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Efficiency of Banks in the Third Federal Reserve District

by
Loretta J. Mester

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Efficiency of Banks in the Third Federal Reserve District [1]

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Abstract : I use the stochastic econometric cost frontier approach to investigate efficiency of banks operating in the Third Federal Reserve District, which comprises the eastern two-thirds of Pennsylvania, the southern half of New Jersey, and Delaware. The results indicate that, in general, banks in the district are operating at cost-efficient output levels and product mixes. Thus, there appears to be little potential cost savings from banks' changing their scale or scope of operations. However, I find a significant level of X-inefficiency at the banks, indicating potential cost savings from more efficient use of inputs. The second part of the article relates the inefficiency measures to several correlates.

Loretta J. Mester is at the Federal Reserve Bank of Philadelphia and the Finance Department of the Wharton School, University of Pennsylvania.

EFFICIENCY OF BANKS IN THE THIRD FEDERAL RESERVE DISTRICT

1. Introduction

In recent years banks have had to operate in an increasingly competitive environment. This trend is expected to continue as interstate banking restrictions fall, the number of nonbank competitors increases, and competition from foreign banks picks up, partly in response to the North American Free Trade Agreement (NAFTA), but also in response to the general globalization of markets. How banks will be affected by the increased competitive pressures depends in part on how efficiently they are run.

This paper uses the stochastic econometric cost frontier approach to study efficiency at banks in the Third Federal Reserve District, which comprises the eastern two-thirds of Pennsylvania, the southern half of New Jersey, and Delaware, and is the first to examine efficiency at Third District banks. The paper looks at scale efficiency—whether banks are operating with the efficient *level of outputs;* scope efficiency—whether banks are operations with the efficient *mix of outputs;* and X-efficiency—whether banks are using their *inputs* efficiently. The cost model differs from that used in previous efficiency studies in that it explicitly accounts for the quality of banks' assets and the probability of failure, which can influence banks' costs in a number of ways. For example, a large proportion of nonperforming loans may signal that a bank used fewer resources than usual in the initial credit evaluation and monitoring of its loans. Unless quality and risk are controlled for, one might erroneously conclude that banks scrimping on the credit evaluation or producing excessively risky loans were efficiently producing output. The paper also differs from previous efficiency studies as it treats financial capital as an input into the production process. In addition to providing a cushion against losses, financial capital can be used to fund loans as a substitute for deposits or other borrowed funds. Previous efficiency studies (except for Hughes and Mester (1993), which did not study X-efficiency) included neither the price of capital nor its level. Omitting the price and level of capital makes sense on theoretical grounds only if it is assumed that financial capital is not used to fund loans, or that its price is the same across all banks or is perfectly correlated with another input price for all banks *and* that the banks use the cost-minimizing level of financial capital, none of which seems plausible. Since there is good reason to believe that cost-minimization does not fully explain a bank's capital level—e.g., regulations set minimum capital-to-asset ratios, and bank managers may be risk-averse—here, the level of financial capital, instead of its price, is included in the cost function.[1]

Another difference between this and previous studies is that I report confidence intervals for the bank-specific measures of inefficiency. Since these bank-specific measures are based on the conditional distribution of the one-sided part of the composed error term in the stochastic cost function, there is no good theoretical basis for considering merely the mean or mode of this distribution, as in previous studies.[2] The confidence intervals give a better indication of the degree of inefficiency at any bank in the sample.

The second part of the paper attempts to identify some of the characteristics of the efficient banks in the district. While the results are not intended to imply causation, i.e., that a particular characteristic causes a bank to be efficient or inefficient, they do indicate where banks might look for clues toward increasing efficiency. Ultimately, perhaps the best way to determine what banks should do to raise efficiency is to go on site to the banks identified as most efficient and see what they are doing differently from banks operating least efficiently.

The rest of the paper is organized as follows. Section 2 provides a brief literature review of bank efficiency studies and the methods used for measuring efficiency. Section 3 presents the specification of the frontier cost function and the stochastic econometric frontier model to be estimated. The inefficiency measures, including the confidence intervals for the bank-specific measures, are derived. Section 4 discusses the scale and scope economies measures that were estimated. The model specification and data are discussed in Section 5. Section 6 presents the empirical results and Section 7 concludes.

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[1] See Hughes and Mester (1993) for further discussion.

[2] To my knowledge, only one other paper—Jondrow et al. (1982)—reports confidence bands. Note, however, that the bands reported here and in Jondrow et al. do not account for the fact that the parameters of the conditional distribution are estimated. The mean and mode of the conditional distribution are highly nonlinear functions of the parameters, and while it would be possible to linearize these functions and obtain an approximate standard error for the estimated mean and mode, it is not clear that this would be of much value.

2. Previous literature and methodologies

Bank efficiency studies can be divided into those that examine scale and scope efficiency alone, and those that also examine X-efficiency. There have been a very large number of scale and scope efficiency studies—see Mester (1987), Clark (1988), Evanoff and Israilevich (1991) and Berger and Humphrey (1992) for summaries of these studies' results. There has been a much smaller number of bank X-inefficiency studies—see Berger and Humphrey (1992), Evanoff and Israilevich (1991), and Mester (1994) for reviews of these studies.

The scale and scope studies estimate an *average practice cost function,* which relates bank cost to output levels and input prices. The technique implicitly assumes all banks in the sample are using their inputs efficiently—in other words, there is no X-inefficiency—and that the banks are using the same production technology. A two-sided error term is included in the cost function to represent measurement error or any unpredicted factors that affected a bank's costs over the period when the data were collected. In general, most of these studies find that there is little in the way of cost savings to be gained from banks changing their product levels or mix. Most studies have focused on smaller banks, with assets less than $1 billion, and have found that scale economies are exhausted between $75 million and $300 million in assets. Moreover, the measured scale economies for small banks are fairly small: a 1 percent increase in all output levels typically leads to about a 0.95 percent increase in total cost, which means a 0.05 percent decrease in the average cost of production. A few studies have examined large banks, with assets over $1 billion. Some found scale economies at very large sized banks, with economies exhausted at between $2 billion and $10 billion in assets, depending on the study. Still, the measured scale economies are not very large. Similarly, although there are a few exceptions, most studies found little evidence of either economies or diseconomies of scope.

Studies concerned with X-efficiency estimate a *best practice cost function*, which represents the predicted cost function of banks that are X-efficient, and then measure the degree of inefficiency of banks in the sample relative to this beSt practice technology. Three common methodologies are *data envelopment analysis* (DEA), *"thick frontier" analysis,* and *stochastic econometric cost frontier analysis.*

None of these methodologies is without problems.[3] DEA uses data on costs, outputs, and input prices for the sample of banks and determines which bank in the sample produces that output combination at the given input prices at least cost. This defines the “best practice bank” for that output/input prices combination. A bank’s relative efficiency is measured by the ratio of its own cost to the cost of the “best practice” bank that faces the sample input prices and produces the same output bundle. A benefit of DEA is that it is flexible—it does not posit a particular functional form for the best practice banks’ cost function. But a serious drawback of the approach is that it does not allow for any error in the data. Banks that have been lucky or whose costs have been under-measured would be labeled as most efficient; any unfavorable influence beyond a bank’s control would be attributed to inefficiency. Since all data are subject to measurement error, this approach seems very wanting.

The “thick frontier” approach divides the banks in the sample into four quartiles based on total cost per unit of assets.[4] By assumption, the estimated cost function for banks in the least average cost quartile is considered to be the cost frontier—banks in the lowest average cost quartile are assumed to be the most efficient, and the error term on this estimated function is assumed to represent only random measurement error and luck instead of differences in efficiency. The estimated cost function for banks in the highest average cost quartile represents the cost function of banks assumed to be of less than average efficiency. Again, the error on this estimated function is assumed to represent measurement error and luck rather than efficiency differences. Differences between the cost functions estimated for banks in the least average cost quartile and for banks in the highest average cost are assumed to reflect differences in efficiency alone. But as Berger and Humphrey (1991) themselves point out, these assumptions about the error term do not hold exactly and are sensitive to whether banks are divided into quartiles or quantiles or another number of groups. Further, there is the potential for econometric problems, since the banks are pre-sorted using average cost, which is essentially a dependent variable.

[3]This discussion of DEA is based on Mester (1994).

[4]See Berger and Humphrey (1991).

On the other hand, in addition to being simple to implement, a benefit of the thick-frontier approach is that it is more flexible regarding the statistical properties of the inefficiency measures than is the stochastic econometric frontier approach.

In the stochastic econometric frontier approach, a bank is labeled as inefficient if its costs are higher than the costs predicted for an efficient bank producing the same output/input combination *and* the difference cannot be explained by statistical noise. The cost frontier is obtained by estimating a cost function with a composite error term, the sum of a two-sided error and a one-sided error. Since random fluctuations mean a bank's cost can be either greater or less than a frontier bank's costs, it is represented by an error that can be either positive or negative. But since inefficient banks always have costs that are greater than the frontier bank's, X-inefficiency is represented by an error term that can only be positive. The one-sided error can be used to measure the average level of inefficiency in the sample of banks or bank-specific inefficiency. Most of the previous work, as does this paper, assumes that the two-sided error is normally distributed and the one-sided error is half-normally distributed. A drawback of this approach compared with DEA and thick frontier is that it is less flexible, since assumptions have to be maintained about the form of the frontier and error terms. However, this seems less serious than DEA's assumption of no noise at all and is arguably less ad hoc than thick frontier analysis. Moreover, if panel data are available, some of the stochastic frontier's maintained assumptions can be weakened.[5] Stochastic econometric frontier analysis is used here.

The handful of X-inefficiency studies that used either the thick frontier or stochastic econometric methodologies generally used data from the 1970s and 1980s, and have found X-inefficiency on the order of about 20 to 30 percent in banking, meaning that the average bank could produce a cost savings of about 20 to 30 percent if it eliminated X-inefficiency. Since DEA attributes statistical noise to inefficiency, these studies have found X-inefficiencies on the order of 20 to 50 percent. These results

[5] See Schmidt and Sickles (1984). Unfortunately, since it is important that the banks in the sample be operating with the same production technology, and since branching restrictions have only recently been eliminated in Pennsylvania—branching throughout the state became totally unrestricted only on March 4, 1990—panel data techniques were not available here.

indicate there is substantial room for improvement at U.S. banks and that elimination of X-inefficiency could produce larger cost savings than if banks change the scale or scope of their operations.

3. Stochastic econometric cost frontier model and inefficiency measures

The stochastic econometric frontier model posits that a bank'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,

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

where C_i is observed cost of bank i, y_i is the vector of output levels for bank i, w_i is the vector of input prices for bank i, q_i is a vector of variables characterizing the quality of bank i's output, k_i is the level of financial capital at bank i, B is a vector of parameters, $\ln C(y_i, w_i, q_i, k_i; B)$ is the predicted log cost function of a cost-minimizing bank operating at (y_i, w_i, q_i, k_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. Here, 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

[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.

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 $(\frac{2}{\pi})^{1/2}\hat{\sigma}_u$.

Bank-level measures of inefficiency are usually given by the mean and mode of the conditional distribution of u_i given ϵ_i. For the normal-half normal stochastic model, the conditional distribution of u_i given ϵ_i is a normal distribution, $N(\mu_*,\sigma_*^2)$ truncated at zero, where $\mu_* = \frac{\epsilon_i\sigma_u^2}{\sigma^2}$ and $\sigma_*^2 = \frac{\sigma_u^2\sigma_v^2}{\sigma^2}$.[7] As given in Greene (1993, p. 683), the density function for a variable x that is distributed $N(\tilde{\mu},\tilde{\sigma}^2)$ truncated at zero is

$$f(x) = \frac{\frac{1}{\tilde{\sigma}}\phi\left[\frac{x-\tilde{\mu}}{\tilde{\sigma}}\right]}{1-\Phi\left[-\frac{\tilde{\mu}}{\tilde{\sigma}}\right]}, \quad x > 0, \tag{3}$$

where $\Phi(\cdot)$ is the standard normal cumulative distribution function and $\phi(\cdot)$ is the standard normal density function. For $(u_i|\epsilon_i)$, $\tilde{\mu} = \mu_* = \frac{\epsilon_i\sigma_u^2}{\sigma^2}$ and $\tilde{\sigma}^2 = \sigma_*^2 = \frac{\sigma_u^2\sigma_v^2}{\sigma^2}$, so substituting these into (3) yields

$$f(u_i|\epsilon_i) = \frac{\frac{\sigma}{\sigma_u\sigma_v}\phi\left[\frac{\sigma}{\sigma_u\sigma_v}(u_i|\epsilon_i) - \frac{\epsilon_i\lambda}{\sigma}\right]}{1-\Phi\left[-\frac{\epsilon_i\lambda}{\sigma}\right]}, \quad (u_i|\epsilon_i) > 0. \tag{4}$$

The mean and the mode of this conditional distribution are

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[7]This can be seen by adapting for the cost function the equation for the production function derived in Jondrow et al. (1982).

$$E(u_i|\epsilon_i) = \left[\frac{\sigma_u\sigma_v}{\sigma}\right]\left[\frac{\phi(\frac{\epsilon_i\lambda}{\sigma})}{\Phi(\frac{\epsilon_i\lambda}{\sigma})} + \frac{\epsilon_i\lambda}{\sigma}\right] \quad \text{and} \quad M(u_i|\epsilon_i) = \begin{cases} \frac{\sigma_u^2}{\sigma^2}\epsilon_i & \text{if } \epsilon_i \geq 0 \\ 0 & \text{if } \epsilon_i < 0 . \end{cases} \tag{5}$$

$E(u_i|\epsilon_i)$ is an unbiased but inconsistent estimator of u_i, since regardless of the number of observations, N, the variance of the estimator remains nonzero [see Greene (1991), p. 18]. To get estimates, $\hat{E}(u|\epsilon)$ and $\hat{M}(u_i|\epsilon_i)$, of these measures, we evaluate (5) 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.

However, one can calculate confidence intervals for $(u_i|\epsilon_i)$. Integrating (3) over x and substituting $\tilde{\mu} = \mu_*$ and $\tilde{\sigma}^2 = \sigma_*^2$ yields the distribution function for $(u_i|\epsilon_i)$:

$$F(u_i|\epsilon_i) = \frac{1}{1-\Phi\left(-\frac{\mu_*}{\sigma_*}\right)}\left[\Phi\left(\frac{(u_i|\epsilon_i)-\mu_*}{\sigma_*}\right) - \Phi\left(-\frac{\mu_*}{\sigma_*}\right)\right], \quad (u_i|\epsilon_i) > 0 \cdot \tag{6}$$

Using (6), the $(u_i|\epsilon_i)$ that solves $F(u_i|\epsilon_i) = \alpha$ is

$$(u_i|\epsilon_i)_\alpha = \sigma_*\Phi^{-1}\left[\alpha\left(1-\phi\left(-\frac{\mu_*}{\sigma_*}\right)\right) + \Phi\left(-\frac{\mu_*}{\sigma_*}\right)\right] + \mu_* \cdot \tag{7}$$

Thus, the 90 percent confidence interval for $(u_i|\epsilon_i)$ is $[(u_i|\epsilon_i)_{0.05}, (u_i|\epsilon_i)_{0.95}]$ and the 95 percent confidence interval for $(u_i|\epsilon_i)$ is $[(u_i|\epsilon_i)_{0.025}, (u_i|\epsilon_i)_{0.975}]$.

4. Scale and within-sample scope economies

The scale economies measures consider the effect on cost of a *proportional variation in the levels of all ouputs, financial capital, and quality.* That is, since bank default risk is measured by the level of financial capital relative to bank size and quality is measured by the level of nonperforming loans relative to bank size, the measure of scale economies used here considers the effect of a scaled variation in size, holding the individual and aggregate capital-asset ratios (i.e., k/y_i and $k/\Sigma_i y_i$), and quality ratios (i.e., q/y_i and $q/\Sigma_i y_i$) constant [see Hughes and Mester (1993)].

Consider a composite output quantity, financial capital, and output quality bundle, $\zeta^0 \equiv (y^0, k^0, q^0)$. Then the change in C due to a scaled increase in ζ^0 is well defined and the capital-asset ratios and quality-asset ratios (individual and aggregate) remain constant for such a change. Consider $\zeta = t\zeta^0$. Then, the total differential of cost for the scaled variation is

$$\begin{aligned}
\frac{dC}{dt}(\zeta) &= \frac{dC}{dt}(t\zeta^0) \\
&= \sum_i \frac{\partial C}{\partial y_i}(t\zeta^0)\frac{dy_i}{dt} + \frac{\partial C}{\partial k}(t\zeta^0)\frac{dk}{dt} + \frac{\partial C}{\partial q}(t\zeta^0)\frac{dq}{dt} \\
&= \sum_i \frac{\partial C}{\partial y_i}(\zeta)\frac{dty_i^0}{dt} + \frac{\partial C}{\partial k}(\zeta)\frac{dtk^0}{dt} + \frac{\partial C}{\partial q_j}(\zeta)\frac{dtq_j^0}{dt} \\
&= \sum_i \frac{\partial C}{\partial y_i}(\zeta)\, y_i^0 + \frac{\partial C}{\partial k}(\zeta)\, k^0 + \frac{\partial C}{\partial q}(\zeta)\, q^0 \\
&= \sum_i \frac{\partial C}{\partial y_i}(\zeta)\frac{y_i}{t} + \frac{\partial C}{\partial k}(\zeta)\frac{k}{t} + \frac{\partial C}{\partial q}(\zeta)\frac{q}{t} \ .
\end{aligned} \tag{8}$$

Therefore,

$$\left[\frac{dC}{dt}(\zeta)\right] t = \sum_i \frac{\partial C}{\partial y_i}(\zeta)\, y_i + \frac{\partial C}{\partial k}(\zeta)\, k + \frac{\partial C}{\partial q}(\zeta)\, q \ , \tag{9}$$

and our measure of scale economies is

$$SCL \equiv \frac{\dfrac{dC}{\left(\frac{dt}{t}\right)}}{C} = \frac{\sum_i \dfrac{\partial C}{\partial y_i} y_i + \dfrac{\partial C}{\partial k} k + \dfrac{\partial C}{\partial q} q}{C} = \sum_i \frac{\partial lnC}{\partial lny_i} + \frac{\partial lnC}{\partial lnk} + \frac{\partial lnC}{\partial lnq} \ . \tag{10}$$

SCL < 1 implies multiproduct economies of scale; SCL > 1 implies multiproduct diseconomies of scale;

and SCL = 1 implies constant returns to scale.[8]

Economies of scope exist between outputs when the cost of producing them together in a single firm is less than the cost of producing them in different firms. Here I estimate *within-sample economies of scope*. In the case of three outputs (which will be used below), the degree of within-sample global economies of scope evaluated at y is defined as $\text{WSCOPE}(y) = [C(y_1-2y_1^m, y_2^m, y_3^m) + C(y_1^m, y_2-2y_2^m, y_3^m) + C(y_1^m, y_2^m, y_3-2y_3^m) - C(y_1, y_2, y_3, y_4, y_5)] / C(y_1, y_2, y_3)$, where y_i^m is the minimum value of y_i in the sample.[9] Within-sample economies of scope is a better measure than the conventional scope economies measure because it avoids having to extrapolate outside of the sample. That is, the conventional measure involves evaluating the cost function at zero levels of the outputs even when no bank in the sample is operating at a zero level of any output. The within-sample measure instead evaluates the cost function at the minimum levels of the outputs in the sample, and measures the percentage increase in cost of dividing up the outputs into relatively specialized banks, but none more specialized than the most specialized bank in the sample.[10] In addition, since some cost functions, like the translog, imply cost is zero if any output level is zero, conventional scope economies cannot be measured for these cost functions, while within-sample scope economies can be.[11]

5. The model specification and data

It remains to choose a functional form for the cost frontier $\ln C(y_i, w_i, q_i, k_i; B)$. Here I used the translog specification

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[8]Note that this measure is the reciprocal of the measure used in Hughes and Mester (1993).

[9]One subtracts *two* times y_i^m from y_i so that the sum of the output levels across the three relatively specialized firms equals y, the point at which scope economies are being evaluated. For n outputs, one would subtract $(n-1)$ times y_i^m.

[10]See Mester (1991) and Mester (1992) for more discussion.

[11]One difficulty in interpreting even the within-sample measures of scope economies is that they are evaluated at a fixed level of financial capital, k, and quality, q. Hence, risk and quality are not held constant across the specialized banks.

$$\begin{aligned} lnC = {} & a_0 + \sum_i a_i ln y_i + \sum_j b_j ln w_j + \frac{1}{2}\sum_i \sum_j s_{ij} ln y_i ln y_j + \frac{1}{2}\sum_i \sum_j g_{ij} ln w_i ln w_j \\ & + \sum_i \sum_j d_{ij} ln y_i ln w_j + f_k ln k + f_q ln q + \frac{1}{2} r_{kk} ln k\, ln k + r_{kq} ln k\, ln q \\ & + \frac{1}{2} r_{qq} ln q\, ln q + \sum_j h_{kj} ln k\, ln y_j + \sum_j h_{qj} ln q\, ln y_j \\ & + \sum_j t_{kj} ln k\, ln w_j + \sum_j t_{qj} ln q\, ln w_j \end{aligned} \tag{11}$$

where: $s_{ij} = s_{ji}$ and $g_{ij} = g_{ji}$ by symmetry,

$\sum_j b_j = 1, \;\; \sum_j g_{ij} = 0, \forall i, \;\; \sum_j d_{ij} = 0, \forall i,$

$\sum_j t_{kj} = 0,$ and $\sum_j t_{qj} = 0$ by linear homogeneity.

C = total cost

y_i = quantity of output i

w_j = price of input j

k = financial capital

q = quality measure.

I used 1991-92 data from the Consolidated Reports of Condition and Income that banks must file each quarter. Since I wanted to estimate the cost frontier of standard commercial banks that are using the same production technology, some banks were omitted from the sample.[12] The sample of 214

[12]Since efficiency is measured relative to the cost frontier, it is important that all banks in the sample have access to the same frontier; hence, they should be using the same technology. (Whether one technology is better than another is a separate issue.) One advantage to restricting the sample to the Third District rather than using a U.S. sample is that banks in the Third District are likely to have more in common with each other, thus making it more likely they are using the same production technology. It should be remembered that the results presented below apply only to the 1992 period. Since branching

banks included all the banks in the Third Federal Reserve District except for the special purpose banks in Delaware (legislated under the Financial Center Development Act and the Consumer Credit Bank Act), de novo banks (i.e., banks less than five years old as of December 1992, which have start-up costs that more mature banks do not have), banks that were involved in a merger in 1992, and three very large banks (which very likely use different production techniques than the other banks).[13] (None of the banks in the sample had changed holding company status, charter type, or Federal Reserve System membership status over 1991-92.) The median asset size of banks included was $144 million, and the average asset size was $325 million.

There continues to be some debate about what constitutes the outputs and inputs of a financial institution. I used the intermediation approach here, which views the institution as using labor, physical capital, and deposits to produce earning assets [see Sealey and Lindley (1977)]; this is the approach most commonly used in the conventional cost function literature.[14] Three outputs were included: y_1 = real estate loans, y_2 = commercial and industrial loans, lease financing receivables, agricultural loans, loans to depository institutions, acceptances of other banks, loans to foreign governments, obligations of states

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restrictions have only recently been eliminated in Pennsylvania—branching throughout the state became totally unrestricted only on March 4, 1990—more years of data were not included in the study.

[13]If the banks in the District are ordered by asset size, the sizes grow relatively smoothly from about $13 million to about $3.8 billion; then there is a jump to $7.8 billion, then to $9.3 billion, and then to $16 billion. Since there is empirical evidence that very large banks use a different production technology than other banks (e.g., findings of scale economies differ for smaller and large banks), and large banks also produce different outputs from small banks (e.g., they have more off-balance sheet business), these three largest banks were not included in the sample. Also, a few banks were excluded because of misreported data.

[14]Different approaches to measuring output have 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. Moreover, Hughes and Mester (1993) developed a test to determine whether deposits are outputs or inputs. A variable cost (VC) function in which insured and uninsured deposits are entered in levels is estimated. If the derivative of VC with respect to insured deposits is positive, then insured deposits are an output; if the derivative is negative, then insured deposits are an input. The same test can be applied for uninsured deposits. For their sample, Hughes and Mester (1993) found that both types of deposits were inputs.

and political subdivisions, and other loans, and y_3 = loans to individuals. Each of these was measured by the average dollar volume that the bank held in 1992 (i.e., the difference between the volumes in December 1992 and December 1991). These three outputs account for nearly all of a bank's non-securities earning assets. The average volume of each of these three outputs at banks in the sample was about $120 million, $52 million, and $31 million, respectively. Thus, about 60 percent of the average bank's loan portfolio is in real estate, about 25 percent is business loans, and the rest is loans to individuals.

The inputs (whose prices are used to estimate the cost frontier) included labor, physical capital, and borrowed money (including deposits, federal funds, and other borrowed money) used to fund the outputs. The wage rate w_1 was proxied by [salaries and benefits expenses in 1992/number of full-time equivalent employees at year end 1992]. The unit price of physical capital, w_2, was constructed as the [premises and fixed assets (net of rental income) expenses in 1992/average value of premises and fixed assets in 1992]. The borrowed money price, w_3, was constructed as (interest expense on deposits, net of service charges + interest expense of fed funds purchased and securities sold under agreements to repurchase + interest on demand notes issued to the U.S. Treasury and on other borrowed money + interest on subordinated notes and debentures in 1992)/average dollar volume of these types of funds in 1992. Total costs, C, were labor, premises, and fixed assets expense, and (interest expense on deposits, net of service charges + interest expense of fed funds purchased and securities sold under agreements to repurchase + interest on demand notes issued to the U.S. Treasury and on other borrowed money + interest on subordinated notes and debentures in 1992)x(real estate loans, commercial and industrial loans, lease financing receivables, agricultural loans, loans to depository institutions, acceptances of other banks, loans to foreign governments, obligations of states and political subdivisions, other loans, and loans to individuals/total earning assets).[15] To account for the quality of the banks' outputs and bank

[15]As in Hunter, Timme, and Yang (1990), Mester (1992), and Hughes and Mester (1993), the interest expense was weighted by total output/total earning assets to reflect the interest expense that can be allocated to the bank's loan output.

risk (and so to avoid labeling as efficient banks that are not monitoring their loans), quality was proxied by q = average volume of nonperforming loans in 1992, and financial capital was measured as k = average volume of equity capital in 1992, and both were included as arguments in the cost function. The volume of nonperforming loans relative to the level of bank output is inversely related to quality: the higher the bank's nonperforming loans for a given volume of loans, the less resources the bank likely spent on monitoring its loan portfolio.[16] The higher the bank's level of financial capital relative to the level of output, the lower the bank's probability of failure and so the bank's interest costs. Financial capital is also included because capital can be used as a funding source for loans. Table 1 summarizes the data (included are some variables not yet discussed that will be used in Section 6).

6. Empirical results

6.1 Scale economies and within-sample scope economies

Table 2 reports the parameter estimates. **Table 3** reports measures of scale economies and within-sample scope economies. The measures are based on the estimated cost frontier and so indicate whether a bank 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 banks 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. The scale and scope measures are evaluated at the mean output, input price levels, quality, and financial capital levels over the entire sample or for the size quartiles given.

The estimated average cost frontier for Third District banks seems to be quite flat. The efficient bank producing the average level of each output and facing the average input prices is producing with constant returns to scale—the point estimate of SCL is 0.9525 with standard error 0.02019, and so is insignificantly different from one. Thus, a 1 percent increase in the level of all outputs, holding risk and

[16]Nonperforming loans are loans that are 30 or more days past due but still accruing interest plus loans that are not accruing interest. While the macroeconomy can affect nonperforming loans, its effect is felt equally across banks. It is the differences in nonperforming loans across banks that capture differences in quality across banks.

the quality of the output constant, would lead to about a 1 percent increase in costs. Moreover, over the entire size range of banks operating in the district, efficient banks are operating with constant returns to scale. As shown in Table 3, the point estimates of SCL for the average efficient bank in each of the four asset size quartiles in the sample are insignificantly different from one. (Although the point estimates suggest decreasing average costs, a flat average cost curve cannot be ruled out statistically.) Therefore, there do not seem to be many cost efficiency gains to be made from Third District banks' changing their sizes, and these results are much like those obtained in studies using U.S. samples.

The within-sample scope economies measures reported in Table 3 indicate there is no evidence of either scope economies or diseconomies at the average efficient bank in the Third District, nor at banks in different size categories, since the measures are statistically insignificant from zero. Thus, there do not appear to be many cost efficiency gains to be made by a bank's changing its loan mix (which for the typical bank in the sample is weighted toward real estate loans). While the scope measures suggest there is no cost justification for joint production, there could be revenue (i.e., demand-side) benefits, which would not be captured in the scope measures.

6.2 *Inefficiency*

Table 4 reports estimates of the inefficiency measures discussed in Section 3. Summary measures of inefficiency include an estimate of the mean of $u_i = (\frac{2}{\pi})^{1/2} \hat{\sigma}_u$ (with its approximate standard error), and estimates of the average value of the bank-specific measures, $E(u_i|\epsilon_i)$ and $M(u_i|\epsilon_i)$, across the sample. (Note that the average value of $E(u_i|\epsilon_i)$ equals average(u).) The table also indicates the minimum and maximum values of $E(u_i|\epsilon_i)$, and the 90 percent and 95 percent confidence intervals for the most efficient and least efficient banks in the sample. Since the correlation between $\hat{E}(u_i|\epsilon_i)$ and $\hat{M}(u_i|\epsilon_i)$ is extremely high (at 0.9855), one can focus on one of the inefficiency measures without any loss. Table 4 also shows the average of the bank-specific X-inefficiency estimates, $\hat{E}(u_i|\epsilon_i)$ and $\hat{M}(u_i|\epsilon_i)$, and the minimum and maximum of $\hat{E}(u_i|\epsilon_i)$ for each of the three states in the Third District.

As shown in Table 4, average X-inefficiency at banks in the Third District is on the order of 6 to 9 percent. That is, given its particular output level and mix, if the average bank were to use its inputs as efficiently as possible, it could reduce its production cost by roughly 6 to 9 percent. The average annual cost of output production at banks in the sample was about $12 million, so a 6 percent reduction in cost could potentially add about $720,000 to bank profits, which, given the average bank's size of $325 million in assets, constitutes a potential increase of 0.2 percent in before-tax return on assets, or about 0.15 percent in after-tax ROA. This is not a trivial amount, as the average bank in the District had an after-tax ROA of 1 percent in 1992. In competitive markets not all of this gain would be retained by the bank—the savings would be passed on to customers in the form of lower loan rates and higher deposit rates. In any case, increased efficiency would increase welfare.

Of course, not all banks are the "average" bank. Figure 1 gives the frequency distribution of the X-inefficiency estimates, $\hat{E}(u_i|\epsilon_i)$, for the sample. While the distribution is weighted in the 6 to 9 percent range, some banks are quite efficient but others show a good deal of inefficiency. According to the point estimates of $\hat{E}(u_i|\epsilon_i)$, the most efficient bank in the sample (with $\hat{E}(u_i|\epsilon_i) = 0.02941$) has $\hat{\epsilon} = -0.2465$, which implies $\mu_* = -0.1193$ and $\sigma_* = 0.07114$.[17] Thus, for this observation, the 90 percent confidence interval for $(u_i|\epsilon_i)$ is [0.001736, 0.08190] and the 95 percent confidence interval is [0.0008592, 0.09719]. These confidence intervals show that the most efficient bank in the sample could still be operating with a moderately large level of inefficiency. The most inefficient bank in the sample (with $\hat{E}(u_i|\epsilon_i) = 0.22974$) has $\hat{\epsilon} = 0.4742$, which implies $\mu_* = 0.2296$ and, again, $\sigma_* = 0.07114$.[18] Thus, for this observation, the 90 percent confidence interval for $(u_i|\epsilon_i)$ is [0.1130, 0.3466] and the 95 percent confidence interval is [0.09090, 0.3690]. These confidence intervals are quite wide; nevertheless, they do indicate that there is a statistically significant (at the 10 percent level) difference between inefficiency at the least and most inefficient banks (since the 90 percent confidence intervals do not intersect for these two banks).[19]

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[17]Note that $\hat{E}(u_i|\epsilon_i)$ does not equal zero for the most efficient bank in the sample, since no efficient bank is expected to lie precisely on the estimated cost frontier.

[18]Note that σ_* is independent of i, i.e., it is the same for all banks in the sample.

[19]The confidence intervals for all other observations in the sample are available from the author,

When compared with results of other studies using U.S. samples that found average X-inefficiency on the order of 20 to 30 percent, Third District banks seem to be outperforming U.S. banks on average. It is difficult to determine whether this is a statistically significant difference, however. It might just reflect that this study is based on more recent data, or it might be because banks in the U.S. samples are more diverse, making efficiency measurement more difficult.[20] In any case, as with U.S. banks in general, it appears that many Third District banks have room for improvement.

6.3 Correlates with inefficiency

It remains to discuss the characteristics of inefficient banks in the Third District. I calculated simple correlations between the bank-specific inefficiency measure, $\hat{E}(u_i | \epsilon_i)$, and characteristics of the banks and I also regressed the $\hat{E}(u_i | \epsilon_i)$ on the characteristics to determine how the efficient and inefficient banks in the sample differed.[21] (Of course, a relationship need not imply causality. That is, I am not saying these characteristics *cause* inefficiency, only that they seem to be more prevalent in inefficient banks.[22])

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 regression model, as in Mester (1993). The general form of this regression equation is

$$\hat{E}(u_i | \epsilon_i) = \frac{\exp(X_i'\gamma)}{1 + \exp(X_i'\gamma)} + \xi_i \tag{12}$$

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[20]It might also be because Third District banks use a different production technology than other U.S. banks. Another possibility is that here I controlled for differences in bank risk and output quality, while other studies did not. This does not appear to be a source of the difference, since re-estimating my model omitting financial capital and quality still yields relatively low X-inefficiency estimates.

[21]Saxonhouse's (1976) method for treating heteroskedasticity that can arise when estimated parameters are used as dependent variables was not applicable here, since the model I estimated is nonlinear. Note that $\hat{E}(u_i | \epsilon_i)$ is very highly correlated with $\hat{M}(u_i | \epsilon_i)$, and also with the endpoints of the 90 percent and 95 percent confidence intervals for $(u_i | \epsilon_i)$; thus, any of these alternative X-inefficiency measures would produce results similar to the ones reported below.

[22]Another reason to interpret the results as providing information on correlation only instead of causality is that there may be some endogeneity, since the characteristics are for the same period as the inefficiency measures. Causality may run from inefficiency to the characteristics instead of the other way around. For example, inefficient firms may choose to invest in real estate rather than investing in real estate leading to inefficiency.

where X_i is a vector of independent variables for the i^{th} firm, γ is the parameter vector, and ξ_i is a normally distributed error term. I used nonlinear OLS to estimate equation (12).[23]

The 15 independent variables included are:[24] **CONST** = constant term, **YEAR** = year the bank opened, **CHAR** = 1 if the bank is state-chartered and 0 if it is federally chartered, **HOLD** = 1 if the bank is a member of a holding company and 0 otherwise, **FR** = 1 if the bank is a member of the Federal Reserve System and 0 otherwise, **BRANCH** = number of bank offices (at the end of 1992), NJ = 1 if the bank's headquarters is located in New Jersey and 0 otherwise, **DEL** = 1 if the bank's headquarters is located in Delaware and 0 otherwise, **TOTA** = total assets (measured in billions of dollars), **TQCA** = total qualifying capital (i.e., capital that is included in Tier 1 and Tier 2 capital)/total assets, **ROA** = net income/total assets, **UDEP** = uninsured deposits/total deposits, **LCLDTL** = construction and land development loans/total loans, **RETL** = real estate loans/total loans, and **INTL** = loans to individuals/total loans.

YEAR is included to see if the bank's age is related to its degree of inefficiency; CHAR, HOLD, FR, and BRANCH are included to account for organizational and regulatory structure; NJ and DEL are included to see if inefficiency differs by bank location within the district; TOTA controls for the overall size of the bank; TQCA measures capital adequacy (moral hazard theory suggests that TQCA should be inversely related to inefficiency); ROA is a measure of performance (higher efficiency is expected to be correlated with better performance); UDEP measures reliance on noncore deposits (uninsured depositors might impose market discipline on bank managers, but banks that are relying on these deposits rather than core deposits might be in bad shape); and LCLDTL, RETL, and INTL account for portfolio mix.

As shown in **Table 5,** the simple correlation, which does not hold constant the other characteristics, and the regression results, which do hold constant other characteristics of the bank, indicate that inefficient banks in the District tend to be younger than more efficient banks. This might

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[23]Using $\hat{M}(u_i | \epsilon_i)$ as the dependent variable and estimating a nonlinear Tobit model leads to similar results as the ones reported below.

[24]All are measured as of year-end 1992.

be evidence that banking involves "learning by doing," or it might indicate that more efficient banks are more likely to survive. (Recall that the de novo banks were not included in the sample, so the result probably doesn't merely reflect younger banks' higher start-up costs, for example, the costs of establishing customer relationships.)

Even though the point estimates in Table 5 show differences in inefficiency among banks in the three states, once other bank characteristics are controlled for, there is no statistically significant difference in inefficiency across the states.[25] That is, the coefficients on NJ and DE are insignificantly different from zero, which indicates that, holding other factors constant, there is no significant difference in inefficiency between New Jersey banks and Pennsylvania banks or between Delaware and Pennsylvania banks. Similarly, the coefficients on NJ and DE are not significantly different from one another, suggesting that, holding other factors constant, there is no significant difference in inefficiency between New Jersey banks and Delaware banks. (The test statistic is the difference in coefficients on NJ and DE; its value is 0.3536 with standard error 0.2257.)

Similarly, there is no evidence that larger banks are more or less X-efficient than smaller banks, since the coefficient on TOTA is insignificantly different from zero. This result, coupled with our results on scale economies, suggests that banks of all sizes in our District can be equally competitive when it comes to cost efficiency. Also, there is no evidence that greater reliance on uninsured deposits is correlated with greater inefficiency, since the Coefficient on UDEP is insignificantly different from zero. This result differs from Mester (1993) who found that reliance on uninsured deposits at both stock and mutual S&Ls was correlated with greater inefficiency.

There are a few other statistically significant relationships, For example, inefficient banks tend to have a higher percentage of their loans in construction and land development and in loans to individuals, since the coefficients on LCLDTL and INTL are significantly positive (at the 5 percent and

[25]The simple correlation coefficient indicates that being located in New Jersey is significantly related to being inefficient, but this is because the New Jersey banks in the sample tend to have lower capital than Pennsylvania and Delaware banks in the sample. Once capital is controlled for (as in the regression), being located in New Jersey is not significantly related to inefficiency.

10 percent levels of significance, respectively). National banks appear to be less efficient than state banks that are members of the Federal Reserve System but seem to have the same level of efficiency as state nonmember banks.[26] That is, the coefficients on FR and CHART are significantly less than zero (at the 10 percent and 5 percent levels of significance, respectively), but they are not significantly different from one another. (The difference in the coefficients is -0.04157 with standard error 0.06827.)

Among the statistically significant relationships, one of the more interesting is the negative relationship between inefficiency and the capital-asset ratio—the coefficient on TQCA is significantly negative, as is the simple correlation coefficient between TQCA and $\hat{E}(u_i|\epsilon_i)$. This result should not be interpreted as saying that if a bank increases its capital-asset ratio then its efficiency will increase. But it may be an indication that higher capital ratios may prevent moral hazard. As is often cited in discussions of the thrift crisis, as an institution's capital level decreases it has an increasing incentive to take on excessive risk, since it keeps any upside gain and loses only the amount of capital it has invested in the bank if the risk does not pay off. Similarly, the managers of banks with lower capital levels might have more of an incentive to engage in perk-taking, and they face less shareholder scrutiny than banks with higher capital ratios. The capital-asset ratio might also be significantly related to inefficiency because inefficient banks have lower profits, which might lead to lower capital-asset ratios in the future.[27] Mester (1993) also found that for both stock and mutual S&Ls, higher capital-asset ratios were correlated with greater efficiency.

[26] Note, all nationally chartered banks are Fed member banks, but their primary regulator is the Office of the Comptroller of the Currency, not the Fed.

[27] But this is probably not the entire reason, since the relationship between capital-assets and inefficiency holds even when return-on-assets is held constant—that is, the coefficient on TQCA is significant in the regression, which includes ROA as an independent variable—and while return-on-assets and capital-assets are significantly correlated, they are not collinear—their correlation coefficient is 0.4538.

7. Conclusions

This paper uses the stochastic econometric cost frontier approach to investigate efficiency of banks operating in the Third Federal Reserve District using 1991-92 data. I modify the cost frontier so that both bank default risk and output quality can be held constant when comparing the efficiency of the banks. I present estimates of scale economies and within-sample scope economies for banks operating on the cost frontier. I also present estimates of the average X-inefficiency in the sample and bank-specific measures of X-inefficiency. In addition, I present the 90 percent and 95 percent confidence intervals for the most and least X-efficient banks in the sample. These show that there is a significant (at the 10 percent level) difference between X-efficiency at these banks. The second part of the paper relates the bank-specific inefficiency measures to several correlates.

The study indicates that banks in the Third District appear to be operating at cost-efficient output sizes and product mixes, but there appears to be a significant level of X-inefficiency at the banks. In terms of coping with the increased competitive pressures, inefficient banks in the Third District have more to fear from banks that are efficient producers than from banks that are producing a particular output volume or product mix. There is less to be gained in terms of cost savings from changing output size or mix than from using inputs more cost effectively. Case studies that focus on the more efficient banks in the District might shed light on how greater efficiency can be achieved. Theoretical advances may enable us to better identify the sources of the inefficiencies and verify that measured differences in inefficiency are true differences and do not result just from omitting factors that affect cost or misspecifying the cost function.

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Table 1. Data Summary*

Variable			Third District Banks (214 bank)
	Total assets (thousands $)	min	13,407
		mean	325,013.2
		max	3,852,997
y_1	Real estate loans (thousands $)	min	801.5
		mean	119,979.7
		max	1,265,413
y_2	Commercial and industrial and other loans (thousands $)	min	110.5
		mean	52,300.3
		max	1,784,893
y_3	Loans to individuals (thousands $)	min	107
		mean	31,144.65
		max	693,107
w_1	Price of labor (thousands $ per employee)	min	19.9
		mean	29.3
		max	137.6
w_2	Price of physical capital (thousands $ per thousand $)	min	0.12
		mean	0.36
		max	3.69
w_3	Price of deposits and other borrowed money (thousands $ per thousand $)	min	0.026
		mean	0.043
		max	0.058
k	Financial capital (thousands $)	min	1,138
		mean	25,015.3
		max	325,911.5
q	Nonperforming loans (thousands $)	min	43
		mean	9,819.9
		max	258,996
C	Total cost (thousands $)	min	249.9
		mean	12,362.7
		max	175,601.4
YEAR	Year the bank opened	min	1810
		mean	1909.4
		max	1987
CHAR	1 if bank is state-chartered 0 otherwise	min	0
		mean	0.42
		max	1
HOLD	1 if bank is member of a holding company 0 otherwise	min	0
		mean	0.78
		max	1

Table 1, continued.

Variable			Third District Banks (214 bank)
FR	1 if bank is member of Federal Reserve System 0 otherwise	min mean max	0 0.65 1
BRANCH	Number of branches	min mean max	1 9.3 84
DEL	1 if bank is headquartered in Delaware 0 otherwise	min mean max	0 0.03 1
NJ	1 if bank is headquartered in New Jersey 0 otherwise	min mean max	0.0 0.12 1
TOTA	Total assets (billions $)	min mean max	0.0134 0.325 3.853
TQCA	Total qualifying capital/total assets	min mean max	0.041 0.098 0.20
ROA	Net income/total assets	min mean max	−0.04 0.010 0.026
UDEP	Uninsured deposits/total deposits	min mean max	0.038 0.18 0.87
LCLDTL	Construction and land development loans/total loans	min mean max	0.0 0.025 0.16
RETL	Real estate loans/total loans	min mean max	0.075 0.70 0.94
INTL	Loans to individuals/total loans	min mean max	0.0027 0.14 0.54

*The mean of a dummy variable equals the fraction of banks in the sample for which the variable equals 1.

Table 2. Parameter Estimates

Parameter	Estimate (Approx. Std. Error)	Parameter	Estimate (Approx. Std. Error)	Parameter	Estimate (Approx. Std. Error)
a_0	−2.526 (8.692)	g_{22}	−0.1767 (0.1268)	r_{qq}	−0.02087 (0.05238)
a_1	−0.3792 (0.9407)	g_{23}	0.2035** (0.1197)	h_{k1}	−0.07696 (0.09951)
a_2	1.045** (0.5485)	g_{33}	−0.4747 (0.3216)	h_{k2}	0.003287 (0.05955)
a_3	−0.2497 (0.5130)	d_{11}	0.06840 (0.1517)	h_{k3}	0.05402 (0.06326)
b_1	1.801 (2.621)	d_{12}	−0.01924 (0.08013)	h_{q1}	0.07598 (0.06199)
b_2	0.5103 (0.9001)	d_{13}	−0.04915 (0.1296)	h_{q2}	−0.02651 (0.02643)
b_3	−1.311 (2.282)	d_{21}	−0.1070 (0.08152)	h_{q3}	0.01441 (0.02830)
s_{11}	0.2325* (0.07784)	d_{22}	0.04766 (0.04260)	t_{k1}	−0.01822 (0.1742)
s_{12}	−0.1076* (0.05242)	d_{23}	0.05930 (0.06811)	t_{k2}	−0.04930 (0.08451)
s_{13}	−0.08270 (0.05282)	d_{31}	0.04165 (0.08271)	t_{k3}	0.06753 (0.1475)
s_{22}	0.1333* (0.03719)	d_{32}	0.01291 (0.04720)	t_{q1}	0.03153 (0.08115)
s_{23}	−0.01591 (0.02541)	d_{33}	−0.05456 (0.06403)	t_{q2}	0.01715 (0.04109)
s_{33}	0.05734** (0.02935)	f_k	0.2659 (1.085)	t_{q3}	−0.04868 (0.07226)
g_{11}	−0.2443 (0.4218)	f_q	−0.3014 (0.5602)	σ^2	0.02026* (0.007754)
g_{12}	−0.02688 (0.1569)	r_{kk}	0.06403 (0.1170)	λ^2	0.9385 (1.537)
g_{13}	0.2712 (0.3478)	r_{kq}	−0.05261 (0.04922)		

*Significantly different from zero at the 5 percent level, two-tailed test.
**Significantly different from zero at the 10 percent level, two-tailed test.

Table 3. Scale Economies and Within-Sample Scope Economies'

	All Banks (214 banks)	Banks with Assets Under \$72 Million (53 banks)	Banks with Assets Between \$72 Million and \$144 Million (54 banks)	Banks with Assets Between \$144 Million and \$280 Million (53 banks)	Banks with Assets Over \$280 Million (54 banks)
Scale Economies[a]	0.9525[c] (0.02019)	0.8918[c] (0.02990)	0.9179[c] (0.02008)	0.9416[c] (0.01531)	0.9911[c] (0.02866)
Within-Sample Scope Economies[b]	0.3740[d] (1.050)	0.006303[d] (0.2824)	0.2185[d] (0.5197)	0.4976[d] (0.9455)	1.101[d] (2.645)

*Statistics are calculated at the mean values of outputs, input prices, quality, and financial capital levels for the overall sample in column 1 and for the size categories specified in columns 2-5. Approximate standard errors in parentheses.

[a]The scale economies measure is SCL = $(\partial ln\ C/\partial ln\ y_1) + (\partial ln\ C/\partial ln\ y_2) + (\partial ln\ C/\partial ln\ y_3) + (\partial ln\ C/\partial ln\ k) + (\partial ln\ C/\partial ln\ q)$ where C is the predicted cost of producing the average output bundle at the average input prices, financial capital, and quality; y_i is the volume of output i; k is the level of financial capital; and q is quality, proxied by the volume of non-performing loans. SCL < 1 implies increasing returns to scale; SCL > 1 implies decreasing returns to scale; SCL = 1 implies constant returns to scale.

[b]The within-sample scope economies measure is WSCOPE = $\{[C(y_1, y_2^m, y_3^m) + C(y_1^m, y_2, y_3^m) + C(y_1^m, y_2^m, y_3)] - C(y_1, y_2, y_3)\} / C(y_1, y_2, y_3)$ where y_i is the volume of output i; y_i^m is the minimum amount of output i produced by any bank in the sample; and $\bar{C}(\bullet)$ is the predicted cost of producing an output bundle at the average input prices, financial capital, and quality. WSCOPE > 0 implies economies of scope; WSCOPE < 0 implies diseconomies of scope.

[c]Significantly different from zero but insignificantly different from one at the 5 percent level, two-tailed test.

[d]Insignificantly different from zero at the 5 percent level, two-tailed test.

Table 4. X-Inefficiency Measures

	All Banks (214 banks)	Pennsylvania (182 banks)	New Jersey (26 banks)	Delaware (6 banks)
Mean $u_i = (2/\pi)^{1/2}\sigma_u$ (Approx Std. Err.)	0.07903* (0.04800)			
Average $\hat{M}(u_i \mid \epsilon_i)$	0.04681	0.04489	0.06500	0.02630
Average $\hat{E}(u_i \mid \epsilon_i)$	0.07893	0.07737	0.09343	0.06323
Min $\hat{E}(u_i \mid \epsilon_i)$	0.02941	0.02941	0.03713	0.03692
Max $\hat{E}(u_i \mid \epsilon_i)$	0.2297	0.1915	0.2297	0.08582
90 percent confidence interval for most efficient bank	[0.001736, 0.08190]			
95 percent confidence interval for most efficient bank	[0.0008592, 0.09719]			
90 percent confidence interval for least efficient bank	[0.1130, 0.3466]			
95 percent confidence interval for least efficient bank	[0.09090, 0.3690]			

*Significantly different from zero at the 10 percent level, two-tailed test.

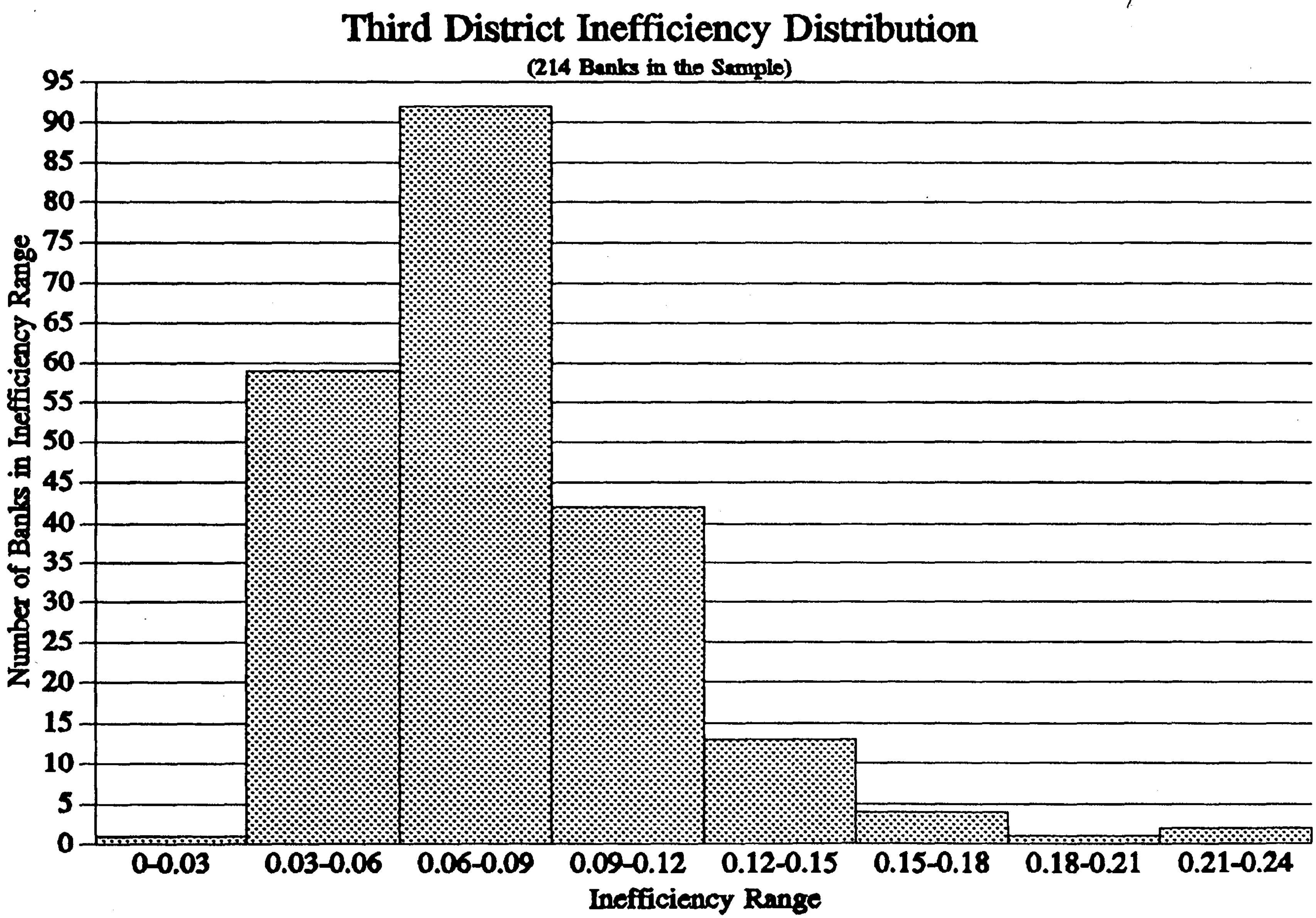
Table 5. Inefficiency Correlates–Logistic Regression Parameter Estimates and Simple Correlation Coefficients with $\hat{E}(u_i | \epsilon_i)$

Independent Variable	Logistic Regression Parameter Estimates γ_i (Standard error)	Simple Correlation Coefficients (Significance level)
CONST	−5.949* (1.879)	
YEAR	0.001906* (0.0009562)	0.1396* (0.0413)
CHAR	−0.2772* (0.1356)	−0.04491 (0.5135)
HOLD	−0.05755 (0.07668)	0.03108 (0.6512)
FR	−0.2356** (0.1350)	0.00045 (0.9947)
BRANCH	0.008608 (0.008898)	0.03891 (0.5714)
NJ	0.09284 (0.9043)	0.1711* (0.0122)
DEL	−0.2597 (0.2153)	−0.08458 (0.2178)
TOTA	−0.1885 (0.2080)	0.01334 (0.8462)
TQCA	−3.884* (1.506)	−0.2301* (0.0007)
ROA	2.355 (4.255)	−0.1174** (0.0867)
UDEP	−0.01954 (0.4345)	0.00079 (0.9909)
LCLDTL	2.767* (1.295)	0.1293** (0.0591)
RETL	0.4445 (0.3341)	0.04623 (0.5011)
INTL	0.8207** (0.4859)	−0.02385 (0.7287)

Value of the likelihood function = 451.94.

*Significantly different from zero at the 5 percent level, two-tailed test.
**Significantly different from zero at the 10 percent level, two-tailed test.

Figure 1


Third District Inefficiency Distribution
(214 Banks in the Sample)
Number of Banks in Inefficiency Range
95
90
85
80
75
70
65
60
55
50
45
40
35
30
25
20
15
10
5
0
0-0.03
0.03-0.06
0.06-0.09
0.09-0.12
0.12-0.15
0.15-0.18
0.18-0.21
0.21-0.24
Inefficiency Range