EFFICIENCY IN THE SAVINGS AND LOAN INDUSTRY

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ABSTRACT

I modify the stochastic econometric cost frontier approach to investigate efficiency in mutual and stock S&Ls using 1991 data on U.S. S&Ls. My methodology allows both the cost frontier and error structures to differ between S&Ls of these two ownership forms. A likelihood ratio test indicates that the data support this unrestricted model, which implies efficient mutual and stock S&Ls use different production technologies. Various measures of inefficiency show that on average stock S&Ls are less efficient than mutual S&Ls. The second part of the article relates the inefficiency measures to several correlates.

EFFICIENCY IN THE SAVINGS AND LOAN INDUSTRY

1. Introduction

The crisis in the savings and loan industry has brought attention to the fragility of the U.S. financial services industry. A number of culprits for the decline in the S&L industry over the 1980s have been cited, including fraud, interest rate deregulation, expanded powers, and inefficiency. In the aftermath of the thrift bailout, there has been re-regulation of the industry, including increased capital requirements under the Financial Institutions Reform, Recovery and Enforcement Act (FIRREA) of 1989. There has also been a reorganization of the industry's structure, including a large number of S&L conversions from the mutual form of organization to the stock form.[1] A mutual S&L is formally owned by its depositors and possibly its borrowers, although these owners often sign over their ownership rights to the S&L's managers. A stock S&L is owned by its shareholders. The two types of S&Ls also differ in that the stock S&L can increase its capital by issuing new stock while the mutual increases capital via retained earnings.

Whether the conversion phenomenon will lead to a more efficient industry structure is an empirical question. I modify the stochastic econometric cost frontier approach to study efficiency in mutual and stock S&Ls. My methodology accounts for possible differences in the production technologies and efficiency distributions of mutual and stock institutions. Only if potential differences are accounted for can one reach valid conclusions about the relative efficiency of the two types of institutions and the determinants of efficiency. The methodology is a general one that can be used to study whether the production technology or efficiency distribution is the same for any two groups of firms (e.g., banks in unit and branching states).

This article first determines whether there are differences in the average efficiency of mutual and stock S&Ls. Theoretical arguments and empirical evidence suggest that, prior to interest rate deregulation (completed in 1986), the mutual form of organization was a less efficient one than the stock form [see Mester (1991)], since the separation between owners and managers in mutuals is generally larger than in stock S&Ls and the amount of an S&L's profit that could be passed on to depositors was limited by the interest rate ceilings. Mester (1991) found evidence of agency problems at California mutual S&Ls operating in 1982. Whether these problems still exist in today's increasingly competitive and deregulated market is open to investigation. The article then identifies some of the characteristics of efficient mutual and stock S&Ls.

The results have important policy implications. A finding that stock S&Ls are more efficient than mutual S&Ls implies that the conversion phenomenon is likely to continue and should be encouraged. The converse suggests that the conversion phenomenon, if it continues, may not increase the industry's average efficiency level from today's level.

The rest of the article is organized as follows. Section 2 discusses previous research concerning cost efficiency in S&Ls. Section 3 presents the basic stochastic econometric frontier model and my more flexible model. The specification for the frontier cost function and the data are discussed in Section 4. Section 5 presents the empirical results and Section 6 concludes.

2. Previous literature

Mester (1989) studied whether an agency problem in mutual S&Ls showed itself in management's choosing inefficiently large amounts of certain inputs (expense preference). That article showed that to obtain valid conclusions, the possibility of differing production technologies between mutual and stock S&Ls must be taken into account. Otherwise cost-minimizing behavior on the part of mutual S&Ls that use a different production structure than stock S&Ls could be interpreted as inefficient behavior. Without assuming that mutual and stock S&Ls use the same production technology or that stock S&Ls were producing efficiently, Mester (1989) showed that one could not reject the hypothesis that mutual organizations minimize cost. But since the test was weak for the sample of S&Ls studied, Mester (1991) examined the cost structures of mutual S&Ls directly for evidence that they were operating at inefficient output levels or mixtures and found evidence of agency problems at mutual S&Ls.

One purpose of this article is to investigate differences in stock and mutual S&L behavior with a post-deregulation recent sample.[2] The article also looks at inefficiency in more general terms, measuring the degree to which an S&L produces a given level of output at elevated cost (known as X-inefficiency), in addition to the divergence of an S&L's output mix or output level from the efficient one.

The stochastic econometric cost frontier approach is used. A cost frontier (i.e., the cost function of the most efficient producers) is estimated, and an institution's deviation from the frontier consists of random error and inefficiency. The part of the error term representing random deviations from the frontier is assumed to be drawn from a two-sided distribution, while the part representing inefficiency is assumed to be drawn from a one-sided distribution, since inefficiency raises costs.

Two other papers have investigated general inefficiency in savings and loans.[3] Cebenoyan *et al.* (1992) used the stochastic cost frontier approach to study S&Ls operating in the fourth FHLB District in 1988 and concluded that mutual S&Ls were less efficient than stock S&Ls. However, they assumed mutual and stock S&Ls were operating with the same production function (and hence the same cost frontier) and with the same error distribution.[4] As my results indicate below, whether these restrictions are imposed can affect conclusions about the average inefficiency and characteristics of inefficient mutual and stock S&Ls.[5]

Hermalin and Wallace (1992) adapt the nonparametric tests of Varian (1984) to study efficiency in S&Ls. This methodology avoids the strong maintained hypotheses of the parametric tests implicit in the stochastic frontier approach and the nonfrontier cost function approach. But it cannot be used to measure the magnitude of a firm's inefficiency. In the nonparametric approach, an S&L is considered to be inefficient if it could have produced more output at lower cost using at least one other S&L's input mix. This is a severe test, given that data are always measured with error and it takes just one firm *reportedly* doing better to condemn another firm as inefficient. Thus, the authors also define other measures of inefficiency which classify firms as inefficient if the firm could have produced more output using several of the S&Ls' input mixes. Using a national sample and 1986-88 data, they find that product mix was more significantly related to inefficiency than ownership type.

3. Stochastic econometric cost frontier model

3.1 Basic model

The basic stochastic econometric frontier model posits that a firm's observed cost will deviate from the cost frontier because of random noise, v_i, and possible inefficiency, u_i. That is, for N firms in the sample,

$$\ln C_i = \ln C(y_i,w_i;B) + u_i + v_i, \quad i=1,\ldots,N, \tag{1}$$

where C_i is the observed cost of firm i, $\mathbf{y}_i$ is the vector of output levels for firm i, $\mathbf{w}_i$ is the vector of input prices for firm i, **B** is a vector of parameters, $\ln C(y_i,w_i,B)$ is the predicted log cost function of a cost-minimizing firm operating at output level $\mathbf{y}_i$ and input prices $\mathbf{w}_i$, v_i is a two-sided error term representing the statistical noise, and u_i is a one-sided error term representing inefficiency. The v_i are assumed to be independently and identically distributed, and the u_i are assumed to be distributed independently of the v_i. Usually it is assumed that the v_i are normally distributed with mean 0 and variance σ_v^2 and the u_i are half normally distributed, i.e., the u_i are the absolute values of a variable that is normally distributed with mean 0 and variance σ_u^2.[6] With these distributional assumptions, the log-likelihood function of the model is

$$\ln L = \frac{N}{2} \ln \frac{2}{\pi} - N \ln \sigma - \frac{1}{2\sigma^2} \sum_{i=1}^{N} \epsilon_i^2 + \sum_{i=1}^{N} \ln \left[\Phi \left(\frac{\epsilon_i \lambda}{\sigma} \right) \right] \tag{2}$$

where N is the number of firms, $\epsilon_i = u_i + v_i$, $\sigma^2 = \sigma_u^2 + \sigma_v^2$, $\lambda = \frac{\sigma_u}{\sigma_v}$, and $\Phi(\cdot)$ is the standard normal cumulative distribution function. The model can be estimated using maximum likelihood techniques.

Once the model is estimated, inefficiency measures are calculated using the residuals. First, the average level of inefficiency can be measured as average(u), which is estimated as average($\hat{\epsilon}_i$), where $\hat{\epsilon}_i$ is the estimated residual for firm i, since u is independent of v and E(v)=0. The mean inefficiency is given by E(u), which for the half-normal case is $(\frac{2}{\pi})^{1/2}\sigma_u$. This is estimated as $(\frac{2}{\pi})^{1/2}\hat{\sigma}_u$, where $\hat{\sigma}_u$ is the estimate of σ_u. Since the distribution of the maximum likelihood estimates is known, one can calculate an approximate standard error of $(\frac{2}{\pi})^{1/2}\hat{\sigma}_u$. Firm-level measures of inefficiency are usually given by the mean and mode of the condition distribution of u_i given ϵ_i. For the normal-half normal stochastic model these are

$$E(u|\epsilon) = \left(\frac{\sigma_u \sigma_v}{\sigma}\right) \left[\frac{\phi(\frac{\epsilon\lambda}{\sigma})}{\Phi(\frac{\epsilon\lambda}{\sigma})} + \frac{\epsilon\lambda}{\sigma} \right] \quad \text{and} \quad M(u|\epsilon) = \begin{cases} \frac{\sigma_u^2}{\sigma^2}\epsilon & \text{if } \epsilon \geq 0 \\ 0 & \text{if } \epsilon < 0 \end{cases} \tag{3}$$

where $\Phi(\cdot)$ is the standard normal cumulative distribution function and $\phi(\cdot)$ is the standard normal density function. $E(u|\epsilon)$ is an unbiased but inconsistent estimator of u_i, since regardless of N, the variance of the estimator remains nonzero [see Greene (1991), p. 18]. To get estimates, $\hat{E}(u|\epsilon)$ and $\hat{M}(u|\epsilon)$, of these measures, we evaluate (3) at the estimates of σ_u and σ_v. To derive standard errors for these estimates, one would need to account for the variability of the estimates of σ_u^2 and σ_v^2 and this is typically not done.[7]

3.2 A more flexible model

To compare the efficiency of mutual and stock S&Ls, one could estimate the model given in equation (1), calculate the firm-specific inefficiency measures in equation (3), and see if these measures were different on average for mutual and stock S&Ls. However, a drawback of this approach is that it assumes that the cost frontiers of the two types of S&Ls are the same. Moreover, it assumes that the error structures (in particular, σ_u and σ_v) are the same for stock and mutual S&Ls. If these assumptions do not hold, then differences in production technology might be counted as inefficiency. To allow the data to tell us whether these assumptions are correct, I derive more flexible models.

The most flexible model is one that allows all the parameters of the model to differ between mutual and stock S&Ls, i.e., it allows the cost frontier and the error structure to differ. Suppose there are N_m mutual S&Ls and N_s stock S&Ls, with $N_m+N_s = N$. Then, the cost model for mutual S&Ls can be written,

$$ln\, C_i^M = ln\, C(y_i^M,w_i^M,B^M) + u_i^M + v_i^M, \quad i=1,\ldots,N_m, \tag{4}$$

and the cost model for stock S&Ls can be written,

$$ln\, C_i^S = ln\, C(y_i^S,w_i^S,B^S) + u_i^S + v_i^S, \quad i=1,\ldots,N_s, \tag{5}$$

where C_i^K, denotes the observed cost of the i[th] S&L of type K, K=M,S (i.e., mutual or stock), y_i^K is the vector of output levels for firm i of type K, w_i^K is the vector of input prices for firm i of type K, $ln\, C(y_i^K,w_i^K,B^K)$ is the predicted log cost function of a cost-minimizing firm of type K operating at output level y_i^K and input prices w_i^K, v_i^K is distributed $N(0,\sigma_v^{K2})$, K=M,S, and the u_i^K are the absolute values of a variable distributed $N(0,\sigma_u^{K2})$, K=M,S.

Estimating a single cost frontier and error structure over the entire sample of mutual and stock S&Ls, as proposed in Section 3.1, amounts to imposing the restrictions: $\mathbf{B}^M = \mathbf{B}^S$, $\sigma_u^{M2} = \sigma_u^{S2}$, and $\sigma_v^{M2} = \sigma_v^{S2}$. This is the most restrictive model. We could relax the restriction that the frontier cost functions for mutual and stock S&Ls are the same by dropping the restrictions $\mathbf{B}^M = \mathbf{B}^S$. We could also relax the restriction that the inefficiency component of the error term has the same distribution for mutual and stock S&Ls. This amounts to dropping the restriction $\sigma_u^{M2} = \sigma_u^{S2}$. Finally, dropping the restriction $\sigma_v^{M2} = \sigma_v^{S2}$ (in addition to the others) yields the least restrictive model.

To estimate these four models and to test which the data support, it is convenient to write the log-likelihood function in a general way that nests the models. Let $D_i = 0$ if firm i is a mutual S&L and $D_i = 1$ if the firm is a stock S&L. Then the log-likelihood function of the most flexible model (which will be called Model 1), which allows the cost structures and error structures of mutual and stock S&Ls to differ, can be written

$$ln\ L = \sum_{i=1}^{N} \Bigg\{ (1 - D_i) \left[\frac{1}{2} \ln \frac{2}{\pi} - ln\ \sigma^M - \frac{1}{2\sigma^{M2}} \epsilon_i^{M2} + ln \left[\Phi \left(\frac{\epsilon_i^M \lambda^M}{\sigma^M} \right) \right] \right] \tag{6}$$

$$+ D_i \left[\frac{1}{2} \ln \frac{2}{\pi} - ln\ \sigma^S - \frac{1}{2\sigma^{S2}} \epsilon_i^{S2} + ln \left[\Phi \left(\frac{\epsilon_i^S \lambda^S}{\sigma^S} \right) \right] \right] \Bigg\} ,$$

where $\epsilon_i^M = u_i^M + v_i^M$, $\epsilon_i^S = u_i^S + v_i^S$, $\sigma^{M2} = \sigma_u^{M2} + \sigma_v^{M2}$, $\sigma^{S2} = \sigma_u^{S2} + \sigma_v^{S2}$, $\lambda^M = \frac{\sigma_u^M}{\sigma_v^M}$, and $\lambda^S = \frac{\sigma_u^S}{\sigma_v^S}$.

A slightly less flexible model, Model 2, is obtained by imposing the restriction $\sigma_v^{M2} = \sigma_v^{S2}$ on equation (6). Model 3 assumes that the error structure is the same for stock and mutual S&Ls but allows the frontiers differ and is obtained by imposing the restrictions $\sigma_v^{M2} = \sigma_v^{S2}$ and $\sigma_u^{M2} = \sigma_u^{S2}$. Finally, Model 4 assumes that mutuals and stock S&Ls share the same frontiers and error structures and is obtained by imposing the restrictions $\sigma_v^{M2} = \sigma_v^{S2}$, $\sigma_u^{M2} = \sigma_u^{S2}$, and $\mathbf{B}^M = \mathbf{B}^S$ on equation (6). Likelihood ratio tests can be used to test whether any of the restricted models are supported by the data.

4. The cost frontier specification and data

It remains to choose a functional form for the cost frontiers $ln\ C(y_i^K, w_i^K, \mathbf{B}^K)$, K=M,S. Here I used the translog specification. (I am currently working on an extension of this article that uses the hybrid translog.) Let the superscript K = M denote variables and coefficients pertaining to mutual S&Ls, and the superscript K = S denote variables and coefficients pertaining to stock S&Ls. Then, the translog cost frontier for S&Ls of type K is (where I have dropped the subscript denoting firm i for notational ease)

$$\ln C^K = a_0^K + \sum_{\ell=1}^{n} a_\ell^K \ln y_\ell^K + \sum_{j=1}^{m} b_j^K \ln w_j^K + \frac{1}{2}\sum_{\ell=1}^{n}\sum_{j=1}^{n} s_{\ell j}^K \ln y_\ell^K \ln y_j^K + \frac{1}{2}\sum_{j=1}^{m}\sum_{k=1}^{m} g_{jk}^K \ln w_j^K \ln w_k^K + \sum_{\ell=1}^{n}\sum_{j=1}^{m} d_{\ell j}^K \ln y_\ell^K \ln w_j^K , \quad K = M,S \tag{7}$$

where symmetry and linear homogeneity in input prices is imposed: $s_{\ell j} = s_{j\ell},\ \ell,j = 1,\ldots,n$, $g_{jk} = g_{kj},\ j,k = 1,\ldots,m$, $\sum_{j=1}^{m} b_j = 1$, $\sum_{k=1}^{m} g_{jk} = 0,\ j = 1,\ldots,m$, and $\sum_{j=1}^{m} d_{\ell j} = 0,\ \ell = 1,\ldots,n$.

I use 1991 data from the Statements of Condition and Statements of Operations that S&Ls must file with the Office of Thrift Supervision each quarter. (I obtained the data from the Federal Reserve Board.) The 1015 S&Ls in the sample (807 mutual S&Ls and 208 stock S&Ls) include all the U.S. S&Ls that had positive equity in each quarter of 1991, did not change holding company status in 1991, had been in operation at least five years as of December 1991, and had not changed their ownership form over that period. (It was important to drop from the sample those S&Ls that had recently changed ownership form, as they may not have reached their equilibrium cost structure.)[8]

There continues to be debate about what constitutes the outputs and inputs of a financial institution. I use the asset approach here, which views the institution as using labor, physical capital, and deposits to produce earning assets [see Sealey and Lindley (1977)]. This approach is consistent with that used by Cebenoyan *et al.* (1992) and Hermalin and Wallace (1992), and is the most common in the conventional cost function literature for S&Ls.[9] I consider three outputs: y_1 = mortgage loans, y_2 = other loans including commercial loans and consumer loans, and y_3 = securities and other investments.[10,11] All outputs are measured as the average quarterly dollar volume in 1991.

The three inputs are labor, physical capital, and deposits and other borrowed money. The wage rate w_1 is proxied by the quarterly average of [labor expenses/number of full-time equivalent employees]. The unit price of physical capital, w_2, is constructed as the quarterly average of [office occupancy and equipment expense/total office premises and equipment]. The deposit and other borrowed money price, w_3, is the quarterly average of [(interest expense on deposits + interest cost of other borrowed money)/(dollars of deposits and other borrowed money)].[12,13] Total costs, C, is the quarterly average of all expenditures on labor, office occupancy and equipment expense, and interest expense of deposits and other borrowed money. **Table 1** summarizes the data (included are some variables not yet discussed that will be used in Section 5.4 below).

5. Empirical results

5.1 Model selection

I estimated Models 1 to 4 using maximum likelihood techniques. Likelihood ratio tests of each of the restricted models 2, 3, and 4 versus Model 1 indicated that the restricted models are strongly rejected by the data at the 0.005 level of significance--the values of the likelihood ratio test statistics for Models 2, 3, and 4 versus Model 1 are 136.55, 136.61, and 182.23, respectively. This means the cost frontiers (and, hence, the production technologies) differ between mutual and stock S&Ls and so do the error structures. Unless otherwise noted, the discussion will be in terms of Model 1, since this is the model the data support. However, since it might be instructive to see if the results qualitatively change when the differences between the mutual and stock S&L technology are ignored, I also present results for Model 4. (See the Appendix, Tables A1 and A2 for the parameter estimates for these models.)

5.2 Scale economies and within-sample scope economies

Table 2 reports measures of scale economies and within-sample scope economies for the mutual and stock S&L samples, evaluated at the mean levels of input prices and output levels for the respective samples. These measures can be thought of as the scale and scope economies for the representative efficient mutual and stock S&Ls. The measures are based on the estimated cost frontiers and so indicate whether an S&L that was minimizing the cost of producing a particular output bundle could lower costs proportionately by choosing another level of output or by changing its output mix--they are for the efficient firms only. In contrast, in the conventional nonfrontier cost function methodology, the scale and scope measures apply to all firms in the sample and might be distorted if they are correlated with efficiency. (However, as will be discussed below, this is not the case here.)

The ***degree of scale economies*** measures the percentage change in costs due to a proportionate increase in all outputs. At a given output vector $y = (y_1,y_2,y_3)$, it is measured as $S(y) \equiv C(y) / \Sigma_{\ell=1}^{n} y_\ell \frac{\partial C}{\partial y_\ell}(y)$. Returns to scale are increasing, decreasing, or constant when $S(y)$ is $>$, $<$, or $=$ 1, respectively. The top half of Table 2 indicates that the representative cost-minimizing mutual S&L is operating at output levels where there are only slightly increasing returns to scale--its average cost is within 1 percent of the average cost of a mutual firm at minimum efficient scale. Little efficiency gain would be possible from changing the scale of operations. The representative stock S&L is operating with constant returns to scale.[14] The results of Model 4 are essentially the same. This result is consistent with Mester (1991) and supports the conclusion that the impact of a possible capital constraint on mutual S&Ls is not likely to motivate conversions to stock ownership.

The ***within-sample degree of economies of scope*** compares the cost of joint production with the cost of producing the same total output at more specialized firms, but none more specialized than that observed in the sample [see Mester (1991)]. For three outputs this measure is $WSC(y) \equiv [C(y_1-2y_1^m,y_2^m,y_3^m) + C(y_1^m,y_2-2y_2^m,y_3^m) + C(y_1^m,y_2^m,y_3-2y_3^m) - C(y_1,y_2,y_3)] / C(y_1,y_2,y_3)$, where y_i^m is the minimum value of y_i for the appropriate sample (mutual or stock).[15] The scope measures reported in the top half of Table 2 indicate significant economies of scope between the three outputs for both mutual and stock S&Ls, so joint production is justified from a cost efficiency standpoint.[16] Again, the results of Model 4 are similar. This result differs from Mester (1991), who found diseconomies of scope for mutual S&Ls using 1982 data on California S&Ls, and is consistent with the theory that the removal of interest rate ceilings in 1986 reduced the ability of mutual S&L managers to pursue their own goals.[17]

It is interesting to note that estimation of the conventional cost function yields similar results--i.e., nearly constant returns to scale and economies of scope for both types of firms. These estimates are reported in the bottom half of Table 2.

5.3 Inefficiency

Table 3 reports estimates of the inefficiency measures discussed in Section 3. Summary measures of inefficiency include an estimate of the mean of u_i, which is $\left(\frac{2}{\pi}\right)^{1/2} \hat{\sigma}_u^M$ for mutual S&Ls and $\left(\frac{2}{\pi}\right)^{1/2} \hat{\sigma}_u^S$ for stock S&Ls, an estimate of the average value of $E(u_i|\epsilon_i)$, and an estimate of the average value of $M(u_i|\epsilon_i)$ for the mutual and stock firms. (Note that the average value of $E(u_i|\epsilon_i)$ equals average(u).) Since the correlation between $\hat{E}(u_i|\epsilon_i)$ and $\hat{M}(u_i|\epsilon_i)$ is extremely high (at 0.99), we really only need to focus on one of the inefficiency measures.

The most striking thing about Table 3 is that regardless of the model, the average level of inefficiency for mutual S&Ls is less than the average level of inefficiency for stock S&Ls. Average inefficiency is in the 0.08 to 0.10 percent range for mutual S&Ls and in the 0.12 to 0.16 percent range for stock S&Ls. These measures are smaller than those found in other stochastic econometric frontier studies of S&Ls and commercial banks. Cebenoyan *et al.* (1992) found average inefficiency of 0.22 at S&Ls. Bauer *et al.* (1992), Ferrier and Lovell (1990), and Berger (1993) found average inefficiency at commercial banks in the 0.15 to 0.17, 0.20 to 0.30, and 0.10 to 0.40 ranges, respectively.

I tested the null hypothesis that the mean of u_i for mutuals equals the mean of u_i for stock S&Ls using the estimates of σ_u^M and σ_u^S. Since the value of the t-test statistic was 4.3, this null hypothesis can be rejected at the 0.05 level in favor of the alternative hypothesis that, on average, stock S&Ls are less efficient than mutual S&Ls.[18] One possibility is that the average $\hat{E}(u_i|\epsilon_i)$ is not a very good summary measure because it is skewed by outliers, i.e., by firms with very high costs relative to the most efficient firm. However, this is not the case here, since the *median* value of $\hat{E}(u_i|\epsilon_i)$ is also lower for mutuals than for stock S&Ls.[19] Although not reported in the table, on average, the level of inefficiency per unit of output is nearly the same for mutual and stock S&Ls in Model 1, and is lower for mutuals than for stocks in Model 4.

This result differs from that of Cebenoyan *et al.* (1992), who found that the average inefficiency of mutual S&Ls is greater than that of stock S&Ls. The difference in results does not appear to stem from my permitting the cost frontiers of stock and mutual S&Ls to differ while they did not, since my result obtains even in Model 4. It may stem from Cebenoyan *et al.*'s inclusion in their sample S&Ls that have recently changed from one ownership form to the other. My result seems to be very robust--e.g., it is not due to the sample of mutual S&Ls being much larger than the sample of stock S&Ls. Re-estimating the model with a randomly selected sample of 208 mutual S&Ls (which is the number of S&Ls in the stock sample) does not change the result, nor does re-estimating the model including only those stock S&Ls with total assets less than or equal to that at the largest mutual S&L in the sample.

The evidence of agency problems at mutual S&Ls that Mester (1991) found in the period prior to deregulation does not appear to be present post-deregulation. One plausible explanation is that deregulation of interest rates along with increased competition from other financial intermediaries has had the desirable effect of lessening agency problems at mutual S&Ls. Increased competition means that any given level of perquisite-taking or inefficiency on the part of a mutual S&L manager has become more costly (in terms of increased chance of bankruptcy and job loss), so the benefits of remaining a mutual have been reduced. And the manager gets a positive benefit from converting, since he/she usually receives rights to purchase the newly issued stock, which is typically underpriced [as in other initial public offerings; see Masulis (1987)]. Thus, converting has become attractive.

This does not explain, however, my finding of greater inefficiency for stock S&Ls than for mutual S&Ls in the recent sample. This could be explained if it is the relatively more inefficient of the mutual S&Ls that have been converting. This seems reasonable if a manager's perk-taking is private information, because then the new stock of a perk-taking mutual should be relatively more underpriced than the new stock of an efficient mutual (provided the manager can make his S&L efficient upon conversion, i.e., perk-taking caused the inefficiency, not low ability). Thus, the potential benefit from converting will be higher for the more inefficient mutuals. I am currently estimating the model for a sample of S&Ls that have recently converted to stock ownership to test this hypothesis.

5.4 Correlates with inefficiency

It remains to discuss the characteristics of inefficient S&Ls. To investigate these characteristics, I regressed the firm-specific measures of inefficiency, $\hat{E}(u_i|\epsilon_i)$ and $\hat{M}(u_i|\epsilon_i)$, on several independent variables. These regressions provide information on correlation only and not causality. The correlations should be interpreted with care as one could argue that the significant correlates should be included in the cost model from which the efficiency measures were derived. Doing this, however, did not seem to have much effect here. For example, as discussed below, the capital-asset ratio was a significant correlate, but including financial capital as a quasi-fixed input in the cost model did not affect any of the results on efficiency or scale and scope economies of mutual and stock S&Ls.[20,21] Since the results are generally the same for both measures, I report the $\hat{E}(u_i|\epsilon_i)$ results in Table 4.

Since the values of $\hat{E}(u_i|\epsilon_i)$ range between 0 and 1, I used the logistic functional form rather than a linear model. The general form of this regression equation is

$$\hat{E}(u_i|\epsilon_i) = \frac{\exp(X_i'\gamma^K)}{1 + \exp(X_i'\gamma^K)} + \xi_i^K, \qquad K = M,S \tag{8}$$

where X_i is a vector of independent variables for the i^{th} firm, γ^K, $K=M,S$ are the parameter vectors for mutual and stock S&Ls, respectively, and ξ_i^K, $K=M,S$ are normally distributed error terms. I used nonlinear OLS to estimate equation (8) for mutual S&Ls and stock S&Ls separately. (Likelihood ratio tests reject at the 0.005 level pooling the mutual and stock S&L samples and estimating equation (8), even when allowing the coefficient vector γ^K to differ for mutual and stock S&Ls.)

Because $\hat{M}(u_i|\epsilon_i)$ is less than 1 when $\epsilon_i > 0$, and equal to 0 when $\epsilon_i < 0$, for the regressions with $\hat{M}(u_i|\epsilon_i)$ as dependent variable, I estimated nonlinear Tobit models for mutual and stock S&Ls of the form

$$\hat{M}(u_i|\epsilon_i) = \begin{cases} \dfrac{\exp(X_i'\gamma^K)}{1+\exp(X_i'\gamma^K)} + \xi_i^K & \text{if } \hat{M}(u_i|\epsilon_i) > 0 \\ 0 & \text{if } \hat{M}(u_i|\epsilon_i) \le 0 \end{cases} \qquad K = M,S \tag{9}$$

where ξ_i^K is an i.i.d. normally distributed error term with mean 0 and standard error ρ. Defining δ_i = 0 when $\hat{M}(u_i|\epsilon_i) \le 0$ and $\delta_i = 1$ when $\hat{M}(u_i|\epsilon_i) > 0$, the log-likelihood function for this model is

$$ln\,L^K = \sum_{i=1}^{N_K} -\delta_i\,[\tfrac{1}{2}\,ln\,(\rho^{K2})] + \sum_{i=1}^{N_K} \delta_i\,ln\,\phi\,(\frac{\xi_i^K}{\rho^K}) + \sum_{i=1}^{N_K} (1-\delta_i)\,ln\,\Phi\,(\frac{-\xi_i^K}{\rho^K}), \quad K = M,S \quad (10)$$

where $\phi(\cdot)$ is the standard normal density function and $\Phi(\cdot)$ is the standard normal cumulative distribution function. Maximizing this function with respect to γ^K and ρ^K yields maximum likelihood parameter estimates. (Likelihood ratio tests reject at the 0.005 level pooling the mutual and stock S&L samples and estimating this model, even when allowing the coefficient vector γ^K to differ for mutual and stock S&Ls.) See the Appendix, Table A3 for these estimates. Since the results are nearly the same as the ones obtained for $\hat{E}(u_i|\epsilon_i)$, I discuss the $\hat{E}(u_i|\epsilon_i)$ results below.

The 14 independent variables included are: **CONST** = constant term, **CHAR** = 1 if the S&L is state chartered and 0 if the S&L is federally chartered, **STAT** = 1 if the S&L is located in Florida, Texas, or California and 0 otherwise, **TOTA** = total assets, **CAPA** = capital/total assets, **ROA** = net income/total assets, **NONP** = nonperforming loans/total assets, **REPO** = repossessed assets/total assets, **COMM** = commercial loans/total assets, **CONS** = consumer loans/total assets, **MPSE** = mortgage pool securities/total assets, **REAL** = real estate owned/total assets, **BROK** = brokered deposits/total deposits, and **UDEP** = uninsured deposits/total deposits.

CHAR is included to account for organizational structure;[22] STAT is included because California, Texas, and Florida S&Ls were considered to have less conservative regulators and markets in which expansion was strong [see Hermalin and Wallace (1992)]; TOTA controls for the overall size of an S&L; CAPA measures capital adequacy (moral hazard theory suggests that CAPA should be inversely related to inefficiency); ROA, NONP, and REPO are measures of performance (higher efficiency is expected to be correlated with better performance); COMM, CONS, MPSE, and REAL measure some of the expanded activities in which S&Ls were permitted to engage (some suggest that expansion into these activities exacerbated the S&L debacle); and BROK and UDEP measure reliance on noncore deposits (some claim brokered deposits are used by less efficient S&Ls, but substitution of brokered for core deposits might save on labor and physical capital cost; uninsured depositors might impose market discipline on S&L managers, but S&Ls that are relying on these deposits rather than core deposits might be in bad shape).

Table 4 shows the coefficient estimates of equation (8) for Models 1 and 4. The estimates indicate that different variables significantly correlate with inefficiency in mutual and stock S&Ls. There are also some differences between Models 1 and 4. Focusing on Model 1, I find that for both mutual and stock S&Ls, inefficiency is significantly negatively correlated to CAPA, i.e., better capitalized thrifts are more efficient. This accords with the moral hazard theory that suggests managers of thrifts closer to bankruptcy might be inclined to increase perquisite-taking.

Other than this variable, only two other variables (CONS and UDEP) are significant correlates with inefficiency for both mutual and stock S&Ls, but the sign on CONS differs depending on S&L type. For mutual S&Ls, a higher proportion of assets in consumer loans is correlated with lower inefficiency. This suggests that expanding activities permitted of mutual S&Ls has not had a deleterious effect on their efficiency (the coefficient estimates for COMM, MPSE, and REAL are insignificantly different from zero) and may have led to improved efficiency. For stock S&Ls, a higher proportion of assets in consumer loans is correlated with greater inefficiency, suggesting, at the least, that expanded activities have not led to greater efficiency at stock institutions (the coefficient estimates for COMM, MPSE, and REAL are insignificant). A greater reliance on uninsured deposits (UDEP) is significantly correlated with greater inefficiency at both mutual and stock S&Ls, suggesting uninsured depositors are not imposing market discipline on S&L managers (so regulators may be better off relying on nondeposit creditors and equity holders rather than depositors for market discipline).

The other significant correlates for mutual S&Ls are ROA, REPO, and BROK. Higher profitability is correlated with less inefficiency at mutuals (the causality may run from efficiency to profitability), but surprisingly so is a higher proportion of repossessed assets. Thus, the relationship between performance and inefficiency is ambiguous for mutual S&Ls. A greater reliance on brokered deposits is significantly correlated with greater inefficiency at mutual S&Ls, so regulations to restrict the use of brokered deposits at poorly performing mutual S&Ls may be justified.

For stock S&Ls there are no other significant correlates with inefficiency aside from the variables already discussed. The fact that ROA is insignificantly related to inefficiency discredits the possibility that my finding of greater inefficiency, on average, at stock than at mutual S&Ls is attributable to stock S&Ls providing better quality output, which is not measured in the model. (If it were, we would expect ROA to be significantly positively related to inefficiency at stock S&Ls.)

Hermalin and Wallace (1992) used a different set of explanatory variables, making it difficult to directly compare their results with mine. In general, their results seem more consistent with my results for stock S&Ls than for mutuals. Like me, Cebenoyan *et al.* (1992) did not find a statistically significant relationship between inefficiency and asset size, but unlike me, they found that Florida S&Ls were less efficient than S&Ls in the other states in their sample.

To compare the inefficiency of the average stock S&L and average mutual S&L, I used the estimated equations (8) for Model 1 to calculate the predicted value of $\hat{E}(u_i | \epsilon_i)$ at the mean levels of the explanatory variables for stock S&Ls and for mutual S&Ls and tested whether their difference was statistically different from zero. The value of the test statistic was 7.21, indicating that inefficiency at the average stock S&L was greater than that at the average mutual S&L.[23] Relying on Model 4 instead of Model 1 would have yielded generally similar results but would have led to some incorrect conclusions about stock S&Ls, implying that it is important when studying inefficiency to test whether mutual and stock S&Ls share the same production technology.

6. Conclusions

This article modifies the stochastic econometric cost frontier approach to investigate efficiency of mutual and stock S&Ls using 1991 data on U.S. S&Ls. My methodology permits both the cost frontier and error structures to differ between the two types of S&Ls. A likelihood ratio test indicates that the data support this unrestricted model, which implies that efficient mutual and stock S&Ls use different production technologies. Various measures of inefficiency indicate that, on average, stock S&Ls are less efficient than mutual S&Ls. Using 1982 data, Mester (1991) found evidence of agency problems at mutual S&Ls. The results here suggest that deregulation of interest rates and increased competition may have had the predicted effect of curtailing agency problems in mutual S&Ls. This might partly explain the large number of conversions of S&Ls from mutual to stock ownership. The finding that stock S&Ls now are, on average, less efficient than mutual S&Ls seems to suggest that further increases in competition will be needed to weed out inefficient firms.

The second part of the article relates the inefficiency measures to several correlates. I find that higher capital-asset ratios are correlated with greater efficiency in both mutual and stock S&Ls, and that a greater reliance on uninsured deposits is correlated with lower efficiency. Other variables are correlated with efficiency in mutual S&Ls or in stock S&Ls but not both.

I am currently investigating whether my results are robust to other specifications of the composite error structure and cost frontier, whether data from other recent periods support similar conclusions, and whether recently converted S&Ls behave similarly to long-standing stock S&Ls.

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Table 1. Data Summary*

Variable			Mutual S&Ls (807 institutions)	Stock S&Ls (208 institutions)
TOTA	Total assets (thousands $)	min	3,866.50	5,478.25
		mean	155,803.75	723,555.27
		max	3,654,910.00	41,111,000.00
y_1	Mortgage loans (thousands $)	min	542.00	3,360.00
		mean	96,881.74	473,546.58
		max	3,159,070.00	32,046,400.00
y_2	Other loans (thousands $)	min	5.50	1.25
		mean	6,276.42	16,512.20
		max	367,135.50	549,693.25
y_3	Securities and other investments (thousands $)	min	4.75	497.75
		mean	45,057.32	184,402.82
		max	1,329,646.00	5,470,438.00
w_1	Price of labor (thousands $ per employee)	min	4.14	3.75
		mean	8.47	8.25
		max	19.00	22.74
w_2	Price of physical capital (thousands $ per thousand $)	min	0.01	0.02
		mean	0.13	0.23
		max	1.56	3.91
w_3	Price of deposits and other borrowed money (thousands $ per thousand $)	min	0.01	0.01
		mean	0.02	0.02
		max	0.02	0.02
C	Total cost (thousands $)	min	73.25	109.75
		mean	2,892.86	13,477.87
		max	63,523.50	758,257.00
CAPA	Capital/assets	min	0.003	0.01
		mean	0.08	0.06
		max	0.28	0.15
ROA	Net income/assets	min	−0.02	−0.01
		mean	0.001	0.001
		max	0.01	0.01
NONP	Nonperforming loans/assets	min	0.00	0.00
		mean	0.01	0.02
		max	0.16	0.13
REPO	Repossessed assets/assets	min	0.00	0.00
		mean	0.01	0.01
		max	0.11	0.14
COMM	Commercial loans/assets	min	0.00	0.00
		mean	0.004	0.01
		max	0.10	0.16
CONS	Consumer loans/assets	min	0.00	0.00
		mean	0.04	0.04
		max	0.23	0.35
MPSE	Mortgage pool securities/assets	min	0.00	0.00
		mean	0.12	0.11
		max	0.73	0.85
REAL	Real estate owned/assets	min	0.00	0.00
		mean	0.0005	0.002
		max	0.06	0.04
BROK	Brokered deposits/deposits	min	0.00	0.00
		mean	0.002	0.01
		max	0.15	0.89
UDEP	Uninsured deposits/deposits	min	0.00	0.00
		mean	0.05	0.08
		max	0.31	0.44

*Data are quarterly averages over the four quarters of 1991.

Table 2. Scale Economies and Within-Sample Scope Economies

Stochastic Cost Frontier				
	Model 1		Model 4	
	Mutual S&Ls	Stock S&Ls	Mutual S&Ls	Stock S&Ls
Scale Economies	1.0128† (0.00438)	1.0100 (0.01878)	1.0125† (0.00382)	1.0052 (0.00647)
Within-Sample Scope Economies	16.9115* (2.5541)	4.3267* (1.5792)	17.2322* (2.0101)	2.0252* (0.3037)

Non-Frontier Cost Function				
	Model 1		Model 4	
	Mutual S&Ls	Stock S&Ls	Mutual S&Ls	Stock S&Ls
Scale Economies	1.0120† (0.00436)	1.0297† (0.01127)	1.0153† (0.00364)	1.0083 (0.00656)
Within-Sample Scope Economies	23.2445* (4.8234)	5.4570* (1.5838)	28.5833* (5.1144)	3.1174* (0.5711)

Statistics for mutual S&Ls are calculated at the mean values of output levels and input prices for mutual S&Ls. Statistics for stock S&Ls are calculated at the mean values of output levels and input prices for stock S&Ls.

Approximate standard errors in parentheses.

* significantly different from zero at the 5% level, two-tailed test
† significantly different from one at the 5% level, two-tailed test

Table 3. Inefficiency Measures

	Model 1		Model 4	
	Mutual S&Ls	**Stock S&Ls**	**Mutual S&Ls**	**Stock S&Ls**
Mean $u_i = (2/\pi)^{1/2}\sigma_u$ (Approx Std. Err.)	0.09526* (0.00475)	0.13286* (0.00725)	0.11709* (0.00330)	
Average $\hat{M}(u_i \mid \epsilon_i)$	0.08549	0.12212	0.09512	0.15370
Average $\hat{E}(u_i \mid \epsilon_i)$	0.09455	0.12615	0.10276	0.15747
Min $\hat{E}(u_i \mid \epsilon_i)$	0.01465	0.01250	0.01239	0.01874
Median $\hat{E}(u_i \mid \epsilon_i)$	0.07648	0.09829	0.08644	0.12282
Max $\hat{E}(u_i \mid \epsilon_i)$	0.56821	0.69256	0.63025	0.72687
Std. Dev. $\hat{E}(u_i \mid \epsilon_i)$	0.06295	0.10373	0.06871	0.11950

In Model 1, the estimate of the mean of u_i for mutual S&Ls is statistically different from the estimate of the mean of u_i for stock S&Ls at the 0.05 level--the value of the test statistic is 4.3383.

In Model 4, the estimate of the mean of u_i for mutual S&Ls equals the estimate of the mean of u_i for stock S&Ls, since $\sigma_u^M = \sigma_u^S$ in Model 4.

* significantly different from zero at the 5% level, two-tailed test

Table 4. Inefficiency Correlates–Logistic Regressions (8)

	Model 1		Model 4	
Independent Variable	**Mutual S&L Parameter Estimates γ_i^M (Std err)**	**Stock S&L Parameter Estimates γ_i^S (Std err)**	**Mutual S&L Parameter Estimates γ_i^M (Std err)**	**Stock S&L Parameter Estimates γ_i^S (Std err)**
CONST	−1.5111* (0.09649)	−1.7200* (0.2864)	−1.3708* (0.09830)	−1.9457* (0.2732)
CHAR	0.02628 (0.04792)	0.09910 (0.1723)	0.03269 (0.04876)	0.2866** (0.1698)
STAT	0.1371 (0.09859)	0.1535 (0.1314)	0.1470 (0.1007)	0.1589 (0.1228)
TOTA	-0.1010×10^{-6} (0.8463×10^{-7})	-0.6082×10^{-7} (0.6820×10^{-7})	-0.9988×10^{-7} (0.8615×10^{-6})	-0.1757×10^{-7} (0.2786×10^{-7})
CAPA	−8.0593* (0.9406)	−14.7446* (3.5783)	−8.1943* (0.9583)	−12.5528* (3.2477)
ROA	−64.5178* (11.0816)	15.9914 (23.1812)	−68.8500* (11.3577)	45.3450* (22.4964)
NONP	0.3586 (1.5429)	1.1185 (3.8398)	0.07227 (1.5876)	4.7228 (3.6118)
REPO	−6.3606* (2.4826)	−2.1795 (3.7551)	−7.2132* (2.5705)	2.2894 (2.9752)
COMM	−0.5892 (1.9310)	3.4120 (2.4204)	−0.3185 (1.9434)	2.4474 (2.4989)
CONS	−3.1480* (0.7397)	3.1565* (0.9856)	−3.1153* (0.7454)	1.6491 (1.0816)
MPSE	0.02747 (0.1682)	0.02528 (0.4894)	−0.1254 (0.1746)	0.8851* (0.3824)
REAL	−0.2499 (8.1423)	9.6547 (7.7615)	−1.5922 (8.5197)	5.5706 (7.7224)
BROK	4.5984* (1.4485)	−2.7809 (2.1100)	4.4052* (1.5119)	−2.4208 (1.5190)
UDEP	1.1249** (0.6362)	3.4612* (0.8086)	0.9490 (0.6555)	3.8583* (0.7617)

Value of the likelihood function in Model 1 for mutual S&Ls = 1172.87; for stock S&Ls = 204.60
Value of the likelihood function in Model 4 for mutual S&Ls = 1100.50; for stock S&Ls = 177.70
* significantly different from zero at the 5% level, two-tailed test
** significantly different from zero at the 10% level, two-tailed test

APPENDIX

Table A1. **Maximum Likelihood Parameter Estimates of Stochastic Cost Frontier: Model 1**

Parameter	Variable	Estimate (Std Err)	Parameter	Variable	Estimate (Std Err)
a_0^M	$1-D_i$	−1.7515 (1.4585)	a_0^S	D_i	5.1181 (3.7030)
a_1^M	$ln\ y_1^M$	0.1008 (0.1267)	a_1^S	$ln\ y_1^S$	1.3196* (0.2349)
a_2^M	$ln\ y_2^M$	0.2722* (0.0598)	a_2^S	$ln\ y_2^S$	−0.0860 (0.1362)
a_3^M	$ln\ y_3^M$	0.7251* (0.0778)	a_3^S	$ln\ y_3^S$	−0.1646 (0.2058)
b_1^M	$ln\ w_1^M$	0.8743* (0.3841)	b_1^S	$ln\ w_1^S$	−1.6072 (1.0360)
b_2^M	$ln\ w_2^M$	0.0667 (0.1065)	b_2^S	$ln\ w_2^S$	−0.1004 (0.2271)
s_{11}^M	$ln\ y_1^M ln\ y_1^M$	0.1832* (0.0078)	s_{11}^S	$ln\ y_1^S ln\ y_1^S$	0.1933* (0.0165)
s_{12}^M	$ln\ y_1^M ln\ y_2^M$	−0.0119* (0.0035)	s_{12}^S	$ln\ y_1^S ln\ y_2^S$	−0.02016* (0.0055)
s_{13}^M	$ln\ y_1^M ln\ y_3^M$	−0.1527* (0.0043)	s_{13}^S	$ln\ y_1^S ln\ y_3^S$	−0.1687* (0.0122)
s_{22}^M	$ln\ y_2^M ln\ y_2^M$	0.0213* (0.0018)	s_{22}^S	$ln\ y_2^S ln\ y_2^S$	0.0210* (0.0053)
s_{23}^M	$ln\ y_2^M ln\ y_3^M$	−0.0044 (0.0027)	s_{23}^S	$ln\ y_2^S ln\ y_3^S$	−0.0021 (0.0060)
s_{33}^M	$ln\ y_3^M ln\ y_3^m$	0.1391* (0.0028)	s_{33}^S	$ln\ y_3^S ln\ y_3^S$	0.1723* (0.0122)
g_{11}^M	$ln\ w_1^M ln\ w_1^M$	−0.1098* (0.0547)	g_{11}^S	$ln\ w_1^S ln\ w_1^S$	0.3338* (0.1561)
g_{12}^M	$ln\ w_1^M ln\ w_2^M$	−0.0053 (0.0164)	g_{12}^S	$ln\ w_1^S ln\ w_2^S$	0.0210 (0.0362)
g_{22}^M	$ln\ w_2^M ln\ w_2^M$	−0.0200* (0.0086)	g_{22}^S	$ln\ w_2^S ln\ w_2^S$	0.0025 (0.0125)
d_{11}^M	$ln\ y_1^m ln\ w_1^M$	0.0265 (0.0186)	d_{11}^S	$ln\ y_1^S ln\ w_1^S$	−0.1554* (0.0346)

Table A1, continued.

Parameter	Variable	Estimate (Std Err)	Parameter	Variable	Estimate (Std Err)
d^M_{12}	$ln\ y^M_1 ln\ w^M_2$	−0.0037 (0.0056)	d^S_{12}	$ln\ y^S_1 ln\ w^S_2$	0.0049 (0.0115)
d^M_{21}	$ln\ y^M_2 ln\ w^M_1$	−0.0326* (0.0086)	d^S_{21}	$ln\ y^S_2 ln\ w^S_1$	0.0369** (0.0205)
d^M_{22}	$ln\ y^M_2 ln\ w^M_2$	0.0013 (0.0035)	d^S_{22}	$ln\ y^S_2 ln\ w^S_2$	0.0012 (0.0073)
d^M_{31}	$ln\ y^M_3 ln\ w^M_1$	−0.0228** (0.0129)	d^S_{31}	$ln\ y^S_3 ln\ w^S_1$	0.0961* (0.0296)
d^M_{32}	$ln\ y^M_3 ln\ w^M_2$	0.0039 (0.0037)	d^S_{32}	$ln\ y^S_3 ln\ w^S_2$	−0.0083 (0.0121)
σ^{M2}		0.0163* (0.0012)	σ^{S2}		0.0290* (0.0027)
λ^{M2}		6.8280* (1.8723)	λ^{S2}		22.0479 (13.9334)

Value of log-likelihood function = 1285.37
* significantly different from zero at the 5% level, two-tailed test
** significantly different from zero at the 10% level, two-tailed test

Table A2. Maximum Likelihood Parameter Estimates of Stochastic Cost Frontier: Model 4

Parameter	Variable	Estimate (Std Err)	Parameter	Variable	Estimate (Std Err)
a_0	constant	−1.7313 (1.1037)	d_{12}	*ln* y_1*ln* w_2	0.0001 (0.0043)
a_1	*ln* y_1	0.3253* (0.0871)	d_{21}	*ln* y_2*ln* w_1	−0.0243* (0.0068)
a_2	*ln* y_2	0.2408* (0.0468)	d_{22}	*ln* y_2*ln* w_2	0.0023 (0.0024)
a_3	*ln* y_3	0.6054* (0.0696)	d_{31}	*ln* y_3*ln* w_1	−0.0011 (0.0112)
b_1	*ln* w_1	0.6802* (0.3089)	d_{32}	*ln* y_3*ln* w_2	0.0010 (0.0033)
b_2	*ln* w_2	0.1197 (0.0796)	σ^2		0.0234* (0.0010)
s_{11}	*ln* y_1*ln* y_1	0.1851* (0.0060)	λ^2		11.3236* (2.5482)
s_{12}	*ln* y_1*ln* y_2	−0.0131* (0.0028)			
s_{13}	*ln* y_1*ln* y_3	−0.1546* (0.0038)			
s_{22}	*ln* y_2*ln* y_2	0.0207* (0.0015)			
s_{23}	*ln* y_2*ln* y_3	−0.0047* (0.0023)			
s_{33}	*ln* y_3*ln* y_3	0.1408* (0.0027)			
g_{11}	*ln* w_1*ln* w_1	−0.0560 (0.0461)			
g_{12}	*ln* w_1*ln* w_2	−0.0214** (0.0119)			
g_{22}	*ln* w_2*ln* w_2	−0.0023 (0.0070)			
d_{11}	*ln* y_1*ln* w_1	−0.0093 (0.0135)			

Value of log-likelihood function = 1194.26
* significantly different from zero at the 5% level, two-tailed test
** significantly different from zero at the 10% level, two-tailed test

Table A3. Inefficiency Correlates–Nonlinear Tobit Regressions (9)

	Model 1		Model 4	
Independent Variable	Mutual S&L Parameter Estimates γ_i^M (Std err)	Stock S&L Parameter Estimates γ_i^S (Std err)	Mutual S&L Parameter Estimates γ_i^M (Std err)	Stock S&L Parameter Estimates γ_i^S (Std err)
CONST	−1.2766* (0.1283)	−1.6156* (0.3935)	−1.1644* (0.1245)	−1.9471* (0.3226)
CHAR	0.04221 (0.06988)	0.07904 (0.3359)	0.04940 (0.06767)	0.3048 (0.2295)
STAT	0.1339 (0.1291)	0.1784 (0.1591)	0.1438 (0.1279)	0.1671 (0.1271)
TOTA	-0.1228×10^{-6} (0.1368×10^{-6})	-0.7787×10^{-7} (0.1498×10^{-6})	-0.1138×10^{-6} (0.1316×10^{-6})	-0.1842×10^{-7} (0.8987×10^{-7})
CAPA	−13.2156* (1.3977)	−18.6228* (4.4215)	−12.5922* (1.3239)	−14.1442* (3.6752)
ROA	−69.8141* (15.9300)	14.3958 (25.8949)	−73.6707* (15.9792)	46.4894* (17.4309)
NONP	0.2053 (1.9467)	0.3876 (4.1989)	−0.07809 (1.8424)	4.7774 (2.9765)
REPO	−8.7904* (3.2308)	−2.3823 (5.2904)	−9.4987* (3.2987)	2.3837 (3.8236)
COMM	−1.8238 (2.5964)	3.8143 (2.8145)	−1.2646 (2.4616)	2.5432 (2.1671)
CONS	−4.3681* (1.0632)	3.4027* (1.0596)	−3.8867* (1.0058)	1.7351 (1.0893)
MPSE	−0.04300 (0.2160)	0.01036 (0.6979)	−0.2090 (0.2200)	0.9290* (0.4455)
REAL	1.3639 (21.8727)	9.8938 (8.8515)	−0.7499 (22.6303)	5.8388 (7.8123)
BROK	5.2578* (1.0264)	−3.7160 (3.9895)	4.9198* (1.0336)	−3.3820 (2.3646)
UDEP	1.6464* (0.7736)	4.0859* (0.7628)	1.3472** (0.7791)	4.1503* (0.6354)

Model 1: Estimate and standard error of ρ^{M2} = 0.004854* (0.0001866) and of ρ^{S2} = 0.009400* (0.0006781)
Value of the likelihood function for mutual S&Ls = 787.58; for stock S&Ls = 168.08

Model 4: Estimate and standard error of ρ^{M2} = 0.005485* (0.0002038) and of ρ^{S2} = 0.01155* (0.0009447)
Value of the likelihood function for mutual S&Ls = 764.43; for stock S&Ls = 160.24

* significantly different from zero at the 5% level, two-tailed test
** significantly different from zero at the 10% level, two-tailed test

NOTES

1. While the speed up in conversions began in the early 1980s after the Garn-St. Germain Act eliminated state restrictions on the conversion of federally chartered S&Ls, conversions have continued at a strong pace. There have been over 550 conversions since 1980 [see Cebenoyan *et al.* (1992)].

2. This article also uses a national sample rather than a sample of California S&Ls, which are generally larger than S&Ls elsewhere in the U.S.

3. In addition several papers have focused more specifically on expense preference behavior at savings and loans. See Mester (1989) for a critique.

4. Their F-test indicated that the hypothesis that mutual and stock S&Ls have the same cost frontier could not be rejected at the 5 percent level of significance, but could be rejected at the 10 percent level.

5. I know of no other stochastic econometric frontier study of S&Ls. The stochastic econometric cost frontier methodology has been more extensively applied to commercial banks, including the studies by Ferrier and Lovell (1990), Bauer *et al.* (1992), and Berger (1993). These studies generally find that X-inefficiency is a more significant form of inefficiency at commercial banks than their choosing inefficient output levels.

6. Other distributions have also been used. For example, Stevenson (1980) used the normal-truncated normal model, in which $v_i \sim N(0,\sigma_v^2)$ and u_i is the absolute value of a variable that is independent of v and is distributed as $N(\mu,\sigma_u^2)$. Stevenson (1980) and Greene (1990) also used the normal-gamma model. I am currently extending this research to check the robustness of my results for different distributions of the error terms.

7. A drawback of this approach is the strong distributional assumptions that must be maintained. With panel data some of the stronger assumptions can be avoided [see Schmidt and Sickles (1984), Bauer *et al.* (1992), and Berger (1993)] if the time dimension of the panel is long enough so that any firm's v_i's can be assumed to be zero on average over the time covered by the panel. Unfortunately, since there have been many regulatory changes in the S&L industry, in particular FIRREA in 1989, one would not

want to estimate the model with data from both before and after 1989 without allowing the parameters and error structures to change over time. Thus, panel data techniques would not be very useful here.

8. In addition, a few S&Ls had to be dropped because of missing or misreported data.

9. The banking literature has found that different approaches to measuring output has generally led to similar conclusions concerning the cost structures of financial firms. For example, Mester (1992) found that including transactions deposits as an output did not change any of the conclusions concerning production economies for large banks.

10. The variable y_3 includes mortgage pool securities, repossessed assets, real estate held for investment, U.S. government securities, federal agency securities, equity securities except Federal Home Loan Bank (FHLB) stock, mortgage derivative securities, fed funds sold, state and municipal obligations, other investment securities, and interest-earning deposits in FHLBs.

11. Reliable data on mortgage loans sold or securitized were unavailable, so I could not include them as an additional output. I did obtain data on the volume of mortgage loans sold or securitized in the last month of each quarter of 1991, but the Board of Governors' staff did not think them too reliable. Preliminary work with these data suggests that including securitized loans does not change my result on the relative efficiency of mutual and stock S&Ls.

As a further robustness check, I estimated a model that included noninterest income as a rough proxy to off-balance-sheet activities as a fourth output. Again, this did not change my efficiency results. Similarly, adding mortgage loan servicing fees to y_1 yielded similar results.

12. Of the 1015 S&Ls in the sample, 650 reported a zero volume of other borrowed money for at least one quarter of 1991; hence deposits and other borrowed money had to be aggregated. Measuring w_3 as just the price of deposits yields similar results to those reported below.

13. Changing the specification to include the level of financial capital as a quasi-fixed input in the cost model did not change my results regarding efficiency. Hughes and Mester (1992) discuss this specification for commercial banks.

14. I also estimated scale economies at the minimum output levels and maximum output levels for both mutual and stock S&Ls. These estimates show that scale economies differ little with output level--the average cost curve is flat.

15. Note that we subtract $2y_i^m$ from the output of the firm specializing in output i so that the total output of the three firms will sum to y.

16. The within-sample scope economies estimates are large, indicating that even the within-sample measures involve extrapolation.

17. The difference in results does not appear to stem from Mester's (1991) using a sample of California S&Ls, which are large by national standards, since she found diseconomies of scope at the smallest California mutual S&L in her sample, and this S&L was smaller than the average size S&L in the national sample used here.

18. I could not test whether the other inefficiency measures differed significantly for mutual and stock S&Ls because the distribution of the efficiency measures is unknown.

19. This abstracts from any effect outliers might have on the measurement of the cost frontier itself.

20. Another reason to interpret the results as providing information on correlation only is that, since the independent variables are for the same period as the efficiency measures, there may be some endogeneity. For example, inefficient firms may choose to invest in real estate.

21. Saxonhouse's (1976) method for treating heteroscedasticity that can arise when estimated parameters are used as dependent variables was not applicable here, since the models I estimated are nonlinear.

22. Only one mutual S&L was a member of a holding company, so a variable accounting for holding company membership was not included.

23. In Section 5.3, I calculated the average inefficiency of stock and mutual S&Ls. But since inefficiency is a nonlinear function of the characteristics of the firms, the average inefficiency is not necessarily equal to the inefficiency of the average stock or mutual S&L.