to lead to early adoption by large banks, and in what stages of network growth, is also possible with the approach used in this study.

Banking firms contemplating shared network adoption can estimate the present value of the net benefits of network adoption as a basis for adoption decision. In addition, by examining their own characteristics, the shared network growth data, and the various parameters or features influencing the flow of benefits and costs, banks are able to assess the impact of those variables on the business value of the shared network so as to obtain positive flow of net benefits.

6.2. Future Research

Some of the variables in our analytical model do not yield an unambiguous impact on the perceived network business value. We can investigate the various conditions under which perceived network value will increase using the general analytical model. The interactions between major variables can be further examined and analyzed. Other variables influencing the perceived network business value, e.g, wage rate and features affecting the ATM value platform, can also be incorporated in the analytical model and tested with real data.

Although the context of this study is shared electronic banking networks, the empirical results of this study have implications for other IOSs, such as electronic data interchange (**EDI**), SWIFT, nationally shared electronic funds transfer networks, and credit card switching. The analytical framework can be modified to study the adoption of other shared networks or further extended to model the adoption of competing networks. The approach in this study can also be applied to study the adoption of non-network products or technology standards that have significant network externalities, such as computer operating systems (OS/2, UNIX, and MS-DOS), computer architecture design (RISC and SISC), software engineering tools, and video standards (VHS versus Beta).

Several shortcomings and limitations of this study should be acknowledged. Although network externalities have been suggested in the theoretical network literature to impact technology adoption, there has been very little attempt to operationalize network externalities. The extent of network externalities is often characterized as the size of network installed base. A direct estimation of network adoption with installed base as an explanatory variable, however, may cause serious interpretational problems. As pointed out by Cabral (1990), the adoption path may be discontinuous (have a catastrophe point) if network externalities are strong. If a large number of potential adopters choose to adopt within the same observation period, we may observe a negative relationship between the installed base (extent of network externalities) and current adoptions. Therefore, we employed several firm and market specific characteristics, which are likely to enhance the business value of shared network as observable proxies for network externalities.

This study may be limited in the sense that several other factors that may potentially affect adoption decisions, such as marketing mix variables, decision making structure variables and supply side characteristics, were not present in the data set. Also, we only consider Connecticut-based banks in this study. Separate analysis and model estimation for banks in other New England states can be undertaken in the future.

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