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The diffusion of production processes in the U.S. banking industry: A finite mixture approach

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Abstract

This article applies finite mixture distributions to the estimation of cost functions for financial firms through time. The mixture approach allows the estimation of multiple technologies when firms' technology choices are unobservable. Technology switching ('diffusion') and underlying technical change are simultaneously evaluated. An application to large samples of U.S. banks for the years 1982–1986 illustrates the approach. Results suggest banks switch to lower cost production technologies when unburdened by strict branching regulations. © 1997 Elsevier Science B.V.

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1. Introduction

As primary determinants of human welfare, technological diffusion and technical change have long been a focus of economic research. This article proposes and illustrates a new empirical method for examining these fundamental processes. Our approach applies finite mixture distributions to the estimation of cost functions in a time series of cross-sections setting. Mixture procedures allow for the

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simultaneous estimation of multiple technologies of production when the researcher is unable to directly identify which firms use which technologies. The mixture approach gives cost function representations of these underlying technologies, and estimates the proportions of firms using one or another technology through time. Both the existence of multiple technologies and the presence of non-neutral change in the technologies can be statistically tested. Because mixture estimation facilitates cost comparisons between technologies, the extent to which firms' technological choices are consistent with cost advantages is directly measurable. Thus the mixture approach allows one to examine the competitive process at work within an industry.

The conceptual framework for mixture analysis is straightforward. Consider an industry composed of many firms observed at different times. Production is characterized by multiple technologies in simultaneous use. Although individual firms' technological choices are not directly observed, such choices may significantly affect observed costs. Through time firms are able to switch between technologies, and may do so in response to cost advantages. Further, technical progress can occur which affects all technologies in various nonidentical ways. Both switching between technologies ('diffusion') and changes in the underlying technologies themselves ('technical progress') can be empirically evaluated by mixture analysis.

The mixture approach offers a strong reconciliation between the widely used 'diffusion' and 'cost function' methods of analyzing technical progress. Diffusion studies typically analyze the adoption rates of observable, capital-embodied product or process innovations. Evidence from diffusion studies suggests that firms usually will not share a common production technology. In a summary of such work Reinganum (1989) notes, "...an important empirical observation is that adoption is typically delayed and that firms do not adopt an innovation simultaneously". [1] Yet this heterogeneity in production technologies is inconsistent with the cost function approach to evaluating technical progress because firms with different technologies do not share a common cost function. The addition of time variables to the cost regression relationship will not eliminate this specification error. Mixture analysis reconciles the 'diffusion' and 'cost function' conceptualizations by allowing scope for both.

We apply our approach by estimating two-component mixtures of translog cost functions for two large samples of U.S. banks for the years 1982–1986. Cost function specifications allow for non-neutral technical change in the underlying production processes. Interest focuses on analyzing technology switching by firms, estimation and description of the underlying technologies, and evaluation of the extent to which the technology switching is consistent with production cost differentials. Statistical tests for the presence of a mixture are executed using both

[1] Reinganum, 1989, p. 383; see also Romeo (1975) and Spence (1984).

the Wolfe (1971) modified chi square procedure and bootstrap evaluation of Wolfe's statistic.

Our analysis establishes several conclusions. First, the Wolfe test and bootstrap evidence strongly support the presence of a mixture in the data, establishing the simultaneous existence of multiple technologies among sample banks. Second, statistically significant technology switching among banks has occurred over the sample period. Further, this technology switching is consistent with fairly large cost savings between technologies. For banks operating in states without branching restrictions, the proportion of firms selecting the low cost technology increased from about 54% in 1982 to over 68% in 1986. For restrictive branching 'unit state' banks, diffusion of the low cost process was less pervasive, rising from 50% usage in 1982 to 58% in 1986. Additionally, significant non-neutral technical change occurred in the underlying cost functions, although the nature of these changes varied widely. These results are broadly consistent with firm adjustments to heightened competition, and additionally suggest that restrictive regulation may constrain the ability of firms to adopt new, cost-saving technology.

The article is divided into five sections. Section 2 reviews the literature on diffusion and mixture modelling. Section 3 presents the econometric model and data, while Section 4 presents results, hypothesis tests, and discussion. A conclusion completes the paper.

2. Literature and background

Mixture estimation of time dependent cost functions combines ideas from diffusion studies, cost analysis, and mixture modelling. Because all three literatures are relevant, we discuss each in turn.

Diffusion studies arose from the pioneering work of Griliches (1957), Carter and Williams (1957), Mansfield (1968a,b), David (1969), and others. Numerous such studies have been undertaken, and many are summarized by Reinganum (1989). Interest has focused on identifying economic and managerial factors relevant to a firm's decision to adopt new technology. While such studies are useful, all require that the adoption decision be directly observable. As a consequence, analysis has typically been limited to manufacturing or agricultural sectors and capital-embodied innovations. Many diffusion studies find that innovations are adopted slowly even when they significantly lower costs. [2]

Cost function estimation has been applied to the analysis of technical change in several formats. The inclusion of time variables in cost regressions has a long history. [3] Alternatively, separate cost functions can be estimated for each time

[2] Mansfield (1968a) notes that, "... the diffusion of a new technique is generally a rather slow process". (p. 136)

[3] An excellent introduction is offered by Berndt (1991).

period and compared (Gropper, 1991). Apparent changes in cost parameters are then attributed to underlying technical developments. The effects of time can be characterized as input saving or using, neutral or non-neutral, etc. All such procedures rely on the assumption that some specified cost relationship applies to all firms. This requirement, however, is contradicted by the findings of most diffusion studies.

Mixture models are frequently used in the life sciences, but have had only limited applications in economic research. Mixtures arise whenever sampling takes place from a population composed of two or more subpopulations which cannot be directly distinguished. One goal of the analysis is to estimate the relative frequencies of the subpopulations and their distributions. The best known economic application of mixtures is in the generalization of switching regressions proposed by Quandt (1972) and Quandt and Ramsey (1978). Applications to market disequilibrium models are offered by Quandt (1988). More recently, Beard et al. (1991) applied mixture models to cost estimation in a cross-sectional application in an effort to accommodate multiple production technologies.

Mixture analysis involves several interesting problems for hypothesis testing and estimation. Singularities in the likelihood surface defeat many algorithms, although Hartley (1978) and Beard et al. (1991) successfully propose an EM procedure. For hypothesis evaluation, the natural test for the presence of a mixture involves assigning zero frequency to one or another subpopulation. This restriction violates regularity conditions and produces nuisance parameters that arise only under the alternative hypothesis. Testing in such nonstandard cases is an active area of research. [4] No totally satisfactory solution is available, although an approximate test by Wolfe (1971) is usable, as are bootstrap procedures (McLachlan, 1987).

A substantial amount of research has been conducted on cost structure and cost efficiency in the financial services industry. Much of the more recent literature was reviewed in an excellent article by Berger et al. (1993b), while Benston (1994) puts the cost literature in the broader context of a variety of changes in the banking industry. Frontier cost and production functions of the linear programming or stochastic variety have been widely utilized (see Bauer et al., 1993 and other papers in that volume), and the 'profit frontier' methodology of Berger et al. (1993a) has provided insights into both the industry and the estimation techniques used to study it. Recently, the classic article on bank cost frontier estimation by Ferrier and Lovell (1990) was extended by Caudill et al. (1995), while additional insights about the effects of incorporating previously excluded services on estimated bank efficiency were provided by DeYoung (1994). A broad review of

[4] See Davies (1987), Andrews (1993), and Andrews and Ploberger (1993) for some of the issues involved.

moral hazard and agency problems has been provided by Barth and Brumbaugh (1994). The cost effects of moral hazard, managerial competence, and simple 'bad luck' were examined by Berger and DeYoung (1996), while the cost consequences of moral hazard and insolvency were studied by Gropper and Beard (1995). The effects of organizational form on costs were the subject of investigations by Cebenoyan et al. (1993), Grabowski et al. (1993), and Mester (1993, 1995), while the effects of deregulation were analyzed by LeCompte and Smith (1990), Humphrey (1993), Gropper (1991, 1995) and Gropper and Oswald (1996). Recent work by Mahajan et al. (1996) provided a comparison of cost structures for domestic and multinational banks, indicating potential cost advantages for the largest multinational banks, while Miller and Noulas (1996) found that the largest U.S. banks appeared to be more efficient than smaller banks. Finally, DeYoung and Nolle (1996), using a risk-adjusted profit efficiency model, found that foreign-owned banks were significantly less efficient than U.S.-owned banks.

Whether estimating 'average practice' cost functions or frontiers of whatever variety, there is a common thread to the bank cost and efficiency literature summarized above. Conventional average practice or frontier estimations rely on the hypothesis of a single technology which all firms use, whether efficient or not. Mixture models provide a general alternative to the conventional average practice or frontier models; if the existence of a mixture is (statistically) rejected, then the alternative is the conventional model. Failure to reject the presence of a mixture would indicate the presence of multiple technologies, and provide a parametric representation of the cost functions corresponding to those technologies. In the presence of multiple technologies, inferences about technical change based on traditional models may confound the logically separate effects of firm technology switching and underlying change in the technologies themselves. Failure to account for this distinction may lead to erroneous conclusions on the effects of regulatory initiatives in this industry.

Thus mixture estimation may be well suited to the study of banking and financial sectors experiencing both deregulation and rapid technological change. It is critically important, from a policy perspective, to separate these two influences on market structure. While both increased efficiency (arising from firm switching from higher to lower cost technology) and technical progress can improve welfare, the policies that can be expected to promote or undermine these processes are probably quite different. For example, competition, the goal of deregulation, may be more effective in facilitating firm movements to lower cost, extant technologies than in fostering technological innovations.

We note also that a mixture model offers an explanation for apparent firm inefficiency of quite a different character than that provided by frontier cost models. In most frontier models, firms off the minimum cost boundary are regarded as inefficient. The mixture approach, however, allows such firms to be 'efficient' in the sense that they efficiently use an inefficient (i.e., higher cost) technology. Yet the mixture approach does not impose any ex ante restrictions on how the component cost functions are related. Thus the results of mixture analysis can offer an explanation for 'inefficiency' not available within other approaches.

3. Model specification and data

A random variable ϵ on the real line R has a K-component finite mixture distribution if ϵ has marginal density $g(\epsilon)$ given by

$$g(\epsilon) = \sum_{i=1}^{K} \lambda_i f_i(\epsilon), \tag{1}$$

where

$$\lambda_i \geq 0, \forall i,$$

$$\sum_{i=1}^{K} \lambda_i = 1,$$

$$\int_{-\infty}^{\infty} f_i(\epsilon) \mathrm{d}\epsilon = 1, \forall i,$$

and

$$f_i(\epsilon) \geq 0, \forall \epsilon \text{ in } R.$$

The densities f_i are called component densities and the λ_i are called mixing weights. The λ_i are usually interpreted as sampling probabilities for the underlying K subpopulations. Identification conditions for mixtures are given by Teicher (1963), Yakowitz and Spragins (1969) and Chandra (1977). Extended discussions of estimation and hypothesis testing are offered by Everitt and Hand (1981) and Titterington et al. (1985).

Application of the mixture model to cost estimation is straightforward. Assume there are T periods over which firm level observations on costs c, outputs q, and input prices w are available. There are n_t, $t = 1,2,\ldots,T$, observations each period. Let i index observations and t time, so that $\{c_{it}, q_{it}, w_{it}\}$ is a typical observation. Let $C(q, w; \theta, t)$ be a cost function with unknown parameters θ at time t. Then the probability that a randomly selected observation on costs c_{it} was generated by the process $c_{it} = C(q_{it}, w_{it}; \theta^1, t) + \epsilon_{it}^1$ is denoted λ_t, where ϵ_{it}^1 is a normally distributed, zero-mean random variable with variance σ_1^2. The probability that c_{it} was generated by the alternative process $c_{it} = C(q_{it}, w_{it}; \theta^2, t) + \epsilon_{it}^2$, where ϵ_{it}^2 is normal, with zero mean, and has variance σ_2^2, is then just $1 - \lambda_t$. The disturbances ϵ_{it}^1 and ϵ_{it}^2 are assumed stochastically independent and serially uncorrelated. Presumably $\theta^1 \neq \theta^2$, leading to quantitative and qualitative differences between technologies. The inclusion of time t in the cost functions allows for technical change.

The likelihood function L for this mixture model is given as

$$L=\prod_{t=1}^{T}\prod_{i=1}^{n_t}\left[\lambda_t\phi_1\left(c_{it}-C\left(q_{it},w_{it};\theta^1,t\right)\right)\right.$$
$$\left.+(1-\lambda_t)\phi_2\left(c_{it}-C\left(q_{it},w_{it};\theta^2,t\right)\right)\right], \tag{2}$$

where ϕ_1 and ϕ_2 are normal marginal densities with zero means and variances σ_1^2 and σ_2^2, respectively.

The likelihood given in Eq. (2) is maximized utilizing the EM algorithm as adapted to mixture problems by Hartley (1978); details are provided in Appendix A. As a byproduct of this estimation, one obtains observational 'weights' which assign a probability W_{it}, $0 \leq W_{it} \leq 1$, that a particular observation corresponds to technology 1 or technology 2. These weights, combined with the sample mixing probabilities λ_t, provide evidence on technology switching by firms through time, allowing us to determine whether, and to what extent, sample banks have moved to lower cost processes.

Specification of the cost functional form $C(q,w;\theta,t)$ reflects the requirements of linearity, flexibility, theoretical consistency, and simple incorporation of technical change. We utilize the transcendental logarithmic (translog) form. Technical change is incorporated parametrically using a suggestion of Berndt (1991):

$$\ln c=\alpha_o+\Sigma\alpha_j\ln q_j+\Sigma\beta_k\ln w_k+(1/2)\Sigma\Sigma\alpha_{ij}\ln q_i\ln q_j$$
$$+(1/2)\Sigma\Sigma\beta_{lk}\ln w_l\ln w_k+\Sigma\Sigma\delta_{jk}\ln q_j\ln w_k+\psi_1\ln t+\psi_2(\ln t)^2$$
$$+\Sigma\psi_{tk}\ln t\ln w_k+\Sigma\psi_{tj}\ln t\ln q_j. \tag{3}$$

The α's, β's, δ's and ψ's are parameters to estimate and 'ln' denotes the natural logarithm. The time variable 't' measures years plus 1 since 1982. Input price homogeneity requires $\Sigma\beta_k=1$, $\Sigma\beta_{lk}=\Sigma\beta_{kl}=0$ over L and K, $\Sigma\delta_{jk}=0$ for any output q_j, and $\Sigma\delta_{tk}=0$. These restrictions are imposed in all estimations.

Several tests of the cost form in Eq. (3) applied to the mixture specification in Eq. (2) are of interest. Tests for the presence of a mixture use the restriction $\lambda_t=0$, $\forall t$. The test for significant technology switching involves the restrictions $\lambda_1=\lambda_2=\ldots=\lambda_T$. This test can be conducted by conventional means. Finally, the parameter restrictions $\psi_{tk}=0$ for each K provide a test for Hicks-neutral technical change in the component technologies.

The mixture approach is applied to two large samples of solvent U.S. banks operating between 1982 and 1986. Data for all estimations come from the Functional Cost Analysis (FCA) program of the U.S. Federal Reserve System. The FCA program is administered to participating institutions on a voluntary basis by the regional Federal Reserve banks, and is coordinated nationally by the Federal Reserve Bank of New York. The FCA data have been widely used in cost function analysis of U.S. banks. The advantages of using FCA data are that detailed information on both inputs and outputs is provided in a standardized format and their use enables comparison with previously published research; disadvantages include nonrandom sampling of the nation's financial institutions and the omission of the largest institutions. Another drawback is that the data made available to the public has some information masked to protect the confidentiality of the participating institutions. However, detailed information on the various inputs used and the size and number of deposit, loan, and trust accounts is not available from other sources, such as Call Report data.

The vast majority of the roughly fourteen thousand commercial banks in the United States over the time period of this study had total assets comparable in size to the banks in the FCA program. Although the very largest banks are not represented, banks from less than $10 million in total assets to over $2 billion are in the FCA data set. While the FCA data should not be used to draw conclusions about the nation's largest banks, patterns found in the FCA data may provide insights about trends affecting the smaller and medium-sized banks which make up over 90 percent of the firms in the U.S. banking industry.

The years 1982–1986 were selected for study due to the important changes in regulations and technologies prior to and during this time. The disintermediation period of the 1970s was a particularly turbulent era for the U.S. banking industry. High and rising interest rates led depositors to pull funds from banks and reinvest them in money market mutual funds, increasing the growth of banks' competitors and fostering rising market pressures. The Depository Institutions Deregulation and Monetary Control Act of 1980 (DIDMCA) phased out by 1986 the interest rate restrictions which had limited bank responses to competitive pressure, and gave the Federal Reserve greater control over the banking system. While the DIDMCA is viewed as the most important bank regulatory act since the 1930s, the Depository Institutions Act of 1982 also had a significant impact on commercial banks. Technical developments in the 1970s and 1980s included computer and telecommunications advances, and the widespread development and use of ATM technology (Hannan and McDowell, 1984). These ongoing technical advances combined with earlier regulatory shocks make the 1982–1986 sample period fertile ground for analysis.

Given this institutional background, we expect that technical change in the U.S. banking sector will manifest itself in the following form. First, it seems unlikely that the cost minimizing operational structure for banks is the same in both the regulated and (somewhat) deregulated environments. Hence, the important legal changes represented by the DIDMCA and the DIA presumably triggered changes towards more competitively viable bank structures. Yet the literature on diffusion suggests (strongly) that such changes will not occur overnight, and the speed of the adjustments is an empirical question. Second, the widespread integration of

ATM and information systems technologies into bank operations presumably affect bank costs regardless of the particular operational mode the bank has adopted: both banks that have, and have not, altered their managerial practices can use and, perhaps, benefit from capital-embodied innovations such as ATMs. Hence, we expect to see both (i) bank conversions to a lower cost production technology more consistent with a highly competitive environment, and (ii) secular, innovations-driven changes in the underlying production processes represented by shifts through time in underlying cost functions.

Our bank production representations are selected with previous research on bank costs in mind. Specifically, we adopt the 'intermediation' model in which banks combine capital, labor, and funds to produce loans and other outputs. Clark (1988) provides a useful overview of the history and consequences of this paradigm. We exploit production-cost duality by representing the relevant bank production processes by translog cost functions as specified in Eq. (3). Total costs are taken as the sum of labor, capital (both physical and financial), interest costs. Outputs selected for analysis are the dollar volumes of loans, investments, and trust accounts.

Input prices are calculated from the FCA data. The sums of wages, salaries, and benefits divided by the numbers of bank employees provide measures of firm labor costs. [5] Total interest paid on borrowed money divided by the quantities of borrowed funds produce average prices for funds. Capital prices are a weighted composite of the costs of physical and financial capital, calculated by the procedure proposed by Hancock (1985) and utilized by Gropper (1991). Nominal magnitudes are converted to 1982 dollars.

Significant differences in U.S. state branching regulations necessitate a division of the sample into two parts. The FCA data include an indicator variable identifying whether the bank is located in a unit or branch banking state. We used this indicator, which was determined by the Federal Reserve, to separate the data. Observations on banks operating in states with severe branching restrictions (at most one branch in addition to the main office) constitute the unit states sample. Data on banks in states with few or no branching restrictions form the branch states sample. This division is made because branching restrictions are a severe constraint on physical capital input usage. Banks in liberal branching jurisdictions had an average of ten branches during the sample period, suggesting that branching restrictions are binding constraints that will affect cost minimizing input usage. Further, the division of the sample in this way guarantees that any finding of multiple technologies will not merely reflect differences in branching regulations. Finally, separate estimations will allow us to evaluate the effects of regulatory restrictions on costs and technological diffusion.

[5] We conducted additional estimations, not reported here, incorporating two kinds of labor inputs, managerial and staff. Similar results are obtained in that case.

4. Estimation and results

Summary statistics for the unit and branch states samples appear in Table 1. Branch state banks had larger total costs and output levels throughout the sample period, and enjoyed lower average interest costs, possibly as result of their more geographically dispersed operations. While branch state banks experienced higher average capital costs, their lower officer-to-employee ratios reduced their average labor costs about 10%.

Parameter estimates for all models appear in Table 2. Conventional OLS results are presented for comparison purposes. Prior to analyzing Table 2, we first test for the presence of mixtures in our samples.

Wolfe (1971) used evidence from simulations to propose an approximate likelihood ratio test based on a modified chi square distribution. Wolfe's test statistic is

$$S = (2/n)(n - 1 - d - (C_1/2))\log L, \tag{4}$$

where L is the likelihood ratio under the null hypothesis of no mixture, n is the sample size, C_1 is the number of components in the mixture, and d is the dimension of the underlying normal distributions. In the absence of a mixture, S has approximately a chi square distribution with $2d(C_1 - 1)$ degrees of freedom. Everitt and Hand (1981) conducted simulation analyses of S and concluded the test had low power but was reasonable if $n > 10d$. Our sample sizes greatly exceed these limits. Performing the test we obtain values of $S = 390.76$ for the branch sample and $S = 256.56$ for the unit sample. Both these results far exceed the critical level of 13.815 for an $\alpha = 0.001$ Type I error. This is strong evidence for the presence of a mixture.

Because of the approximate nature of Wolfe's test, a Monte Carlo technique is used to bootstrap the distribution of S for both samples. This procedure, analyzed by McLachlan (1987), is equivalent to bootstrapping the likelihood ratio statistic under the null hypothesis of no mixture in the data. The likelihood surface for the

Table 1
Descriptive statistics for unit and branch data sets [a]

	Unit States sample		Branch States sample	
Variable	Mean	Standard deviation	Mean	Standard deviation
Total costs ($)	9,513,679	10,452,189	20,340,839	28,833,590
Investments ($)	28,990,066	31,146,324	60,484,969	75,320,257
Loans ($)	52,247,396	67,864,599	111,999,415	162,144,034
Trust accounts ($)	1,212,509	3,519,930	2,684,051	6,647,691
Wage ($/employee year)	19,995	3,124	18,051	2,685
Price of capital (%)	15.89	5.63	16.40	3.70
Interest rate (%)	7.17	1.16	6.90	1.10

[a] All financial magnitudes in real 1982 dollars, except Price of capital and Interest rate in %. Unit States sample size is 967. Branch states sample size is 1,581. Data are for the years 1982–1986, inclusive. Wage calculations include employee benefits and health insurance costs.

mixture of normals is well known to contain singularities at which points the variance of one component density goes to zero and the likelihood becomes unbounded. [6] We eliminate these degenerate points from our bootstrap replications by discarding trials producing values of λ, $1-\lambda$, σ_1 or σ_2 that are less than 0.01. About 10% of all replications produce such degeneracies. We limit our analysis to 100 valid trials per sample due to the need for 200 iterations of the EM algorithm per bootstrap trial.

The bootstrap results provide support for the presence of a mixture. The 100 bootstrap trials for the branch states sample produce a mean S of 220.42 with standard deviation 86.79. Only four trials produced S values exceeding our Wolfe statistic of 390.76. For the unit state sample a mean S of 134.65 with standard deviation 40.47 was obtained, and only three of 100 trials produced S statistics in excess of our calculated value $S = 256.56$. We conclude that both samples are characterized by multiple technologies of production.

We turn next to an analysis of diffusion. A likelihood ratio test for the presence of significant technology switching over time (utilizing the restrictions $\lambda_1 = \lambda_2 = \ldots = \lambda_T$) was conducted on both samples. We obtained likelihood ratio test statistic values of 8.45 for the unit state banks and 13.12 for the branch banks. The unit state result is significant at the 10% level, while the branch result is significant against a Type I error of 1%. It appears that both samples exhibit significant technology switching (diffusion).

An examination of Table 2 suggests that the technologies arbitrarily denoted MIXU1 and MIXB1 have experienced generally increasing usage rates over the sample period. For the unit sample, MIXU1 increased in popularity from about 50% usage in 1982 to 58% usage in 1986. Results for the technology MIXB1 in the branch sample are similar, rising from 54% to 75% usage in 1985 before retreating in the final year.

The role of technical change in the underlying technologies can be examined by testing the restrictions $\psi_{tk} = 0$ for all K. Inability to reject these restrictions suggests the presence of Hicks neutrality, and such a result would indicate an absence of significant input bias in the technical change. Performing the required calculations yields likelihood ratio statistics of 34.09 for unit banks and 63.26 for the branch sample. Both results are significant at the 1% level, implying non-neutral technical change has occurred in both environments. Thus technical change among banks will be associated with significant alteration in input mixes, the nature of which is examined below. It is important to note, however, that the technological evolution of U.S. banks in the 1980s was characterized by two distinct and significant effects: firms switched between technologies while, simultaneously, the nature of each of those technologies was changing.

[6] Hansen (1992) and Titterington et al. (1985) offer an extended discussion of the pathologies of mixture models.

Table 2
Estimation results for unit and branch state bank mixtures and OLS [a]

	Unit State sample			Branch state sample		
Variable	MIXU1	MIXU2	UOLS	MIXB1	MIXB2	BOLS
Intercept	−0.036	0.065	−0.013	−0.046	−0.019	−0.0045
	(0.008)	(0.023)	(0.008)	(0.006)	(0.018)	(0.005)
INVEST	0.326	0.314	0.318	0.341	0.363	0.353
	(0.012)	(0.027)	(0.012)	(0.008)	(0.018)	(0.008)
LOAN	0.655	0.583	0.620	0.670	0.621	0.654
	(0.010)	(0.030)	(0.010)	(0.008)	(0.020)	(0.007)
TRUST	0.002	0.017	0.007	−0.007	0.0001	−0.005
	(0.003)	(0.010)	(0.004)	(0.003)	(0.007)	(0.003)
WAGE	0.235	0.377	0.261	0.249	0.175	0.253
	(0.038)	(0.084)	(0.038)	(0.024)	(0.075)	(0.024)
TIME	−0.058	−0.009	−0.041	−0.085	−0.068	−0.084
	(0.014)	(0.033)	(0.015)	(0.010)	(0.031)	(0.010)
INTRATE	0.502	0.481	0.512	0.504	0.642	0.553
	(0.038)	(0.079)	(0.038)	(0.023)	(0.068)	(0.022)
$(INVEST)^2$	0.248	0.102	0.175	0.173	0.196	0.181
	(0.015)	(0.026)	(0.015)	(0.010)	(0.027)	(0.011)
$(LOAN)^2$	0.130	0.146	0.164	0.213	0.223	0.199
	(0.017)	(0.030)	(0.015)	(0.013)	(0.035)	(0.014)
$(TRUST)^2$	0.0003	0.001	0.0006	−0.0008	0.0005	−0.0005
	(0.0004)	(0.001)	(0.0004)	(0.0003)	(0.0007)	(0.0002)
$(LOAN)(INVEST)$	−0.173	−0.099	−0.142	−0.187	−0.174	−0.168
	(0.014)	(0.024)	(0.014)	(0.010)	(0.028)	(0.012)
$(LOAN)(TRUST)$	0.0008	−0.003	−0.002	0.0004	−0.005	−0.001
	(0.0009)	(0.002)	(0.0009)	(0.0006)	(0.002)	(0.0001)
$(INVEST)(TRUST)$	−0.003	0.003	−0.0005	0.001	0.002	0.009
	(0.001)	(0.001)	(0.0010)	(0.001)	(0.002)	(0.0006)
$(WAGE)^2$	−0.160	0.148	0.247	0.079	0.767	0.342
	(0.181)	(0.291)	(0.129)	(0.112)	(0.296)	(0.105)
$(TIME)^2$	−0.0002	0.078	0.075	−0.015	−0.082	−0.034
	(0.033)	(0.073)	(0.035)	(0.025)	(0.067)	(0.024)
$(INTRATE)^2$	0.176	0.635	0.783	0.588	0.228	0.545
	(0.177)	(0.231)	(0.121)	(0.092)	(0.236)	(0.082)
$(WAGE)(TIME)$	0.091	−0.081	−0.080	−0.033	−0.115	−0.056
	(0.052)	(0.091)	(0.043)	(0.036)	(0.081)	(0.033)
$(WAGE)(INTRATE)$	−0.009	−0.292	−0.444	−0.319	−0.072	−0.232
	(0.166)	(0.221)	(0.105)	(0.085)	(0.238)	(0.076)
$(TIME)(INTRATE)$	0.003	0.128	0.166	0.124	0.0007	0.079
	(0.053)	(0.080)	(0.042)	(0.030)	(0.074)	(0.026)
$(WAGE)(INVEST)$	−0.168	0.026	−0.016	−0.006	0.114	0.030
	(0.039)	(0.068)	(0.035)	(0.027)	(0.086)	(0.029)
$(WAGE)(LOAN)$	0.075	−0.057	−0.052	−0.006	−0.112	−0.058
	(0.040)	(0.076)	(0.035)	(0.028)	(0.082)	(0.028)
$(WAGE)(TRUST)$	0.008	0.010	0.007	0.006	−0.008	0.004
	(0.003)	(0.007)	(0.003)	(0.002)	(0.006)	(0.002)

Table 2 (continued)

(*TIME*)(*INVEST*)	0.021	−0.041	−0.025	−0.001	−0.015	−0.012
	(0.016)	(0.023)	(0.014)	(0.012)	(0.027)	(0.011)
(*TIME*)(*LOAN*)	−0.006	0.024	0.030	−0.012	0.027	0.014
	(0.015)	(0.023)	(0.013)	(0.012)	(0.026)	(0.010)
(*TIME*)(*TRUST*)	−0.003	0.001	−0.001	−0.003	−0.002	−0.002
	(0.001)	(0.002)	(0.001)	(0.001)	(0.002)	(0.001)
(*INTRATE*)(*INVEST*)	0.108	0.015	−0.034	0.013	−0.035	0.018
	(0.041)	(0.073)	(0.034)	(0.028)	(0.071)	(0.025)
(*INTRATE*)(*LOAN*)	−0.032	0.128	0.096	0.057	0.176	0.088
	(0.041)	(0.069)	(0.034)	(0.028)	(0.073)	(0.027)
(*INTRATE*)(*TRUST*)	−0.006	−0.013	−0.009	−0.007	−0.004	−0.009
	(0.003)	(0.006)	(0.003)	(0.002)	(0.005)	(0.001)
PCAP	0.262	0.140	0.226	0.246	0.183	0.193
	(0.062)	(0.148)	(0.148)	(0.062)	(0.158)	(0.158)
$(PCAP)^2$	−0.002	0.197	0.142	0.029	0.851	0.423
	(0.043)	(0.070)	(0.070)	(0.047)	(0.112)	(0.112)
(*PCAP*)(*WAGE*)	0.169	0.144	0.197	0.239	−0.695	−0.110
	(0.075)	(0.142)	(0.142)	(0.062)	(0.126)	(0.126)
(*PCAP*)(*INTRATE*)	−0.167	−0.342	−0.339	−0.268	−0.156	−0.312
	(0.062)	(0.142)	(0.148)	(0.061)	(0.158)	(0.158)
(*PCAP*)(*INVEST*)	0.060	−0.042	0.002	0.040	−0.079	−0.048
	(0.018)	(0.044)	(0.044)	(0.016)	(0.053)	(0.053)
(*PCAP*)(*LOAN*)	−0.042	−0.071	−0.043	−0.051	−0.063	−0.029
	(0.019)	(0.049)	(0.049)	(0.018)	(0.059)	(0.059)
(*PCAP*)(*TRUST*)	−0.003	0.002	0.001	0.001	0.013	0.004
	(0.002)	(0.004)	(0.004)	(0.001)	(0.003)	(0.004)
(*TIME*)(*PCAP*)	−0.094	−0.047	−0.086	−0.091	(0.114)	−0.022
	(0.025)	(0.044)	(0.044)	(0.024)	(0.055)	(0.055)
λ_{1982}	0.501	–	–	0.539	–	–
λ_{1983}	0.497	–	–	0.617	–	–
λ_{1984}	0.577	–	–	0.713	–	–
λ_{1985}	0.557	–	–	0.752	–	–
λ_{1986}	0.582	–	–	0.682	–	–
σ	0.056	0.121	0.120	0.065	0.115	0.107

[a] Asymptotic standard errors in parentheses.

An examination of the coefficient results in Table 2 sheds light on some of the qualitative differences between the component technologies for both samples. Among unit state banks, technology MIXU1, which enjoyed modestly rising usage during the sample period, exhibits significantly greater technologically-driven cost reductions than does MIXU2. Further and, perhaps, more significantly, MIXU1 exhibits biased (non-neutral) technical change which is capital saving, an effect wholly absent from MIXU2. Hence, the technology to which unit state banks were converting during this period enjoyed rapid technical progress and capital-saving technical change. This suggests strongly that the role of physical and financial capital in bank production was, in fact, diminishing during this period. Since

Table 3
Expected costs and scale returns for mixture and OLS technologies[a]

Output scaling (% of sample means)	Unit States MIXU1	MIXU2	UOLS	Branch states MIXB1	MIXB2	BOLS
Expected costs						
50%	3,615	4,851	4,052	7,180	8,441	7,322
100%	9,161	10,141	9,390	19,405	19,934	19,425
150%	13,281	13,899	13,338	28,334	28,883	28,395
200%	16,582	16,839	16,515	35,494	36,227	35,637
Scale returns (OSE)						
50%	0.965 *	0.881 *	0.909 *	0.996	0.940 *	0.973 *
	(0.011)	(0.016)	(0.010)	(0.005)	(0.013)	(0.005)
100%	0.984 *	0.915 *	0.945 *	1.004	0.986	1.003
	(0.008)	(0.017)	(0.008)	(0.004)	(0.010)	(0.004)
150%	0.994	0.935 *	0.966 *	1.009	1.012	1.020 *
	(0.009)	(0.021)	(0.009)	(0.005)	(0.012)	(0.005)
200%	1.002	0.949 *	0.981 *	1.013 *	1.031 *	1.032 *
	(0.010)	(0.024)	(0.010)	(0.006)	(0.013)	(0.006)

[a] Expected costs in 1000's of 1982 dollars. Scale returns OSE measures have asymptotic standard deviations in parentheses.
* Significant at the 5% level.

physical capital, for example, is typically associated with fixed costs, technologies which reduce dependence on this input may be particularly attractive in a more volatile, competitive environment.

Remarkably similar effects emerge for branch state banks. The 'rising' technology MIXB1, like MIXU1, exhibits strong capital-saving technical change combined with highly significant technical progress. These effects are weaker or wholly absent in the declining technology MIXB2. Thus we conclude that important qualitative differences between technologies emerge for both samples.

Firm technology switching presumably arises from a desire to exploit favorable differences between technologies. Production costs and returns to scale are two important ways in which technologies might differ. These performance dimensions are examined in Table 3. We calculate expected production costs for all samples and technologies using individual sample mean output vectors and input prices. Various radial scalings of the sample mean output vectors are examined. Overall scale economies (OSE) are also calculated at mean prices for all technologies using the measure developed by Baumol et al. (1982):

$$OSE = \Sigma(\partial \ln c / \partial \ln q_j).$$

A value of OSE exceeding 1 indicates decreasing returns, $OSE = 1$ implies constant returns, and $OSE < 1$ suggests increasing returns to scale.

The 'rising' technologies MIXU1 and MIXB1 are seen to be uniformly lower cost than the technologies they supplant. For the unit sample, use of MIXU1 saves almost $1,000,000 at mean prices and outputs at the sample midyear point. Cost savings associated with MIXB1 are smaller yet still amount to over $500,000 at sample mean outputs, an advantage of around 2.7%. These results are consistent with the hypothesis that significant technological conversions occurred in response to opportunities for cost savings.

Evidence on scale economies provides additional insights. For both samples the low cost technologies exhibit more modest scale economies than their higher cost brethren. This observation is suggestive given the significant capital-saving technical changes found for MIXU1 and MIXB1. Lack of large scale economies implies a flexible technology applicable to widely varying output targets. Such a technology would be especially attractive in an unsettled, newly deregulated environment.

The mixture results suggest that the U.S. banking industry experienced significant technical change and technological conversion during the mid 1980s. Technical developments significantly affected production costs, and many firms appeared to alter their production practices towards lower cost operation. These conclusions, while plausible, immediately raise the issue of individual firm behavior. To what extent is the behavior of individual firms consistent with the logic of cost-saving technology switching? Confidentiality masking in our data precludes following individual firms year to year. It is however possible to utilize the observation-specific mixing weights w_{it} to 'classify' firms as users of one or another technology by the criterion $w_{it} \gtrless 1/2$. This allows calculation of the extent to which firms choose technologies that are lower cost given their outputs and input prices. [7]

For the branch state sample, MIXB1 actually is lower cost for between 76.4% of firms (in 1982) and 94.6% of firms (in 1984), a typical value being 89%. More revealing is the evidence on low cost technology selection rates through time. In 1982, the w_{it}'s predict that 59.5% of branch firms probably choose their low cost option given their output and input price vectors. This figure steadily rises to 80.8% by 1985 before declining to about 74% in the last sample year. This suggests that the passage of time generally results in larger proportions of these firms utilizing their lowest cost option.

Results for banks facing severe regulatory branching restrictions are less conclusive. MIXU1 actually is lower cost for between 85.7% and 89.1% of sample firms in every year. The proportions of firms predicted to actually use their lower cost option exhibits almost no time pattern, varying between 56% and 69.5%. Unit banks do not appear to become much more likely to use low cost options as time

[7] This is an informal procedure because no correction is made for the 'degree of belief' w_{it} used to classify firms. A large proportion of firms exhibit weights very close to 1 or 0, indicating highly accurate classification.

passes. Changes in the mixing weights exhibited in Table 2 therefore arise primarily from changes in the w_{it}'s that do not result in firms being reclassified as users of one or another technology. The slow and uncertain pace of diffusion among unit banks may reflect the severity of input usage restrictions they face.

On balance, mixture analysis of the U.S. banking industry paints an interesting picture of the competitive process at work. Both unit and branch banks utilize multiple technologies of production. These production technologies differ in several important qualitative dimensions. In all cases, banks appear to be switching to lower cost production technologies through time. These lower cost processes exhibit rapid technical progress that results in capital savings in production. These new technologies exhibit nearly constant returns to scale over a wide range of output levels. The technologies MIXU2 and MIXB2, which are growing less popular, exhibit greater levels of scale economies, presumably resulting in a narrower range of bank sizes which are competitively viable. Finally and most importantly, branching restrictions, while apparently having little effect on the integration of technical advances into the component cost functions, appear to have a profound and deleterious effect on firm switching to lower cost production processes. This 'regulatory drag' represents an important cost of branching restrictions that may impose significantly higher costs on bank customers in unit state jurisdictions. Branching restrictions themselves apparently limit the incentive of banks to convert to more cost efficient operations, the ability of banks to so convert, or both.

5. Conclusion

Finite mixture models provide a new way to analyze technical change and the diffusion of production practices. Mixture analysis does not require that adoption decisions be observable, facilitating wider application than typical diffusion studies. Because mixture estimation provides cost function representations of underlying technologies, the cost consequences of innovations can be studied. Thus, mixture analysis combines the best features of the cost function and diffusion approaches to measuring technological evolution.

A two-component normal translog cost model was specified and estimated on two large samples of U.S. banks for the years 1982–1986. Both the Wolfe test and bootstrap evidence suggested the presence of multiple technologies in both samples. Increasing firm usage of lower cost technologies was discovered. These lower cost technologies exhibited significant capital-saving technical change and low levels of scale economies. The magnitude of diffusion was greater for branch state banks than unit state banks, providing evidence to suggest regulatory drag on the diffusion process. As the U.S. banking system achieves the elimination of all branching restrictions, our results suggest that the overall banking system will become more efficient.

The potential usefulness of our procedure as an input to policy making arises primarily from the ability of mixture models to distinguish between cost improvements arising from more efficient use of existing technologies, and cost savings driven by technical progress. The relative importance of these two components in banking (or other industries) is an empirical matter requiring the sort of empirical evidence that the mixture approach can provide.

Our study represents the first application of mixture models to diffusion estimation and several extensions of our analysis are possible. First, frontier rather than average practice cost models may be feasible. Second, while confidentiality masking in our data made tracking individual firms impossible, true panel data would allow inclusion of time series properties such as autocorrelation. Third, mixtures of three or more components should be investigated. Finally, mixtures of production or profit functions would be natural extensions of the approach suggested here.

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Appendix A

Maximization of L in Eq. (2) over λ_t, $t = 1,2,\ldots,T$, θ^1, θ^2, σ_1^2, and σ_2^2 is obtained via the EM algorithm proposed by Hartley (1978) and evaluated by Quandt (1988). Let $\phi_{it}^1 = c_{it} - C(q_{it}, w_{it}; \theta^1, t)$ and similarly for ϕ_{it}^2. Define ϕ_{it} as

$$\phi_{it} = \lambda_t \phi_{it}^1 + (1 - \lambda_t)\phi_{it}^2 \tag{A.1}$$

and define the observational weights W_{it}^1 and W_{it}^2 as:

$$\begin{aligned} W_{it}^1 &= \lambda_t(\phi_{it}^1/\phi_{it}), \\ W_{it}^2 &= (1 - \lambda_t)(\phi_{it}^2/\phi_{it}). \end{aligned} \tag{A.2}$$

Clearly $W_{it}^1 + W_{it}^2 = 1$ for any observation. The W_{it} terms are observation level analogues of the sample mixing weights λ_t and play a role in mixture model diagnostics. Define the diagonal matrices W_1 and W_2 by:

$$\begin{aligned} W^1 &= \mathrm{diag}[W_{11}^1, W_{21}^1, \ldots, W_{it}^1], \\ W^2 &= \mathrm{diag}[W_{11}^2, W_{21}^2, \ldots, W_{it}^2]. \end{aligned} \tag{A.3}$$

Let c be the sample costs vector and X data on outputs, prices, and other exogenous variables (if any). When $C(q, w; \theta, t)$ or a transformation of $C(\cdot)$ is linear in X, the EM algorithm calculates at each iteration the values:

$$\begin{aligned} \theta^1 &= [X'W^1X]^{-1}[X'W^1c], \\ \theta^2 &= [X'W^2X]^{-1}[X'W^2c], \end{aligned} \tag{A.4}$$

$$\begin{aligned} \sigma_1^2 &= (1/T_1)(c - X\Theta^1)'W^1(c - X\Theta^1), \\ \sigma_2^2 &= (1/T_2)(c - X\Theta^2)'W^2(c - X\Theta^2), \end{aligned}$$

where $T_1 = \Sigma_{t=1}^{T}\Sigma_{i=1}^{n_t}W_{it}^1$ and $T_2 = \Sigma_{t=1}^{T}\Sigma_{i=1}^{n_t}W_{it}^2$.The mixing weights are then given by

$$\lambda_t = \sum_{i=1}^{n_t} W_{it}^1/n_t. \tag{A.5}$$

Asymptotic standard errors for all estimates are obtained by a single iteration of the algorithm of Berndt et al. (1974).

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