Eisenbeis, Robert A.; Ferrier, Gary D.; Kwan, Simon H.

Working Paper

The informativeness of stochastic frontier and programming frontier efficiency scores: Cost efficiency and other measures of bank holding company performance

Working Paper, No. 99-23

Provided in Cooperation with:
Federal Reserve Bank of Atlanta

FEDERAL
RESERVE
BANK
of ATLANTA

The Informativeness of Stochastic Frontier and Programming Frontier Efficiency Scores: Cost Efficiency and Other Measures of Bank Holding Company Performance

Robert A. Eisenbeis, Gary D. Ferrier, and Simon H. Kwan

Working Paper 99-23
December 1999

Working Paper Series

The Informativeness of Stochastic Frontier and Programming Frontier Efficiency Scores: Cost Efficiency and Other Measures of Bank Holding Company Performance

Robert A. Eisenbeis, Gary D. Ferrier, and Simon H. Kwan

Federal Reserve Bank of Atlanta
Working Paper 99-23
December 1999

Abstract: This paper examines the properties of the X-inefficiencies in U.S. bank holding companies derived from both stochastic and linear programming frontiers. This examination allows the robustness of results across methods to be compared. While we find that calculated programming inefficiency scores are two to three times larger than those estimated using a stochastic frontier, the patterns of the scores across banks and time are similar, and there is a relatively high correlation of the rankings of banks' efficiencies under the two methods. However, when we examine the "informativeness" of the efficiency measured by the two different techniques, we find some large differences. We find evidence that the stochastic frontier scores are more closely related to risk-taking behavior, managerial competence, and bank stock returns. Based on these findings, we conclude that while both methods produce informative efficiency scores, for this data set decision makers should put more weight on the stochastic frontier efficiency estimates.

JEL classification: C13, C14, C21, D21, G21

Key words: stochastic frontier, data envelope analysis, X-inefficiencies, banks and bank holding companies, informativeness principle

---

Please address questions regarding content to Robert A. Eisenbeis, Research Department, Federal Reserve Bank of Atlanta, 104 Marietta Street, NW, Atlanta, Georgia 30303-2713, 404/521-8851, 404/521-8956 (fax), robert.a.eisenbeis@atl.frb.org; Gary D. Ferrier, Department of Economics, College of Business Administration, University of Arkansas, Fayetteville, Arkansas 72701, 501/575-3266, 501/575-7687 (fax); or Simon H. Kwan, Senior Economist, Economic Research Department, Federal Reserve Bank of San Francisco, 101 Market Street, Mail Stop 1130, San Francisco, California 94105, 415/974-3190, 415/974-2168, simon.kwan@ss.frb.org.

The Informativeness of Stochastic Frontier and Programming Frontier Efficiency Scores: Cost Efficiency and Other Measures of Bank Holding Company Performance

I. Introduction

Berger and Humphrey (1997) survey 130 frontier efficiency studies of financial institutions from around the world. While institution type, methodologies, and data vary widely across these studies, the findings are surprisingly similar: X-inefficiencies in financial institutions are large, typically accounting for 20 percent or more of costs, and dominate scale and scope considerations.

This paper offers two contributions to the large and growing literature on the efficiency of financial institutions. First, the time-series properties of the X-efficiency of a group of large U.S. bank holding companies (BHCs) are examined over the period 1986-91. Most previous studies of bank efficiency are based on cross-sectional data; therefore, there is little information on how X-inefficiencies in banking evolve over time.[1] For example, do firm-specific X-inefficiencies tend to persist over time, or do market forces correct them promptly?

The larger contribution of this paper is to explore the "informativeness" of the efficiency scores. The reason for calculating (in)efficiency scores is to assess the relative performance of economic agents, information that can then be used by decision makers (e.g., the agents themselves, managers, shareholders, regulators, etc.). For example, the first published bank efficiency study, Sherman and Gold (1985), is a field test of the ability of data envelopment analysis (DEA) to provide bank management with information on how to improve operating performance.

If the efficiency scores are to be useful to decision makers, then they must be "informative" or

---

[1]Notable exceptions are Bauer, Berger, and Humphrey (1993) and Bauer, et al. (1998).

"valuable." Bauer, et al. (1998) propose six consistency conditions that efficiency measures would ideally meet if they are to be "useful" to decision makers. The value of information in assessing performance is more broadly addressed by the "informativeness principle" (Holmstrom 1979; Shavell 1979). This principle, developed in the principal-agent literature, states that it is generally desirable for the principal to include, with appropriate weighting, in the determination of the agent's compensation any performance indicator that allows an agent's performance to be more accurately assessed (assuming that the indicator is available at low cost). Furthermore, the principle asserts that the more reliable the information (i.e., the more it reduces the noise associated with performance measurement), the more weight it should be given in the determination of compensation (Milgrom and Roberts 1992).

Many methods are available to estimate inefficiencies, and these methods often yield widely disparate results. To date there have been few attempts to link alternative measures of inefficiencies to other performance measures or to determine the relative "informativeness" of the scores produced by alternative frontier methods.[2] Given the large-scale changes in banking markets and banking regulations that have occurred during the past decade (see Berger, Kashyap, and Scalise 1995), the usefulness of efficiency scores in the banking industry is especially interesting.

To examine efficiency over time and its potential usefulness to decision makers, we estimate the X-efficiencies of a sample of 254 bank holding companies over the period 1986 to 1991 using two very different methods—a stochastic cost frontier with a composed error term (Aigner, Lovell, and Schmidt 1977) and a linear programming cost frontier (Färe, Grosskopf, and Lovell 1985). Our

---

[2]Exceptions include Siems (1992), Barr, Seiford, and Siems (1994), Wheelock and Wilson (1995) and Bauer, et al. (1998).

rationale for using two different methods is twofold. First, we would like to examine the robustness of our findings. Charnes, Cooper, and Sueyoshi (1988) advocate the use of "methodological cross-checking" whenever important policy decisions are to be based on results that may depend upon the methodology selected to perform the study. Second, we want to examine the relative informativeness of the efficiency scores obtained using the stochastic and programming methodologies. One need not choose one method over the other; rather, both methods could be used, at relatively low cost, to obtain information about performance. The relevant question is not which is the "better" method but how to weight the information the alternative approaches provide.

In particular, after grouping BHCs into size-based quartiles to allow for different production technologies, separate cost frontiers are estimated for each quartile, and estimates of firm-specific X-inefficiency are derived using both the stochastic and programming frontier methods. Similar to the results reported in previous banking efficiency studies, we find that X-inefficiencies are large. There are some obvious differences in the efficiency scores found by the stochastic and programming frontiers (namely, their magnitudes and variances), but some commonalities are found as well. For example, both the level of X-inefficiencies and their cross-sectional variation are, on average, noticeably smaller for large banking firms than for smaller firms. Second, regardless of firm size, X-inefficiencies appear to have gradually declined over the sample period, though there is some "wiggling" in the trend near the end of the period. Third, although X-inefficiencies have fallen, the rank orderings of firm-specific inefficiencies are highly correlated over time and tend to persist over time, especially for firms in the smaller three quartiles.

Differences in the efficiency scores across the stochastic and programming methods as well as

the finding that inefficient banking firms tend to remain inefficient but somehow survive in the market lead us to investigate how the information content of the efficiency scores. If banking markets are competitive, how can inefficient firms remain economically viable? This question is especially puzzling given recent changes that have taken place in financial markets, which would suggest that competition has increased in part due to substantial entry by nonbank competition. Are markets not as efficient as one would think? Are measured inefficiencies "inflated"? Or do banks somehow compensate for their inefficiencies?

We conjecture that many banking markets were effectively insulated, at least during the time period of this study, thus enabling inefficient firms to continue to survive by earning economic rents (Merton 1978; Buser, Chen, and Kane 1981; and Marcus 1984). Perhaps more important, with fixed premium deposit insurance, which was apparently mispriced, inefficient firms might be induced to compensate for their inefficiencies by extracting subsidies from the FDIC through greater risk taking (Marcus and Shaked 1984; Ronn and Verma 1986; Pennacchi 1987). Managements of inefficient banking firms may be inclined to take on more risk in order to meet shareholders' return targets (Gorton and Rosen 1992). Finally, bank regulators may exacerbate this risk-taking incentive by delaying much needed regulatory actions on problem institutions (Kane 1992; Kane and Kaufman 1993), as was the case with Bank of New England. Taken together, it is quite plausible that inefficient firms may be associated with higher bank risk taking.

We find a strong association between X-inefficiencies and bank risk taking using the stochastic frontier inefficiency estimates, regardless of firm size. Specifically, inefficient firms tend to have higher common stock return variances, higher idiosyncratic risk in stock returns, lower capitalization, and

higher loan charge-offs. Furthermore, firm-specific X-inefficiencies have explanatory power for the banking firms' stock returns after controlling for the market and interest rate factors. The stochastic frontier inefficiency scores are also found to have strong relationships with various proxies of managerial competence. The link between risk taking, management quality, and stock returns is much weaker for the programming inefficiency scores. These results suggest that the stochastic frontier method produces relatively more informative scores as compared to those from the programming frontier method. Thus, for these data, decision makers should give relatively more weight to the stochastic frontier results.

The remainder of this paper is organized as follows: Section II describes the approaches used to estimate firm-specific X-inefficiencies. Section III outlines the data used in this study. The properties of estimated X-inefficiencies are discussed in Section IV. Section V investigates the informativeness of the X-efficiency scores by examining the relationship between the scores and bank risk taking, managerial competence, and bank stock returns. Section VI summarizes and concludes this paper.

II. Measuring Inefficiency in Banking

A variety of methods have been used to derive estimates of firm inefficiencies in the financial services industry (see Berger and Humphrey 1997). One set of methods is based on econometric techniques and involves the estimation of an economic function (e.g., production or cost) and the derivation of efficiency scores from either the residuals or dummy variables. A second approach involves solving linear programs in which an objective function envelops the observed data; efficiency scores are derived by measuring how far an observation lies from the “envelope” or frontier.

Each approach has its advantages and disadvantages. The econometric approach has the virtue of allowing for noise in the measurement of inefficiency; however, it also possesses some vices, including the need to make assumptions about the particular form of the economic function being estimated and the distribution of efficiency. The programming approach has the merit that no functional or distributional forms need to be specified; however, this approach suffers from the drawback that all deviations from the frontier are attributed to inefficiency with no allowance made for noise in the standard models.[3]

We estimate the efficiency of a sample of bank holding companies (BHCs) using one technique from each of the two approaches—the estimation of a frontier translog cost function with a composed error term that includes both noise and inefficiency components and the calculation of a cost frontier using linear programming.[4] This method continues a practice initiated by Ferrier and Lovell (1990) in which a data set is examined using multiple frontier techniques in order to compare results. By using multiple techniques, especially techniques that are based on very different foundations, the robustness of results can be examined. This practice is what Charnes, Cooper, and Rhodes (1981) referred to as methodological cross-checking.

A second reason for using more than one approach to derive efficiency measures is based on the fact that efficiency scores are used for a variety of purposes. It is important to know how

---

[3]Recently, work has been undertaken to explore the "stochastic" nature of programming efficiency scores. See Grosskopf (1996) for a survey of this literature.

[4]Cost efficiency comprises both technical efficiency (operation in the interior of the input requirement set) and allocative efficiency (operation at the wrong point on the boundary of the input requirement set).

informative efficiency scores are prior to using them in decision making. To the extent that the efficiency scores from different techniques contain different information, multiple sets of efficiency scores might be used as the basis for decision making. The efficiency scores derived from different methods could be assigned different weights based on how much information they convey to the decision maker. This possibility is the basic idea of the informativeness principle. As noted by Bauer, et al. (1998), efficiency scores that meet certain consistency conditions are likely to be more useful to decision makers than scores that do not. Among the factors they discuss are the consistencies of efficiency scores with market conditions and traditional measures of firm performance. It could be argued that efficiency scores that satisfy these consistency conditions are more "informative" than those that do not. After deriving and examining the inefficiencies themselves, their informativeness will be investigated by examining the relationship between the inefficiency scores and other measures of bank performance.

A. The Stochastic Cost Frontier

The stochastic cost frontier has the following general (log) form:

$$\ln C_n = f(\ln y_{i,n}, \ln w_{j,n}) + \varepsilon_n,$$

where C_n is total cost for BHC n, $y_{i,n}$ measures the i^{th} output of BHC n, and $w_{j,n}$ is the price of the j^{th} input of BHC n. The error term, ε_n, includes two components:

$$\varepsilon_n = \mu_n + v_n.$$

The first component, v_n, captures the effects of uncontrollable (random) factors while the second component, μ_n, represents controllable factors (Aigner, Lovell, and Schmidt 1977). We assume that v

is distributed as a symmetric normal $N(0,\sigma_{\varepsilon}^2)$ and that u is independently distributed as a half-normal, $|N(0,\sigma_u^2)|$.[5] Following Jondrow, et al. (1982), an estimate of cost efficiency can be derived from the composite error term as follows:

$$CE_n^{SF} = E[\nu_n | \varepsilon_n] = \frac{\sigma\lambda}{(1+\lambda^2)}\left[\frac{\phi(\varepsilon_n\lambda/\sigma)}{\Phi(\varepsilon_n\lambda/\sigma)} - \frac{\varepsilon_n\lambda}{\sigma}\right],$$

where λ is the ratio of the standard deviation of u to the standard deviation of ε (i.e., $\sigma_u/\sigma_\varepsilon$), $\sigma^2 = \sigma_u^2 + \sigma_\varepsilon^2$, and ϕ and Φ are the standard and cumulative normal density functions, respectively.

The multiproduct translog cost function employed to estimated ε_n is of the standard form:

$$\ln TC = \alpha_0 + \Sigma_i \beta_i \ln y_i + \Sigma_j \beta_j \ln w_j + 1/2\,\Sigma_i\Sigma_k \gamma_{ik} \ln y_i \ln y_k + 1/2\,\Sigma_j\Sigma_k \zeta_{jk} \ln w_j \ln w_k + \Sigma_i\Sigma_j \omega_{ij} \ln y_i \ln w_j,$$

where *TC* is total operating cost (including interest expenses), y_i, $i = 1,...,m$, are outputs, and w_j, $j = 1,...,k$, are input prices. The homogeneity restrictions,

$$\Sigma_j \beta_j = 1, \quad \Sigma_k \zeta_{ik} = 0, \quad \Sigma_k \omega_{ik} = 0,$$

are imposed by normalizing total costs and input prices by the price of labor. To allow the cost function to vary across size classes, the sample BHCs are first sorted into size-based quartiles according to average total assets between 1986 and 1991. Assuming the cost function to be stationary over time,

---

[5]The more general truncated normal was originally specified in our empirical work but was rejected in favor of the half-normal.

pooled time-series cross-section observations are used to estimate the stochastic cost function separately for each size-based quartile by the method of maximum likelihood. After computing estimates of the cost efficiency, CE^{SF}, for each sample firm in each sample period, firm-specific X-inefficiencies are calculated as $1 - CE^{SF}$.

B. The Programming Cost Frontier

The second approach we adopt to measure efficiency involves solving linear programming problems that generate a nonparametric, piecewise linear convex frontier that envelops the input and output data relative to which cost is minimized (Färe, Grosskopf, and Lovell 1985). In particular, a sequence of linear programs is used to construct efficient cost frontiers from which measures of cost (in)efficiency are calculated.

The first step in the analysis is to construct a representation of technology that will serve as the point of reference for measuring relative efficiency. The input requirement set consists of all input vectors that are technically feasible for the production of a given level of output. As such, it serves as a representation of technology. A piecewise linear formulation of the input requirement set may be written as

$$L(y) = \{x: z \cdot M \geq y, z \cdot H \leq x, z \in R_+^N, \sum_t z_t = 1\},$$

where $y = (y_1,...,y_m)$ is a vector of outputs, $x = (x_1,...,x_k)$ is a vector of inputs, M is an N x m matrix of m observed outputs for each of N firms, H is an N x k matrix of k observed inputs for each of N firms, and $z = (z_1,...,z_N)$ is an intensity vector that forms convex combinations of observed input and output vectors. The input requirement set given by $L(y)$ imposes no restrictions on returns to scale. For each

observed pair of input-output vectors, the constraint

$z \cdot M \geq y$ says that a convex combination of all BHCs' observed outputs must be at least as great as the vector of outputs of the BHC whose efficiency is being evaluated, while the constraint $z \cdot H \leq x$ requires that the convex combination of all BHCs' inputs can be no larger than the vector of inputs of the BHC whose efficiency is being estimated. The weak inequalities in $L(y)$ mean that the input requirement set displays strong disposability in both outputs and inputs.

Given data on input prices, the minimum cost of production for each firm's observed level of outputs may also be calculated relative to the technology implicit in $L(y)$. Minimum cost can be calculated by solving the following linear programming problem for each firm:

$$\begin{aligned} &Min_x \sum_j w_j^o \cdot x_j \\ &\quad subject\ to: \\ &\quad z \cdot M \geq y^o, \\ &\quad z \cdot M \geq y^o, \\ &\quad\quad z_i \geq 0, i = 1,\ldots,N \\ &\quad \sum_i z_i = 1, \end{aligned}$$

where the superscript o denotes an observed quantity for the BHC whose cost is being minimized. The solution, x^*, is the input vector that minimizes the cost of producing the observed level of output, given input prices and technology. The ratio of the minimized cost to observed cost provides a measure of cost efficiency:

$$CE^{LP} = \frac{w^o \cdot x^*}{w^o \cdot x^o}$$

As for the stochastic frontier, a measure of X-inefficiency is then calculated as $1 - CE^{LP}$.

III. Data

Semiannual Federal Reserve BHC data from 1986 through 1991 are obtained from the Y-9 Reports, and daily stock price data for the sample bank holding companies are taken from the Center for Research in Security Prices (CRSP). Since only BHCs with total consolidated assets of $150 million or more, or with more than one subsidiary bank, are required to file the long form of the Y-9 Reports, the sample consists of larger banking organizations.

Five measures of banking output are included. They are book value of investment securities (y_1), book value of real estate loans (y_2), book value of commercial and industrial loans (y_3), book value of consumer loans (y_4), and off-balance-sheet commitments and contingencies (y_5), which include loan commitments, commercial and standby letters of credit, futures and forward contracts, and notional value of outstanding interest rate swaps. Three input prices are utilized. They include the unit price of capital (w_1), measured as total occupancy expenses divided by fixed plant and equipment; the unit cost of funds (w_2), defined as total interest expenses divided by total deposits, borrowed funds, and subordinated notes and debentures; and the unit price of labor (w_3), defined as total wages and salaries divided by the number of full-time equivalent employees.

Over the twelve periods, 254 BHCs are available, with a total of 2,733 observations. Of the 254 BHCs, 174 had complete time-series data for the entire sample period. The average total assets of these BHCs were used to sort firms into size-based quartiles. The 80 BHCs in the sample with missing observations are then classified into respective size classes using the quartile break points

established by the 174 firms at matching time periods. This classification method ensures that the sample firms stay in the same size class throughout the study period, which is necessary to study the time-series properties of X-inefficiency.[6]

Summary statistics of the output quantities, input prices, total assets, and total costs for the 254 sample firms are reported in Table 1. The data are highly skewed, indicating the desirability of grouping firms into size classes. Although not reported in Table 1, off-balance-sheet activities tend to be concentrated in the larger firms in the sample. This fact suggests that the cost function of large banking firms may potentially be different from those of smaller firms.

IV. Properties of X-Inefficiency in Banking

Table 2 reports descriptive statistics of the cost inefficiency measures derived from the stochastic and programming frontiers for each size-based quartile of BHCs. Consistent with earlier studies (see Berger and Humphrey 1997), we find that substantial inefficiencies exist in banking, averaging between 8 and 19 percent of total costs based on the stochastic frontiers and between 28 and 40 percent for the programming frontiers. In addition to being at least twice as large, the programming frontier inefficiency scores also have wider variations than those found using the stochastic frontier.

While the magnitudes (and, consequently, the variations) of the inefficiency scores are quite

---

[6]Potential misclassification due to intertemporal size changes of individual firms does not seem to be a major concern. If the sample firms had been permitted to move freely from size class to size class intertemporally, there would have been 69 (out of a possible 2,733) instances of firms moving up to the next size class (of which 51 are within 10 percent of the quartile break points), and 77 instances of firms moving down to the next size class (of which 72 are within 10 percent of the quartile break points).

different, there are a number of similarities in the findings across methods. First, cost inefficiency and BHC size are inversely related; both the mean and the median estimates of inefficiency decrease from Quartile 1 to Quartile 4. This result indicates that, on average, smaller BHCs deviate more than do larger BHCs from their respective cost frontiers. Moreover, both the intraquartile range and the standard deviation of inefficiency decrease with BHC size. Hence, not only are smaller banking firms on average less efficient than larger ones, but their variation in inefficiency appears to be greater than that of their larger counterparts. Table 2 also reveals that the inefficiency measures are positively skewed, which is consistent with the truncated normal parameterization of the disturbance term in the stochastic model. Finally, the inefficiency measure appears to be more fat-tailed for firms in Quartiles 1 and 4.

Figure 1 contains time-series plots of the median (rather than the mean due to non-normality), 25^{th}, and 75^{th} percentiles of the cost inefficiency scores for each size-based quartile. In addition to confirming that inefficiency tends to be larger and have higher variation among smaller banking firms, Figure 1 indicates that cost inefficiencies tended to decline over the sample period. The decline in cost inefficiency suggests that the market and regulatory changes instituted during the 1980s may have forced banking firms to respond to increased competition by more effectively controlling costs.

In general, the decline in cost inefficiency was fairly smooth except for a downward blip for the first six months of 1990 for the programming scores and a slight rise in inefficiency in 1991 shown by the stochastic scores. These exceptions to the general trend may be related to regulatory developments that occurred during the period. First, these changes may be driven by the increases in deposit insurance premiums, from 8.33 cents per $100 domestic deposits in 1989 to 23 cents per $100

domestic deposits in 1992. Second, the increase in capital requirements as a result of the Basel Accord may have affected bank efficiencies. The Basel Accord increased banks' cost of capital and might have led to changes in estimated inefficiencies as banks adjusted to this change. Furthermore, banks may have responded to the risk-weighted capital requirement by rebalancing their product mix, such as shifting from loans to investment securities. Although it may be an efficient way to address the new capital constraint, this externality has the effect of resulting in higher observed inefficiency similar to the effect of the increases in deposit insurance premiums. The different behavior of the two sets of inefficiency scores suggests that they may contain different information about how banks responded to these regulatory changes.

While declining, the inefficiency reported in Table 2 and Figure 1 is relatively persistent over time. The next issue to investigate is whether the persistence exists at the firm level as well as at the industry level. Specifically, the cross-sectional rank ordering of inefficiencies over time is examined to determine whether a bank's (in)efficiency carries over across time periods. Table 3 reports the Spearman rank correlations of the stochastic and programming frontier inefficiency estimates for firms that have complete time series of X-inefficiency estimates between June 1986 and eleven subsequent semiannual time periods. For the stochastic frontier estimates, in Quartiles 1, 2, and 3 the rank ordering of inefficiencies is significantly correlated over time at the 1 percent level for at least seven subperiods, suggesting that firm-specific inefficiencies persist for three and one-half years or longer. For the largest firms, Quartile 4, the rank ordering of inefficiencies is significantly correlated at the 1 percent level for

just two subperiods, suggesting that inefficiencies are relatively short-lived for large banking firms.[7]

For the programming estimates the persistence across all the time periods is significantly greater, both in terms of the size of the rank correlation coefficients and the length of time. Across all four size quartiles, rank correlation coefficients are significant for at least five years, suggesting even greater persistence than can be inferred from the stochastic frontier results.

In view of both the differences in the size and the persistence of the estimated inefficiencies for the programming and stochastic frontier inefficiency estimates, it becomes important to investigate the extent to which the two different estimates are capturing the same phenomena (i.e., provide the same information or signal about performance). One way to determine this is to explore the rank correlations between the efficiency scores calculated by the two methods used. Table 4 provides the Spearman rank correlations between the programming and stochastic frontier inefficiency estimates. The correlations are statistically significant at the 1 percent level across all size quartiles and range from a low of 0 .44 for Quartile 3 to a high of 0.58 for Quartile 2. Given the size of the persistence correlations estimates, the cross-estimate correlations are not as high as one might expect, suggesting that there may be some significant differences between the inefficiency estimates provided by the two methods.

The findings in Table 3 for the stochastic cost estimates suggest that the properties of controllable firm-specific inefficiencies for the largest banking firms may be quite different than for the smaller firms. The stochastic frontier estimates suggest that the very large banking firms, as a group,

---

[7]Quantitatively similar results are obtained when different reference periods are used.

operate close to their efficient frontier, and firm-specific X-inefficiencies appear to be transitory. On the other hand, smaller firms, as a group, tend to operate further away from their respective frontiers, and X-inefficiencies seem to be more permanent. In contrast, the programming results, there appear to be fewer differences across the firms, and firm-specific inefficiencies appear to be very large and persist over long periods of time—results that appear more difficult to believe for large firms whose shares are frequently traded, especially if markets are believed to be relatively efficient.

V. The Informativeness of X-Efficiency Scores

Bauer, et al. (1998) propose a set of six consistency conditions that efficiency scores should possess if they are to be useful to decision makers. Among the consistency conditions is the idea that efficiency scores should be related to traditional, nonfrontier measures of performance. It is possible for an efficiency score to signal information about performance that is unique. However, it is more likely that inefficiency scores will be related to other performance measures, though inefficiency scores will (one would hope) help to improve the performance evaluations. In this section, the relationships between the stochastic and programming frontiers' inefficiency scores and other performance indicators are examined.

A. X-Efficiency and Bank Risk Taking

The persistence of inefficiencies prompts us to investigate how inefficient firms can remain economically viable, especially if financial markets are efficient. Specifically, do inefficient firms do anything differently to compensate for their failure to operate on the cost-efficient frontier? One plausible linkage between controllable X-inefficiency and firm behavior: bank risk taking. With fixed premium deposit

insurance during the sample period, an inefficient firm could potentially make up for its inefficiency by taking on more risk, thus extracting a larger deposit insurance subsidy from the Federal Deposit Insurance Corporation. As discussed earlier, bank managers have incentives to take on more risk, and bank regulators have often accommodated that risk taking by engaging in forbearance, as was the case with Bank of New England.

Table 5 reports the Pearson correlation coefficients between the estimated firm-specific stochastic frontier and programming inefficiencies and five measures of bank risk taking. Three of these proxies for risk taking are market-based risk measures, while two are accounting-based risk measures. The standard deviation of daily stock returns measures the total systematic and nonsystematic risks of the banking firm's common stocks. The standard deviation of the residuals from the market model measures the nondiversifiable, idiosyncratic risk. The two capitalization ratios—the market value equity to book value asset ratio and the book value equity to asset ratio—capture the banking firm's financial leverage. The ratio of loan charge-offs to loans outstanding measures the banking firm's exposure to credit risk.

For the stochastic frontier estimates, we find X-inefficiencies significantly positively correlated with both the total risks and idiosyncratic risk of the banking firms' stocks at the 1 percent level, indicating that the existence of inefficiencies is associated with higher levels of risk. X-inefficiency is significantly negatively correlated with market value capitalization for firms in Quartiles 1, 2, and 3 and is significantly negatively correlated with book value capitalization in all four quartiles. Finally, X-inefficiency is significantly positively correlated with loan charge-offs at the 1 percent level for Quartiles 1, 2, and 3 and at the 5 percnet level for Quartile 4. Taken together, these findings suggest that firm-

specific inefficiencies are associated with bank risk taking. Inefficient firms have higher stock return variances, higher idiosyncratic risk, lower capital, and higher loan losses.

The association between the programming inefficiency scores and the measures of risk taking are not nearly as sharp or unambiguous as for the stochastic frontier estimates. The overall level of significance is lower for the programming scores; 10 of the 25 relationships are not statistically significant at even the 10 percent level. In addition, the wrong sign is sometimes found in the correlations. Given that the programming inefficiency estimates are greater in magnitude than the stochastic frontier estimates if markets are efficient and the programming results are informative, then the relationships to risk, if the hypotheses concerning risk-taking are correct, should be even stronger than for the stochastic frontier results. On the other hand, by not allowing for noise, these measures likely confound noise and inefficiency and are thus less informative measures of firm performance.

Reflecting upon the differences in the programming and stochastic frontier results, one might be led to question the believability of the larger programming inefficiency estimates. Despite the evidence of persistence over time, it does not appear that the programming estimates are capturing true measures of firm inefficiencies. To investigate this issue a bit further, especially to see whether the programming estimates have market significance, we now turn to the relationship between X-inefficiency and managerial competency.

B. X-Inefficiency and Managerial Competence

The relationship between various measures of risk and inefficiencies raises the question of whether X-inefficiency is related to managerial competency. In the United States, federal regulators developed the CAMEL rating system to evaluate a bank's health. Financial data are used in fairly straightforward

fashion to determine the "C" (capital adequacy), "A" (asset quality), "E" (earnings ability), and "L" (liquidity position) of CAMEL; determining the management quality, the "M" in CAMEL, is more difficult. Barr, Seiford, and Siems (1994) use technical efficiency scores calculated using Data Envelope Analysis (DEA) as a proxy for management quality in a model to forecast bank failure. Wheelock and Wilson (1995) also use technical efficiency scores to examine bank failures although their scores were derived from a stochastic frontier. Both studies find efficiency scores to be statistically significantly related to bank failures. This suggests that efficiency scores are informative signals of management quality. In this section, the relationships between inefficiency scores and other proxies of managerial competency are examined.

There are at least three proxies of management quality available. The first is the ratio of problem loans to total loans. One index of management quality is the ability to control exposure to credit risk. The ratio of problem loans to total loans captures not only expected risk in the asset portfolio but also reflects management's ability to control that risk. It is hypothesized that higher ratios of problem loans would reflect, ceteris paribus, lax internal controls and hence be associated with inefficient operations.[8]

The second proxy is the ratio of book value of equity to total assets. While this measure captures financial leverage, it also reflects the degree to which shareholders have their own capital at risk in the institution and hence may reflect their incentives to monitor management and assure that the institution operates efficiently. The hypothesis is that the higher the capital ratio, the more efficient the

---

[8]Using Granger-causality tests, Berger and DeYoung (1997) found that cost efficiency scores were good indicators of future problem loans and problem banks.

institution is likely to be.

The final proxy examined is asset growth, as measured by the five-year annual growth rate of the institution. At least over relevant ranges, the ability to manage growth and to keep expenses in line would suggest that slower-growing institutions are likely to be more efficient than more rapidly growing institutions; hence, you would expect a negative sign on the growth variable.

The models estimated to examine the relationship between efficiency and managerial competence are thus:

$$CE_{jt}^{k} = \beta_0 + \beta_1 \cdot BADLOANS_{jt} + \beta_2 \cdot BVCAP/ASSETS_{jt} + \beta_3 \cdot GROWTH\text{-}RATE_{jt} + \epsilon_{jt},$$

where $k = SF, LP$. The results are reported in Table 6. The regressions with the stochastic cost frontier inefficiencies as the dependent variable yield results with the expected signs for the three smallest size classes of banks (Quartiles 1, 2 and 3). Institutions with higher ratios of bad loans, lower capital ratios, and higher growth rates are associated with greater inefficiencies. For the largest size class (Quartile 4), the problem loan coefficient is not statistically significant, and the sign associated with the growth rate is the opposite of what was expected.

As was the case with the risk measures, the overall explanatory power of the regressions employing the programming frontier's estimates of cost inefficiency is lower than for the stochastic frontier estimates. Furthermore, except for the largest size class of banks, only one variable is significant in each regression, and the signs are generally inconsistent with the hypotheses proposed. Interestingly, the results for the largest size class of banks contradict those of the stochastic frontier results, suggesting that there is little relationship between the two inefficiency estimates for this size class

of banking organizations.

C. X-Inefficiency and Stock Market Valuation

A priori, if financial markets are efficient, we would expect a negative relationship between X-efficiency and bank stock returns. Cost inefficient firms, ceteris paribus, should have lower profits and hence offer lower returns to stockholders.[9] Furthermore, the tendency of inefficient firms toward higher risk taking may further depress stock returns. To examine the relationship between efficiency and stock performance, bank stock returns are regressed against X-inefficiency estimates using pooled time series cross-section observations grouped by firm size while controlling for the market return and the change in long-term interest rates.[10] The estimated models are

$$R_{jt} = \beta_0 + \beta_1 R_{mt} + \beta_2 R_{it} + \beta_3 CE_{jt}^{k} + \varepsilon_{jt},$$

where

R_{jt} = return on bank j's stocks for the semiannual period ending at time t,

R_{mt} = return on the CRSP value-weighted market portfolio for the semiannual period ending at time t,

R_{it} = relative change in thirty-year constant maturity Treasury yield (y) from time $t-1$ to time t, i.e., $(y_t - y_{t-1})/y_{t-1}$,

CE_{jt}^{k} = bank j's estimated X-inefficiency (either stochastic frontier or programming; i.e., k =

---

[9]The ceteris paribus condition is important since cost is only one half of the profit equation and therefore does not tell the full story. For example, a bank may offer greater customer service, which, while more costly, also increase revenues.

[10]It is well known that bank stock returns can be modeled by a two-index model with a market return factor and an interest rate factor (see, for example, Flannery and James 1984; Kane and Unal 1990; and Kwan 1991). Using a short-term interest rate provides qualitatively similar results.

SF, *LP*) for the semiannual period ending at time *t*.

The results from estimating the above equation by OLS are reported in Table 7. In both the stochastic and programming score regressions, the coefficient on the CRSP market portfolio return is significantly positive, as expected. While the market betas are all close to unity, they appear to be increasing with firm size. Consistent with prior studies, the relative change in the long-term bond yield is significantly negatively related to bank stock returns, indicating that bank stocks react negatively to interest rate increases. The level of firm-specific inefficiency for the stochastic frontier estimates is negatively correlated with bank stock returns for all four size classes. This finding suggests that stocks of inefficient banks tend to underperform their more efficient counterparts. It should be noted, however, that the negative relationship is statistically significant only for the two smaller size classes. The lack of statistical significance for the larger firms (Quartiles 3 and 4) may be due to the fact that the X-inefficiencies are both smaller in magnitude and have less cross-sectional variation for larger firms, which would make finding a statistically significant relationship more difficult.

The contrast between the stochastic frontier results and the programming results is quite striking. Not only are the signs of the estimated coefficients wrong, but none of the estimated coefficients are statistically significant (see Table 7). This result suggests that, despite the large estimated size of the programming inefficiency estimates and their greater variability, they are not reflected in the market as being important when compared to the stochastic frontier estimates. The finding also calls into question the relative informativeness of the programming results and suggests that the stochastic frontier estimation methods are retaining economically significant measures and variability

in X-inefficiencies that the programming results capture less cleanly (i.e., they send a noisier signal). Clearly, the programming assumption that all deviations from the efficient frontier are due to inefficiencies seems to be inconsistent with the economic evidence and leads to less meaningful estimates than the stochastic frontier methodology.

VI. Summary and Conclusion

As in most previous studies of banking efficiency, we found substantial X-inefficiencies among the bank holding companies in our sample. In addition, several interesting properties of X-inefficiency are detected. For example, after controlling for scale differences, we find that smaller banking firms on average are less efficient than large banking firms. Moreover, small banking firms exhibit larger variation in X-inefficiencies than their large counterparts. Although it is not clear why the larger banking firms, as a group, tend to operate closer to their respective efficient frontier than the smaller firms, future research into the cross-sectional differences in X-inefficiencies appears to be worthwhile.

Though still high, average frontier X-inefficiencies decline over the sample period, suggesting that banks responded to the increased competition that resulted from market and regulatory changes. While X-inefficiency seems to be falling, the rank ordering of firm-specific X-inefficiency is strongly correlated over time. The persistence of X-inefficiency suggests that (in)efficient banking firms tend to remain relatively (in)efficient. The estimated persistence is much greater for the programming estimates than for the stochastic frontier estimates.

The high levels and persistence of firm-specific X-inefficiency as well as differences across the measures produced by the stochastic and programming frontiers lead us to investigate the information

content of the alternative efficiency scores. To the extent that firms compensate for their inefficiency by altering their risk behavior instead of being driven out of the market, efficiency scores and risk-taking behavior should be related. We found a strong correlation between firm-specific X-inefficiencies and bank risk taking when the stochastic frontier estimates of inefficiencies are employed. Specifically, inefficient banking firms exhibit higher stock return variances, greater idiosyncratic risk in stock returns, lower capital ratios, and higher loan charge-offs. Similarly, when proxy measures of managerial quality are regressed on X-inefficiencies, the results for the smaller three size classes of banks suggest that problem loans and growth are negatively related to X-inefficiencies. The findings suggest that with fixed premium deposit insurance, inefficient banking firms may be able to extract larger deposit insurance subsidies from the FDIC to partially offset their operating inefficiencies. Alternatively, inefficient banking firms, being entrenched in banking due to the imperfect exit mechanism, may be more inclined to take risk than efficient firms.

For the smaller banking firms, which tend to have large cross-sectional variation in X-inefficiency, bank stock returns are found to be significantly negatively related to firm-specific inefficiency after controlling for the market factor and the interest rate factor. However, X-inefficiency appears to provide little explanatory power for the stock return of larger banking firms, which tend to be more clustered together in their respective efficient frontiers.

In contrast to the stochastic frontier estimates, when the programming inefficiencies are employed, they show little consistent association with either measures of risk taking, nor do they appear to be reflected in measure of management quality or in bank holding company stock prices. This suggests that, despite their larger magnitude, the estimates are not economically meaningful. Hence, the

larger estimates inappropriately attribute random deviations from the efficient frontier to inefficiencies. In sum, we conclude that the stochastic frontier produces relatively more informative performance measures than does the programming frontier given the former's stronger relationship with other available measures of performance. While both sets of efficiency scores offer decision makers valuable information, and both should be used if available at low cost, at least for this data set the stochastic scores should be given more weight than the programming scores in the decision-making process.

References

Aigner, Dennis, C.A. Knox Lovell, and Peter Schmidt, 1977, Formulation and Estimation of Stochastic Frontier Production Function Models, *Journal of Econometrics* 6, 21-37.

Barr, Richard S., Lawrence M. Seiford, and Thomas F. Siems, 1994, Forecasting Bank Failure: A Non-parametric Frontier Estimation Approach, *Recherches Economiques de Louvain* 60, 417-429.

Bauer, Paul W., Allen N. Berger, Gary D. Ferrier, and David B. Humphrey, 1998, Consistency Conditions for Regulatory Analysis of Financial Institutions: A Comparison of Frontier Efficiency Techniques, *Journal of Economics and Business* 50, 85-114.

Bauer, Paul W., Allen N. Berger, and David B. Humphrey, 1993, Efficiency and Productivity Growth in U.S. Banking, in H. O. Fried, C. A. K. Lovell, and S. S. Schmidt, eds., *The Measurement of Productivity Efficiency: Techniques and Applications*, Oxford, Oxford University Press, 386-413.

Berger, Allen N., and Robert DeYoung, 1997, Problem Loans and Cost Efficiency in Commercial Banks, *Journal of Banking and Finance* 21, 849-870.

Berger, Allen N., and David B. Humphrey, 1997, Efficiency of Financial Institutions: International Survey and Directions for Future Research, *European Journal of Operational Research* 98, 175-212.

Berger, Allen N., A.K. Kashyap, and J.M. Scalise, 1995, The Transformation of the U.S. Banking Industry: What a Long, Strange Trip It's Been, *Brookings Papers on Economic Activity* 2, 55-218.

Buser, Stephen A., Andrew H. Chen, and Edward J. Kane, 1981, Federal Deposit Insurance, Regulatory Policy, and Optimal Bank Capital, *Journal of Finance* 36, 51-60.

Charnes, A. W.W. Cooper, and E. Rhodes, 1981, Evaluating Program and Managerial Efficiency: An Application of Data Envelope Analysis to Program Follow Through, *Management Science* 27, 668-697.

Charnes, A., W.W. Cooper, and T. Sueyoshi, 1988, A Goal-Programming/Constrained Regression Review of the Bell System Breakup, *Management Science* 34, 1-26.

Färe, Rolf, Shawna Grosskopf, and C.A. Knox Lovell, 1985, *The Measurement of Efficiency of Production*, Boston, Kluwer-Nijhoff Publishing.

Ferrier, Gary D., and C.A. Knox Lovell, 1990, Measuring Cost Efficiency in Banking: Econometrics and Linear Programming Evidence, *Journal of Econometrics* 46, 229-245.

Flannery, M., and Christopher James, 1984, The Effect of Interest Rate Changes on the Common Stock Returns of Financial Institutions, *Journal of Finance* 39, 1141-1153.

Gorton, Gary, and Richard Rosen, 1992, Overcapacity and Exit from Banking, working paper, The Wharton School.

Grosskopf, Shawna, 1996, Statistical Inference and Nonparametric Efficiency: A Selective Survey, *Journal of Productivity Analysis* 7, 161-176.

Holmstrom, Bengt, 1979, Moral Hazard and Observability, *Bell Journal of Economics* 10, 74-91.

Jondrow, James, C.A. Knox Lovell, I. S. Materov, and Peter Schmidt, 1982, On the Estimation of Technical Inefficiency in the Stochastic Frontier Production Function Model, *Journal of Econometrics* 19, 233-238.

Kane, Edward, 1992, Taxpayer Losses in the Deposit-Insurance Mess: An Agency-cost and Bonding Perspective, working paper, Boston College.

Kane, Edward, and George G. Kaufman, 1993, Incentive Conflict in Deposit Institution Regulation: Evidence from Australia, *Pacific-Basin Finance Journal* 1, 1-17.

Kane, Edward, and Haluk Unal, 1990, Modeling Structural and Temporal Variation in the Market's Valuation of Banking Firms, *Journal of Finance* 45, 113-136.

Kwan, Simon H., 1991, Re-examination of Interest Rate Sensitivity of Commercial Bank Stock Returns Using a Random Coefficient Model, *Journal of Financial Services Research* 5, 61-76.

Marcus, Alan J., 1984, Deregulation and Bank Financial Policy, *Journal of Banking and Finance* 8, 557-565.

Marcus, Alan J., and I. Shaked, 1984, The Valuation of FDIC Deposit Insurance Using Option-Pricing Estimates, *Journal of Money, Credit, and Banking* 16, 446-460.

Merton, Robert C., 1978, On the Cost of Deposit Insurance When There Are Surveillance Costs, *Journal of Business* 51, 439-452.

Milgrom, Paul and John Roberts, 1992, *Economics, Organization and Management* Englewood

Cliffs, NJ, Prentice-Hall, Inc.

Pennacchi, George C., 1987, A Re-examination of the Over- (Or Under) Pricing of Deposit Insurance, *Journal of Money, Credit, and Banking* 19, 340-360.

Ronn, Ehud, and Avinash Verma, 1986, Pricing Risk-Adjusted Deposit Insurance: An Option-based Model, *Journal of Finance* 41, 871-895.

Shavell, Stephen, 1979, Risk Sharing and Incentives in the Principal and Agent Relationship, *Bell Journal of Economics* 10, 55-73.

Sherman, H. David, and Franklin Gold, 1985, Bank Branch Operating Efficiency, *Journal of Banking and Finance* 9, 297-315.

Siems, Thomas F., 1992, Quantifying Management's Role in Bank Survival, *Federal Reserve Bank of Dallas Economic Review* (1st Quarter), 29-41.

Wheelock, David C., and Paul W. Wilson, 1995, Explaining Bank Failures: Deposit Insurance, Regulation, and Efficiency, *Review of Economics and Statistics* 77, 689-700.

Table 1: Data summary for 254 bank holding companies, based on semiannual data from 1986 to 1991 (N = 2,733).

	25th Percentile	Median	Mean	75th Percentile
Total Assets[a]	1,198,481	2,779,545	9,814,536	8,110,207
Total Costs[a]	50,644	121,354	462,233	346,316
Outputs:				
Real Estate Loans[a]	306,258	689,684	2,136,602	1,857,829
Consumer Loans[a]	139,356	345,852	1,178,900	957,541
Investment Securities[a]	266,438	613,962	1,407,576	1,480,544
Commitments & Contingencies[a,e]	71,486	307,048	17,684,563	1,984,561
Commercial and Industrial Loans[a]	164,143	434,074	1,657,808	1,435,509
Input prices:				
Price of Labor[b]	12.41	14.02	14.85	16.08
Price of Physical Capital[c]	0.126	0.166	0.180	0.219
Price of Funds[d]	0.025	0.027	0.028	0.030

[a] in thousands of dollars.
[b] in thousands of dollars per full-time equivalent employee.
[c] in thousands of dollars per thousands of dollars of fixed assets.
[d] in thousands of dollars per thousands of dollars of deposits and borrowed fund.
[e] include loan commitments, letters of credit, futures and forward contracts, and notional value of outstanding interest rate swaps.

Table 2: Descriptive statistics of measured cost inefficiency

Stochastic Frontier:

	Quartile 1	Quartile 2	Quartile 3	Quartile 4
Mean	0.1855	0.1446	0.1211	0.0808
Median	0.1483	0.1166	0.1003	0.0704
Minimum	0.0146	0.0197	0.0159	0.0208
Maximum	0.9460	0.6144	0.4708	0.3212
Std. Deviation	0.1454	0.0977	0.0819	0.0417
Skewness	1.6447	1.4156	1.2244	1.4741
Kurtosis	3.1797	2.4199	1.4317	3.0111
N	774	657	643	659

Programming Frontier:

	Quartile 1	Quartile 2	Quartile 3	Quartile 4
Mean	0.3973	0.3664	0.3783	0.2848
Median	0.44	0.3953	0.3942	0.2932
Minimum	0	0	0	0
Maximum	0.8258	0.7013	0.7796	0.9751
Std. Deviation	0.1879	0.181	0.1818	0.1627
Skewness	-0.646	-0.598	-0.419	0.28
Kurtosis	2.6	2.446	2.431	3.389
N	774	657	643	659

Table 3: Spearman rank correlation coefficients of the cost inefficiency estimates across time

Stochastic Frontier:

t	Quartile 1	Quartile 2	Quartile 3	Quartile 4
Dec. 86	0.7809***	0.7862***	0.8003***	0.6951***
June 87	0.7792***	0.7171***	0.6727***	0.4737***
Dec. 87	0.7377***	0.6192***	0.4665***	0.2987*
June 88	0.6070***	0.5326***	0.4684***	0.3580**
Dec. 88	0.6077***	0.4769***	0.4644***	0.3082**
June 89	0.6226***	0.5240***	0.3959***	0.2971*
Dec. 89	0.4276***	0.6890***	0.4186***	0.5158***
June 90	0.3582**	0.5353***	0.1356	0.3703**
Dec. 90	0.2576*	0.3882***	0.2486	0.2153
June 91	0.3248**	0.2530*	0.1750	0.1871
Dec. 91	0.2611*	0.2547*	0.1128	0.1718
N	43	44	44	43

***, **, * indicate significance at the 1 percent, 5 percent, and 10 percent levels, respectively.

Table 3 (cont.)

Programming Frontier:

t	Quartile 1	Quartile 2	Quartile 3	Quartile 4
Dec. 86	0.7684***	0.9687***	0.91677***	0.9426***
June 87	0.6842***	0.919***	0.8382***	0.8899***
Dec. 87	0.5849***	0.8975***	0.7546***	0.8198***
June 88	0.5544***	0.8984***	0.7491***	0.7844***
Dec. 88	0.5893***	0.8400***	0.6504***	0.8059***
June 89	0.5092***	0.8061***	0.5969***	0.6642***
Dec. 89	0.5806***	0.7362***	0.5219***	0.7291***
June 90	0.7054***	0.7217***	0.3287***	0.6324***
Dec. 90	0.6303***	0.5707***	0.5717***	0.6042***
June 91	0.5708***	0.04112***	0.4594***	0.5442***
Dec. 91	0.3711**	0.2696***	0.3692**	0.5702***
N	43	44	44	43

***, **, * indicate significance at the 1 percent, 5 percent, and 10 percent levels, respectively.

Table 4: Spearman rank correlation coefficients between inefficiency estimates derived from the stochastic and programming frontiers

	Spearman Correlation Coefficients	N
Quartile 1	0.477***	774
Quartile 2	0.589***	657
Quartile 3	0.444***	643
Quartile 4	0.487***	659

*** indicates significance at the 1 percent level

Table 5: Pearson correlation coefficients between risk and cost inefficiency

Stochastic frontier:

Panel A: Market-Based Measures of Risk				
	Standard Deviation of Daily Stock Returns	Standard Deviation of Residuals from Market Model	Market Value Equity to Book Value Assets	N
Quartile 1	0.3605***	0.3637***	-0.3333***	636
Quartile 2	0.2906***	0.2961***	-0.3636***	596
Quartile 3	0.1786***	0.1791***	-0.2589***	550
Quartile 4	0.1493***	0.1462***	-0.0676	554

Panel B: Accounting-Based Measures of Risk			
	Ratio of Charge-offs to Loans Outstanding	Book Value Equity to Asset Ratio	N
Quartile 1	0.5288***	-0.5355***	774
Quartile 2	0.4708***	-0.3469***	657
Quartile 3	0.3162***	-0.3388***	643
Quartile 4	0.0782**	-0.2531***	659

***, ** indicate significance at the 1 percent and 5 percent levels, respectively.

Table 5 (cont.)

Programming frontier:

Panel A: Market-Based Measures of Risk				
	Standard Deviation of Daily Stock Returns	Standard Deviation of Residuals from Market Model	Market Value Equity to Book Value Assets	N
Quartile 1	0.0756*	0.0824**	-0.0692*	636
Quartile 2	-0.0887**	-0.0893**	-0.0555	596
Quartile 3	0.0436	0.0489	-0.0679	550
Quartile 4	-0.0775*	-0.0866**	0.2155	554

Panel B: Accounting-Based Measures of Risk			
	Ratio of Charge-offs to Loans Outstanding	Book Value Equity to Asset Ratio	N
Quartile 1	0.0457	-0.1523***	774
Quartile 2	0.0333	0.1117***	657
Quartile 3	0.0542	-0.0388	643
Quartile 4	-0.1600***	-0.0280	659

***, **, *indicate significance at the 1 percent, 5 percent, and 10 percent levels,

Table 6: Efficiency and managerial competency

Stochastic frontier:

	Coefficient Estimate				
	$BADLOAN_{mt}$	$BVCAP/ASSETS_{it}$	$GROWTH-RATE_{jt}$	N	Adj. R^2
Quartile 1	1.2123*** (6.093)	-1.9582*** (-9.504)	-0.6730*** (-6.700)	520	0.43
Quartile 2	0.2406 (1.249)	-1.5547*** (-5.501)	-0.4287*** (-4.815)	541	0.17
Quartile 3	0.5540** (2.768)	-1.1345*** (-4.964)	-0.3525*** (-4.374)	612	0.16
Quartile 4	0.1106 (1.262)	-0.9059*** (-5.310)	0.0602*** (2.438)	633	0.07

Programming frontier:

	Coefficient Estimate				
	$BADLOAN_{mt}$	$BVCAP/ASSETS_{it}$	$GROWTH-RATE_{jt}$	N	Adj. R^2
Quartile 1	-0.3160 (-0.992)	0.4530 (1.373)	0.6917*** (4.302)	520	0.06
Quartile 2	-0.4859 (-1.239)	-2.2514*** (-3.916)	0.2670 (1.474)	541	0.03
Quartile 3	0.4850 (1.010)	0.4077 (0.744)	0.7586*** (3.925)	612	0.02
Quartile 4	1.9023*** (5.486)	2.3330*** (3.457)	-0.1827* (-1.870)	633	0.06

*** indicates significance at the 1 percent level, ** indicates significance at the 5 percent level, * indicates significance at the 6 percent level

Table 7: The effect of cost inefficiency on stock returns

Stochastic frontier:

	Coefficient Estimate			N	Adj-R^2
	R_{mt}	R_{it}	$Inefficiency_{jt}$		
Quartile 1	1.0233*** (12.597)	-0.5684*** (-5.115)	-0.3718*** (-5.034)	569	0.30
Quartile 2	1.0706*** (13.368)	-0.6259*** (-5.672)	-0.4349*** (-4.311)	543	0.33
Quartile 3	1.1278*** (16.136)	-0.6608*** (-7.024)	-0.1337 (-1.280)	505	0.43
Quartile 4	1.3554*** (17.433)	-0.4728*** (-4.437)	-0.3148 (-1.365)	512	0.42

Programming fontier:

	Coefficient Estimate			N	Adj-R^2
	R_{mt}	R_{it}	$Inefficiency_{jt}$		
Quartile 1	1.0164*** (12.253)	-0.5503*** (-4.854)	0.0763 (1.328)	569	0.27
Quartile 2	1.0773*** (13.232)	-0.5831*** (-5.219)	0.0400 (0.0702)	543	0.31
Quartile 3	1.1298*** (16.131)	-0.6556*** (-6.961)	-0.0010 (-0.020)	505	0.43
Quartile 4	1.3511*** (17.344)	-0.4475*** (-4.252)	0.0472 (0.835)	512	0.42

*** indicates significance at the 1 percent level.

Figure 1: The 25th, 50th (median), and 75th percentiles of inefficiency estimates over time displayed by firm size for the stochastic (**#**) and programming (**!**) frontiers. Quartile 1 (4) includes the smallest (largest) BHCs.