

Inside the Black Box: What Explains Differences in the Efficiencies of Financial Institutions?*

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Abstract

Over the past several years, substantial research effort has gone into measuring the efficiency of financial institutions. Many studies have found that inefficiencies are quite large, on the order of 20% or more of total banking industry costs and about half of the industry's potential profits. There is no consensus on the sources of the differences in measured efficiency. This paper examines several possible sources, including differences in efficiency concept, measurement method, and a number of bank, market, and regulatory characteristics. We review the existing literature and provide new evidence using data on U.S. banks over the period 1990-95.

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1. Introduction

Over the past several **years**, substantial research effort has gone **into** measuring the efficiency of financial **institutions**, particularly commercial **banks**. The focus has been on estimating an efficient frontier and measuring the average differences between observed banks and banks on the **frontier**. Many studies have found large **inefficiencies**, on the order of **20%** or more of total banking industry **costs**, **and** about half of the industry's potential **profits**. There is no consensus on the sources of the differences in measured **efficiency**. An obvious next step in the efficiency research program is to determine these **sources**. This paper focuses on three **sources**: (1) differences in the efficiency concept **used**; (2) differences in measurement methods used to estimate efficiency within the context of these **concepts**; and (3) potential correlates of **efficiency**—**bank**, **market**, and regulatory characteristics that are at least partially exogenous and may explain some of the efficiency differences that remain **after** controlling for **efficiency** concept and measurement **method**. We review the existing literature on the sources of efficiency of financial institutions and provide new **evidence**.

Estimates of efficiency **often** vary substantially across studies according to the data **source**, as well as the efficiency concepts and measurement methods used in the **studies**. **Berger** and **Humphrey** (1997) documented 130 studies of financial institution **efficiency**, using data from 21 **countries**, from multiple time **periods**, and from various types of institutions including **banks**, bank **branches**, savings and loans, credit **unions**, and insurance **companies**. These variations in the data sets **from** which efficiencies are measured make it virtually impossible to determine how important the different efficiency **concepts**, measurement **techniques**, and correlates used are to the outcomes of these **studies**. Put another **way**, the sources of differences in efficiency across financial institutions are concealed from view within an opaque "**black box**" because the individual studies simultaneously differ **from** one another in so many different **dimensions**.

Our empirical application tries to get around this problem by employing multiple efficiency **concepts**, using a number of different measurement **methods**, and applying a comprehensive set of potential **efficiency** correlates to a single data **set**. We estimate the efficiency of almost **6,000** U.S. commercial banks that were

in **continuous** existence over the six-year period **1990-95** and had no missing or questionable data on any of the variables **used**. Thus, the **differences** we observe **should reasonably accurately** reflect the effects of changes in the **concepts**, measurement **techniques**, and potential correlates that are **used**, rather than any differences in the data set to which these assumptions are **applied**.

We employ three distinct economic efficiency **concepts**—**cost**, standard **profit**, and alternative profit **efficiencies**. We analyze the effects of a number of measurement **methods**, including use of the **distribution-free** approach versus the stochastic frontier **approach**, specification of the Fourier-flexible **functional** form versus the **translog form**, and inclusion of problem loans and financial capital in a number of different **ways**. We find that measured efficiency differs across the three efficiency **concepts**, and that each adds some independent informational **value**. A somewhat surprising result is that the choices made concerning efficiency measurement usually make very little difference to our empirical findings in terms of either average industry efficiency or rankings of individual **firms**, suggesting that the efficiency estimates are fairly robust to differences in **methodology**. Another surprising result is that we also find substantial unexploited cost scale economies for fairly large sizes of banks in the **1990s**, suggesting a change from the **1980s**.

Once the conceptual and measurement issues have been controlled **for**, it is important for the **purposes** of public **policy**, **research**, and managerial performance to explain the remaining differences in efficiency across **banks**. In a **perfectly** competitive or contestable **market**, one would expect inefficient firms to be driven out by efficient **firms**, so that there would be only a residual level of inefficiency across firms remaining at any given **time**. An empirical finding of substantial **inefficiencies**, **therefore**, raises the question as to whether **inefficiencies**, which may have been sustainable in the past because of regulatory limits on **competition**, will continue in the less-regulated **future**. For antitrust and merger **analysis**, it is important to know the effects of market concentration and past mergers on banking **efficiency**. **Similarly**, it is important to know whether one type of organizational **form** is more efficient than **another**, and whether inefficiency manifests itself in the form of poor production **decisions**, risk management **decisions**, or **both**. We review the existing studies that analyzed potential correlates of **efficiency**, but a comparison across studies is hampered by the fact that

different **samples**, efficiency **concepts**, and measurement techniques were **used**. In our empirical **analysis**, we explore the effects of a number of potential correlates of bank efficiency **after** controlling for efficiency concept and measurement **method**. The potential **correlates** include measures of bank **size**, organizational form and corporate governance, other bank **characteristics**, market **characteristics**, state geographic **restrictions**, and federal **regulator**. We find that a number of these **factors** appear to have independent influences on **efficiency**, although many expected effects are not present and some of the effects we find are not consistent with **expectations**.

2. The **Efficiency Concept—Cost, Standard Profit, and Alternative Profit Efficiency**

A fundamental decision in measuring financial institution efficiency is which concept to **use**. This, of course, depends on the question being **addressed**. We discuss here what we consider to be the three most important economic efficiency **concepts—cost, standard profit, and alternative profit efficiencies**. We believe **these** concepts have the best economic foundation for analyzing the efficiency of financial institutions because they are based on economic optimization in reaction to market prices and **competition**, rather than being based solely on the use of **technology**.

2.1 Cost Efficiency. Cost efficiency gives a measure of how close a bank's cost is to what a **best-practice** bank's cost would be for producing the same output bundle under the same **conditions**. It is derived from a cost function in which variable costs depend on the prices of variable **inputs**, the quantities of variable outputs and any fixed inputs or **outputs**, environmental **factors**, and random **error**, as well as **efficiency**. Such a cost function may be written as:

$$C = C(\mathbf{w}, \mathbf{y}, \mathbf{z}, \mathbf{v}, \mathbf{u}_C, \epsilon_C), \quad (1)$$

where C measures variable **costs**, \mathbf{w} is the vector of prices of variable **inputs**, \mathbf{y} is the vector of quantities of variable **outputs**, \mathbf{z} indicates the quantities of any fixed **netputs (inputs or outputs)**, which are included to account for the effects of these **netputs** on variable costs owing to substitutability or complementarity with variable **netputs**, \mathbf{v} is a set of environmental or market variables that may affect **performance**, \mathbf{u}_C denotes an inefficiency factor that may raise costs above the best-practice **level**, and ϵ_C denotes the random error that

incorporates measurement error and luck that may temporarily give banks high or low costs. The inefficiency factor u_c incorporates both **allocative** inefficiencies from failing to react optimally to relative prices of inputs, w , and technical inefficiencies from employing too much of the inputs to produce y . To simplify the measurement of **efficiency**, the inefficiency and random terms u_c and ϵ_c are assumed to be **multiplicatively** separable from the rest of the cost **function**, and both sides of (1) are represented in natural logs:

$$\ln C = f(w,y,z,v) + \ln u_c + \ln \epsilon_c, \quad (2)$$

where f denotes some **functional form**. The term, $\ln u_c + \ln \epsilon_c$, is treated as a composite error **term**, and the various X-efficiency measurement techniques (**described** in section 3.1) differ in how they distinguish the inefficiency **term**, $\ln u_c$, from the random error **term**, $\ln \epsilon_c$. We define the cost efficiency of bank b as the estimated cost needed to produce bank b 's output vector if the bank were as efficient as the best-practice bank in the sample facing the same exogenous variables (w,y,z,v) divided by the actual cost of bank b , adjusted for random error, i.e.,

$$\text{Cost EFF}^b = \frac{\hat{C}^{\min.}}{\hat{C}^b} = \frac{\exp[\hat{f}(w^b, y^b, z^b, v^b)] \times \exp[\ln \hat{u}_c^{\min.}] \hat{u}_c^{\min.}}{\exp[\hat{f}(w^b, y^b, z^b, v^b)] \times \exp[\ln \hat{u}_c^b] \hat{u}_c^b}, \quad (3)$$

where $\hat{u}_c^{\min.}$ is the minimum \hat{u}_c^b across all banks in the sample.

The cost efficiency ratio may be thought of as the proportion of costs or resources that are used efficiently. For **example**, a bank with Cost EFF of 0.70 is 70% efficient or equivalently wastes 30% of its costs relative to a best-practice firm facing the **same conditions**. Cost efficiency ranges over (0,1], and equals one for a best-practice firm within the observed **data**.¹

2.2 Standard Profit Efficiency. Standard profit efficiency measures how close a bank is to producing the maximum possible profit given a particular level of input prices and output prices (**and** other

¹In applications, efficiency is generally defined relative to the best practice observed in the **industry**, rather than to any true minimum **costs**, since the underlying technology is **unknown**. (The usual form of the stochastic frontier measurement technique is an **exception**.) **Fortunately**, for most economic **hypotheses**, relative efficiency rather than absolute **efficiency** is the more appropriate **concept**. For **example**, we investigate below whether larger versus smaller banks are more **efficient**, which requires only comparisons to a consistent frontier.

variables). In contrast to the cost function, the standard profit function specifies variable profits in place of variable costs and takes variable output prices as **given**, rather than holding all output quantities statistically fixed at their **observed**, possibly **inefficient**, levels. That is, the profit dependent variable allows for consideration of revenues that can be earned by varying outputs as **well** as **inputs**. Output prices are taken as **exogenous**, allowing for inefficiencies in the choice of outputs when responding to these prices or to any other arguments of the profit function.

The standard profit function, in log form, is:

$$\ln(\pi + \theta) = f(w, p, z, v) + \ln u_{\pi} + \ln \epsilon_{\pi}, \quad (4)$$

where π is the variable profits of the firm, which includes all the interest and fee income earned on the variable outputs minus variable costs, C , used in the cost function; θ is a constant added to every firm's profit so that the natural log is taken of a positive number; p is the vector of prices of the variable outputs; $\ln \epsilon_{\pi}$ represents random error; and $\ln u_{\pi}$ represents inefficiency that reduces profits.

We define standard profit efficiency as the ratio of the predicted actual profits to the predicted maximum profits that could be earned if the bank was as efficient as the best bank in the sample, net of random error, or the proportion of maximum profits that are actually earned:

$$\text{Std } \pi \text{ EFF}^b = \frac{\hat{\pi}^b}{\hat{\pi}^{\max}} = \frac{\left\{ \exp[\hat{f}(w^b, p^b, z^b, v^b)] \times \exp[\ln \hat{u}_{\pi}^b] \right\} - \theta}{\left\{ \exp[\hat{f}(w^b, p^b, z^b, v^b)] \times \exp[\ln \hat{u}_{\pi}^{\max}] \right\} - \theta} \quad (5)$$

where \hat{u}_{π}^{\max} is the maximum value of u_{π}^b in the sample.²

Standard profit efficiency is the proportion of maximum profits that are **earned**, so that a **Std π EFF** ratio of 0.70 would indicate that, because of excessive costs, deficient revenues, or both, the firm is losing about 30% of the profits it could be **earning**. Similar to the cost efficiency ratio, the profit efficiency ratio

²The profit efficiency does not simplify to a ratio of \hat{u}_{π} 's as in the case of cost efficiency because the addition of θ to the dependent variable before taking logs means that the efficiency factor is not exactly multiplicatively separable in the profit function. A bank's efficiency will vary somewhat with the values of the exogenous variables, so for our efficiency estimates we average the values of the numerator and denominator in (5) over the sample period before dividing to measure the average efficiency of the bank over the sample period.

equals one for a best-practice **firm** that maximizes profits for its given conditions within the observed **data**. Unlike cost **efficiency**, however, profit efficiency can be **negative**, since **firms** can throw away more than 100% of their potential **profits**.

In our **opinion**, the profit efficiency concept is superior to the cost efficiency concept for evaluating the overall **performance** of the **firm**. Profit efficiency accounts for errors on the output side as well as those on the input **side**, and some prior evidence suggested that inefficiencies on the output side may be as large or larger than those on the input side (e.g., **Berger, Hancock, and Humphrey, 1993**). Profit efficiency is based on the more accepted economic goal of profit **maximization**, which requires that the same amount of managerial attention be paid to raising a marginal dollar of revenue as to reducing a marginal dollar of **costs**. That is, a **firm** that spends \$1 additional to raise revenues by \$2, all else held equal, would appropriately be measured as being more profit efficient but might inappropriately be measured as being less cost **efficient**.

Profit efficiency is based on a comparison with the best-practice point of profit maximization within the data **set**, whereas cost efficiency evaluates **performance** holding output constant at its current level, which generally will not correspond to an **optimum**. A **firm** that is relatively cost efficient at its current output may or may not be cost efficient at its optimal **output**, which typically involves a different scale and mix of **outputs**. Thus, standard profit efficiency may take better account of cost inefficiency than the cost efficiency measure **itself**, since standard profit **efficiency** embodies the cost inefficiency deviations from the optimal **point**.³

2.3 Alternative Profit Efficiency. An interesting recent development in **efficiency** analysis is the concept of alternative profit **efficiency**, which may be **helpful** when some of the assumptions underlying cost and standard profit efficiency are not **met**. Efficiency here is measured by how close a bank comes to earning

³A few prior papers have studied standard profit efficiency at U.S. banks (**Berger, Hancock, and Humphrey, 1993, DeYoung and Nolle, 1996, Akhavein, Swamy, and Taubman, 1997, and Akhavein, Berger, and Humphrey, 1997**). The measured average profit efficiencies ranged from 24% of potential profits being earned to 67%. Profit **function** estimation was also used to measure efficiency in terms of the risk-expected return efficient frontier as defined in the finance literature (**Hughes and Moon, 1995, Hughes, Lang, Mester, and Moon, 1996a,b**). A bank with too little expected profit for the amount of risk it is taking on is deemed **inefficient**. Average **efficiency** in terms of the percent of expected profit being earned for a given level of risk relative to the best practice banks was found to be around 85%.

maximum profits given its output **levels** rather than its output **prices**. The alternative profit function employs the same dependent variable as the standard profit function and the same exogenous variables as the cost function. Thus, instead of counting deviations from optimal output as **inefficiency**, as in the standard profit function, variable output is held constant as in the cost function while output prices are free to vary and affect profits. The alternative profit function in log form is:

$$\ln(\pi + \theta) = f(\mathbf{w}, \mathbf{y}, \mathbf{z}, \mathbf{v}) + \ln u_{a\pi} + \ln \epsilon_{a\pi}, \quad (6)$$

which is identical to the standard profit function in (3) except that \mathbf{y} replaces \mathbf{p} in the function, f , yielding different values for the inefficiency and random error terms, $\ln u_{a\pi}$ and $\ln \epsilon_{a\pi}$, respectively.

As with standard profit efficiency, alternative profit efficiency is the ratio of predicted actual profits to the predicted maximum profits for a best-practice bank:

$$\text{Alt } \pi \text{ EFF}^b = \frac{a\hat{\pi}^b}{a\hat{\pi}^{\max}} = \frac{\left\{ \exp[\hat{f}(\mathbf{w}^b, \mathbf{y}^b, \mathbf{z}^b, \mathbf{v}^b)] \times \exp[\ln \hat{u}_{a\pi}^b] \right\} - \theta}{\left\{ \exp[\hat{f}(\mathbf{w}^b, \mathbf{y}^b, \mathbf{z}^b, \mathbf{v}^b)] \times \exp[\ln \hat{u}_{a\pi}^{\max}] \right\} - \theta}. \quad (7)$$

Here, efficiency values are allowed to vary in an important way with output prices, but errors in choosing output quantities do not affect alternative profit efficiency except through the point of evaluation $\hat{f}(\mathbf{w}^b, \mathbf{y}^b, \mathbf{z}^b, \mathbf{v}^b)$ to the extent that the best-practice bank is not operating at the same $(\mathbf{w}, \mathbf{y}, \mathbf{z}, \mathbf{v})$ as bank b .

There would be no reason to estimate alternative profit efficiency if the usual assumptions held. Standard profit efficiency and cost efficiency would appropriately measure how well the firm was producing outputs and employing inputs relative to best-practice firms, given the underlying assumptions. However, alternative profit efficiency may provide useful information when one or more of the following conditions hold:

- (i) there are substantial unmeasured differences in the quality of banking services;
- (ii) outputs are not completely variable, so that a bank cannot achieve every output scale and product mix;
- (iii) output markets are not perfectly competitive, so that banks have some market power over the prices they charge; and

(iv) output prices are not accurately **measured**, so they do not provide accurate guides to opportunities to earn revenues and profits in the standard profit **function**.

The alternative profit **function** provides a **way** of controlling for unmeasured differences in output **quality**, as in condition (i), since it considers the additional revenue that higher quality output can **generate**. If output markets are competitive and customers are willing to pay for the additional services provided by some **banks**, these banks should receive higher revenues that just compensate for their extra **costs**. Banks would be sorted into market niches that differ by service quality or **intensity**, with customers who need or prefer higher quality or more service paying more per dollar of their loan or **deposit**. Since the higher interest rates or fees received by the higher quality providers just cover their extra production **costs**, these banks survive in competitive **equilibrium**. For **example**, banks that take on more information-problematic loans should charge higher interest rates or fees to **cover** their extra **origination, monitoring**, and control costs than banks that lend to equally **risky**, but more **informationally** transparent **borrowers**. The alternative profit function essentially replicates the cost **function** except that it adds revenues to the dependent **variable**. It accounts for the additional revenue earned by high-quality **banks**, allowing it to offset their additional costs of providing the higher service **levels**. So it does not penalize high-quality banks in terms of their efficiency **measure**, whereas the cost **function** might. **Thus**, if banks do not have market **power**, alternative profit **efficiency** should be thought of as a better measure of cost **efficiency**, rather than profit **efficiency**, since it does not take into account any errors in the quantities of variable **outputs**.⁴ Other methods of controlling for differences in output quality are discussed in section 3.3 below.

Alternative profit efficiency might also prove **useful** if the variable outputs are not completely **variable**, as in condition (ii) **above**. Banks differ in size by more than **1000-fold**, even within the same local **markets**. Most banks have fewer than **\$100** million in **assets**, yet they operate side-by-side with **megabanks** with over **\$100** billion in **assets**. **Clearly**, a bank below **\$100** million cannot reach the size of a **megabank** except after

⁴Differences in output quality may also be partially captured in the standard profit **function**. **However**, since it holds output prices **fixed**, the **standard** profit **function** is less able to account for differences in revenue that compensate for differences in product **quality**, since these revenue differences may be partly reflected in measured **prices**. **Berger, Cummins, and Weiss (1996)** found that both standard and alternative profit efficiencies helped control for differences in **service** quality in property-liability insurance **industry**.

decades of growth and mergers and **acquisitions**, yet the standard profit **function** essentially treats these large and small banks as if they should have the same variable outputs when facing the same input and output **prices**, fixed **netputs**, and environmental variables specified in the standard profit **function**. **Thus**, unless the (w,p,z,v) variables give a strong prediction about the size of the **bank**, a scale bias may occur in the standard profit **function**, as larger banks have higher profits that are not explained by the exogenous **variables**. That is, large banks may (**arguably mistakenly**) be labeled as having higher standard profit efficiency than **smaller banks**, by virtue of the fact that small banks **simply** cannot reach the same output **levels**. This potential problem does not occur to the same degree for the alternative profit **function**, since outputs are held constant **statistically**. That is, alternative profit efficiency compares the ability of banks to generate profits for the **same levels** of output and therefore reduces the scale bias that might be present in the standard profit efficiency **measure**.

The alternative profit efficiency concept may also be helpful in situations in which the firms exercise some market power in setting output **prices**, as in condition (iii). The standard profit **function** takes output prices as given and embodies the assumption that the bank can **sell** as much output as it wishes without having to lower its **prices**. This can lead to an understatement of standard profit efficiency for **firms** with output **below** efficient **scale**, since these **firms** might have to reduce their prices to increase output **and, therefore**, cannot earn as much as maximum potential profits as we measure it.⁵

Under **conditions** of market **power**, it may be appropriate to consider output levels as relatively fixed in the short run and allow for **efficiency** differences in the setting of prices and service **quality**. That is, an **optimizing** bank will set each of its prices at the point where the market just clears for its output and choice of service **quality**. Such a bank will also choose an optimizing service quality **niche**. Unlike the **perfect**

⁵Empirical studies have shown that banks with **larger** shares of the local market have some control over **prices**, paying lower rates to small depositors (**Berger and Hannan, 1989**) and charging higher rates to small borrowers (**Hannan, 1991**). These results are supported by studies that have tested price-taking versus price-setting behavior for **banks**, most **often** finding the latter (**Hancock, 1986, Hannan and Liang, 1993**, and English and **Hayes, 1991**). **Berger, Humphrey, and Pulley (1996)** estimated that about **68%** of U.S. bank revenues are from products competed for on a **local** basis **and, therefore**, could be subject to price-setting **behavior**. **However**, it is not known how many of the prices of these products actually do contain significant market power **premiums**.

competition case considered **above**, a **firm** with market power may be able to increase revenues more than costs by increasing service quality because there may not be other competitors or potential competitors at that quality **niche**. It is also-possible that the optimizing choice may be to economize on service quality and keep costs relatively low. Alternative profit efficiency measures the extent to which firms are able to optimize in their choices of prices and service **quality**, as well as their abilities to keep costs low for a given output **level**. Alternative profit efficiency will also incorporate differences across firms in market power and their abilities to exploit it, which is good for the owners of the **bank**, but is not a **social** good in the same way that the other efficiencies **are**. Alternative profit efficiency may be viewed as a robustness check on standard profit **efficiency**, which takes prices as fixed and allows outputs to be totally **variable**.

The measurement of alternative profit efficiency may also be motivated in part by inaccuracies in the output price **data**, as in condition **(iv) above**. If the output price **vector, p**, is well **measured**, it should be strongly related to profits and explain a substantial portion of the variance of profits in the standard profit **function**. If prices are inaccurately measured-as is likely given the available banking data-the predicted part of the standard profit **function, f**, in **(4)** would explain less of the variance of profits and yield more error in the estimation of the efficiency term $\ln u_{\pi}$.⁶ In this **event**, it may be appropriate to try **specifying** other variables in the profit function that might yield a better **fit**, such as the output quantity **vector, y**, as in the alternative profit **function**.⁷

⁶There are good reasons to believe that output prices may be inaccurately measured in banking **data**. Regulatory **reports**, such as the **Call Report form**, require accurate figures on balance-sheet **quantities**, but do not directly measure **prices**. **Rather**, prices used in efficiency studies **often** must be constructed as ratios of revenue flows to stocks of **assets**, which may incorporate noise due to differences in asset **duration, risk, liquidity, collateral, etc.**, as well as problems in matching revenue flows with the assets and time periods on which they were earned.

⁷One way to examine the problem of inaccurate price data is to determine the extent to which measured prices help predict profits in the profit **function**. Humphrey and **Pulley (1997)** specified a bank profit **function** with both **prices, p**, and **quantities, y**, included. A test of the joint hypothesis that all the **p** parameters were zero was not rejected by the **data**, whereas the data did reject the hypothesis that all the **y** parameters were **zero**. These results suggest that measured output prices do **not** have the theoretically predicted strong positive relationship with **profits**, and that output quantities do strongly predict **profits**, perhaps in part reflecting the scale bias problem discussed above that output quantities are not completely variable over the short **term**.

Another possible specification of the profit **function** would be to include neither output **prices, p**, nor

3. Efficiency Measurement Methods

Once the efficiency concepts are **selected**, the next issue is how to go about measuring **them**. Here we explore four **methodological** choices—the estimation **technique**, the functional form specified (**assuming** a parametric technique is **chosen**), the treatment of output **quality**, and the role of financial **capital**.

3.1 Estimation Techniques. The most common efficiency estimation techniques are data envelopment analysis (DEA), free disposable hull analysis (FDH), the stochastic frontier **approach**, the thick frontier **approach**, and the **distribution-free approach**.⁸ The first two of these are **nonparametric** techniques and the latter three are parametric **methods**. **Berger** and **Humphrey** (1997) reported roughly an equal split between applications of **nonparametric** techniques (**69 applications**) and parametric methods (**60 applications**) to depository institutions **data**.

Here, we focus on the **parametric** techniques primarily because they correspond well with the **cost and profit** efficiency concepts outlined **above**. The **nonparametric** methods generally ignore prices and **can, therefore**, account only for technical inefficiency in using too many inputs or producing too few **outputs**. They cannot account for **allocative** inefficiency in **misresponding** to relative prices in choosing inputs and **outputs**, nor can they compare **firms** that tend to specialize in different inputs or **outputs**, because there is no way to compare one input or output with another without the benefit of relative **prices**. In **addition**, similar to the **cost function**, there is no way to determine whether the output being produced is optimal without value information on the **outputs**. Thus, the **nonparametric** techniques typically focus on **technological** optimization rather than **economic optimization**, and do not correspond to the cost and profit efficiency concepts discussed **above**. Another drawback of the **nonparametric** techniques is that they usually do not allow for random error in the **data**, assuming away measurement error and luck as factors affecting outcomes (**although** some progress is

quantities, y. Efficiency would be measured relative to a frontier in which **firms** optimize over output **prices, quantities**, and service quality **jointly**. As argued by **Berger, Humphrey**, and **Pulley** (1996) and **Humphrey and Pulley** (1997), such a specification would likely be too sparse to describe the conditions faced by individual banks and would also be subject to scale **biases**. It is essentially rejected by the data in **Humphrey and Pulley's** (1997) test of the **y parameters** in the profit **function**.

⁸See **Mester** (1994) for further description of these **techniques**.

being made in this regard). In effect, they disentangle efficiency differences from random error by assuming that random error is zero. Studies of U.S. banks that use nonparametric techniques report lower efficiency means on average than those using parametric techniques (an average of 72% versus 84%) with much greater variation (a standard deviation of 17% versus 6%), which could, in part, reflect some random error being counted as variations in measured efficiency in these studies (Berger and Humphrey 1997, Table 2).

In the parametric methods, a bank is labeled inefficient if its costs are higher or profits are lower than the best-practice bank after removing random error—in other words, if the estimated $\ln u_c$, $\ln u_\pi$, $\ln u_{a,\pi}$, in equations (2), (3), and (4), respectively, differ substantially from the best-practice values.⁹ The methods differ in the way $\ln u$ is disentangled from the composite error term $\ln u + \ln \epsilon$. In our study we use both the stochastic frontier approach and the distribution-free approach. As discussed below, the distribution-free approach is our preferred technique.

In the stochastic frontier approach, the inefficiency and random error components of the composite error term are disentangled by making explicit assumptions about their distributions. The random error term, $\ln \epsilon$, is assumed to be two-sided (usually normally distributed), and the inefficiency term, $\ln u$, is assumed to be one-sided (usually half-normally distributed). The parameters of the two distributions are estimated and can be used to obtain estimates of bank-specific inefficiency. The estimated mean of the conditional distribution of $\ln u$ given $\ln u + \ln \epsilon$, i.e., $\ln \hat{u} \equiv \hat{E}(\ln u | \ln u + \ln \epsilon)$ is usually used to measure inefficiency.

The distributional assumptions of the stochastic frontier approach are fairly arbitrary. Two prior studies found that when the inefficiencies were unconstrained, they behaved much more like symmetric normal distributions than half-normals, which would invalidate the identification of the inefficiencies (Bauer and Hancock 1993, Berger 1993).¹⁰ As shown below, the data in the current study are often consistent with the

⁹In the typical application of the stochastic frontier approach, inefficiency is measured relative to the estimated frontier, f , rather than the best-practice bank, i.e., relative to a zero value for $\ln u$, which is not achieved by any firm in the sample. To make our efficiency measures comparable across techniques, we normalize our stochastic frontier efficiency estimates to be deviations from the smallest observed expected value of $\ln u$, so that the most efficient bank in the sample has efficiency of one.

¹⁰Other distributions have also been used, e.g., normal-truncated normal (Stevenson, 1980, Mester, 1996, Berger and DeYoung, 1996), normal-gamma (Stevenson, 1980, and Greene, 1990), and

presence of this potential problem—in many cases, the residuals are simply not skewed in the direction predicted by the assumptions of the stochastic frontier approach.

If panel data are available, some of these maintained distributional assumptions can be relaxed, and the distribution-free approach may be used. This method assumes that there is a core efficiency or average efficiency for each firm over time. The core inefficiency is distinguished from random error (including any temporary fluctuations in efficiency) by assuming that core inefficiency is persistent over time, while random errors tend to average out over time. In particular, a cost or profit function is estimated for each period of a panel data set. The residual in each separate regression is composed of both inefficiency, $in u$, and random error, $in \epsilon$, but the random component, $in \epsilon$, is assumed to average out over time, so that the average of a bank's residuals from all of the regressions, $in \hat{u}$, will be an estimate of the inefficiency term, $in u$. For banks with very low or very high $in \hat{u}$, an adjustment (called truncation) is made to assign less extreme values of $in \hat{u}$ to these banks, since extreme values may indicate that random error, $in \epsilon$, has not been completely purged by averaging. The resulting $in \hat{u}$ for each bank is used to compute its core efficiency.¹¹

3.2 Functional Forms for the Parametric Methods. We next consider the choice of a functional form for the cost and profit functions, f , when one of the parametric methods is used to estimate efficiency. The most popular form in the literature is the **translog**; however, it does not necessarily very well fit data that are far from the mean in terms of output size or mix. McAllister and McManus (1993), and Mitchell and Onvural (1996) showed that some of the differences in results on scale economies across studies may be due to the ill-fit of the **translog** function across a wide range of bank sizes, some of which may be underrepresented in the data.

normal-exponential (Mester, 1996).

¹¹The reasonableness of these assumptions about the error term components depends on the length of period studied. If too short a period is chosen, the random errors might not average out, in which case random error would be attributed to inefficiency (although truncation can help). If too long a period is chosen, the firm's core efficiency becomes less meaningful because of changes in management and other events, i.e., it might not be constant over the time period. Using 1984-94 data on U.S. commercial banks and assuming a **translog** cost model, DeYoung (1997) showed that a six-year time period, such as we use here, reasonably balanced these concerns.

A more flexible **functional form** would help to alleviate this **problem**. The Fourier-flexible functional form augments the **translog** by including Fourier trigonometric **terms**. It is more flexible than the **translog** and is a global approximation to virtually any cost or profit **function**. Several studies have shown that it fits the data for U.S. financial institutions better than the **translog**.¹² Berger and DeYoung (1996) found that measured inefficiencies were about twice as large when the **translog** was specified in place of the Fourier-flexible form.¹³ Here, we estimate the Fourier-flexible **functional form** and allow our cost and profit frontiers to vary each year, but also evaluate the effects of switching to the **translog** by restricting the Fourier **terms** to be **zero**.¹⁴

3.3 Output Quality. Theoretically, in comparing one bank's efficiency to another's, the comparison should be between banks producing the same output **quality**. But there are likely to be unmeasured differences in quality because the banking data does not fully capture the heterogeneity in bank **output**. The amount of service flow associated with financial products is by necessity usually assumed to be proportionate to the dollar value of the **stock** of assets or liabilities on the balance **sheet**, which can result in significant **mismeasurement**. For example, commercial loans can vary in **size**, repayment **schedule**, **risk**, transparency of **information**, type of **collateral**, covenants to be **enforced**, etc. These differences are likely to affect the costs to the bank of loan **origination**, ongoing monitoring and **control**, and financing **expense**. Unmeasured differences in product

¹²See McAllister and McManus (1993), Berger, Cummins, and Weiss (1996), Berger and DeYoung (1996), Berger, Leusner, and Mingo (1996), and Mitchell and Onvural (1996). McAllister and McManus (1993) also used kernel regression and **spline** estimation techniques to obtain better global **properties**.

¹³Other functional forms have also been specified. Mester (1992) estimated a hybrid **translog function**, and Berger, Hancock, and Humphrey (1993) estimated a Fuss **normalized** quadratic variable profit function. Hughes, Lang, Mester, and Moon (1995, 1996a, b) estimated a utility-maximization model based on the Almost Ideal Demand System consisting of profit and input share **equations**. If risk neutrality is imposed on this **system**, it corresponds to the standard **translog** cost function and input share **equations**.

¹⁴To further increase **flexibility**, one can allow the parameters being estimated to differ across banks that may be using different production **technologies**, e.g., banks of different **sizes**, banks facing different regulatory **regimes**, banks operating in different time **periods**, or different types of **institutions**. Numerous studies have allowed the coefficients to vary according to whether the bank operates in a state that restricts branching or a state that allows intrastate branching (e.g., Berger, 1993). Mester (1993) found a significant difference in both the frontier parameters and parameters of the error term distribution in the stochastic frontier method for mutual and stock-owned savings and **loans**. Most studies using the distribution-free method allow the frontier parameters to vary over **time**. Akhavein, Swamy, and Taubman (1997) used random coefficient estimation **techniques**, which allow each bank to have its own **parameters**.

quality may be incorrectly measured as differences in cost **inefficiency**.

We have already discussed how the alternative profit **function** can help control for unmeasured differences in output **quality**. Other studies took another approach and included variables intended to control for the quality of bank **output**. For **example**, Hughes and Mester (1993), Hughes, Lang, Mester, and Moon (1996a,b) and Mester (1996) included the volume of **nonperforming** loans as a control for loan quality in studies of U.S. banks, and Berg, Førsund, and Jansen (1992) included loan losses as an indicator of the quality of loan evaluations in a DEA study of Norwegian bank **productivity**.

Whether it is appropriate **econometrically** to include **nonperforming** loans and loan losses in the bank's cost, standard **profit**, and alternative profit **functions** depends on the extent to which these variables are **exogenous**. **Nonperforming** loans and loan losses would be **exogenous** if caused by negative economic shocks ("bad luck"), but they could be **endogenous**, either because management is inefficient in managing its **portfolio** ("bad management") or because it has made a conscious decision to reduce short-run expenses by cutting back on loan origination and monitoring resources ("skimping").¹⁵ Berger and DeYoung (1996) tested the "bad luck," "bad management," and "skimping" hypotheses and found mixed evidence on the exogeneity of **nonperforming loans**. In our empirical analysis below we attempt to solve this problem using the ratio of **nonperforming loans** to total loans in the bank's **state**. Our state average variable is almost entirely **exogenous** to any individual **bank**, but allows us to control for negative shocks that may affect the **bank**.

3.4 The Role of Financial Capital. Another aspect of efficiency measurement is the treatment of financial **capital**. A bank's insolvency risk depends on its financial capital available to absorb portfolio **losses**, as well as on the portfolio risks **themselves**. Insolvency risk affects bank costs and profits via the risk premium the bank has to pay for uninsured **debt**, and through the intensity of risk management activities the bank **undertakes**. For this **reason**, the financial capital of the bank should be considered when studying

¹⁵Of course, even if the level of **nonperforming** loans does reflect bank choice to some **extent**, it could still be appropriate to include it in the cost and profit **functions** if it is thought to reflect a less frequent decision on the part of the bank (e.g., credit **policy**) than production **decisions**. This is the **same logic** that allows the output **levels**, which are ultimately **endogenous** variables chosen by the **bank**, to be included in the cost and alternative profit **functions**.

efficiency. To some extent, controlling for the interest rates paid on uninsured debt helps account for differences in risk, but these rates are imperfectly measured.

Even apart from risk, a bank's capital level directly affects costs by providing an alternative to deposits as a funding source for loans. Interest paid on debt counts as a cost, but dividends paid do not. On the other hand, raising equity typically involves higher costs than raising deposits. If the first effect dominates, measured costs will be higher for banks using a higher proportion of debt financing; if the second effect dominates, measured costs will be lower for these banks. Large banks depend more on debt financing to finance their portfolios than small banks do, so a failure to control for equity could yield a scale bias.

The specification of capital in the cost and profit functions also goes part of the way toward accounting for different risk preferences on the part of banks. The cost, standard profit, and alternative profit efficiency concepts discussed in section 2 take as given that banks are risk neutral. But if some banks are more risk averse than others, they may hold a higher level of financial capital than maximizes profits or minimizes costs. If financial capital is ignored, the efficiency of these banks would be mismeasured, even though they are behaving optimally given their risk preferences. Hughes, Lang, Mester, and Moon (1995, 1996a,b) and Hughes and Moon (1995) tested and rejected the assumption of risk neutrality for banks.

Despite these arguments, only a few efficiency studies have included financial capital. Hancock (1985, 1986) conditioned an average-practice profit function on financial capital. Clark (1996) included capital in a model of economic cost and found that it eliminated measured scale diseconomies in production costs alone. The Hughes and Mester (1993, 1996) cost studies and the Hughes, Lang, Mester, and Moon (1995, 1996a) profit studies incorporated financial capital and found increasing returns to scale at large-asset-size banks, unlike studies that did not incorporate capital. One possible reason is that large size confers diversification benefits that allow large banks to have lower capital ratios than smaller banks. Akhavein, Berger, and Humphrey (1997) controlled for equity capital and found that profit efficiency increases as a result of mergers of large banks. Merged banks tend to shift their portfolios toward loans and away from securities for a given level of equity. This could reflect diversification benefits available to merged banks-better diversification

would allow the merged bank to manage better the increased portfolio risk with the **same** amount of equity capital. In the **efficiency estimates presented below**, we incorporate financial capital in the **cost and profit function specifications**.

4. Efficiency Correlates

Once we have controlled for the efficiency concepts **and** measurement methods **used**, and applied these concepts and methods to the same data **set**, what explains the remaining differences in **efficiency** across **banks**? The answer to this question has important implications for public **policy, research, and bank management**. A useful first step is to explore the effects of a number of potential correlates of bank efficiency-various **bank, market, and regulatory characteristics** that are at least partially exogenous to efficiency and so may help explain the observed large differences in efficiency across **banks**. Several papers have **performed** analyses along these **lines**.¹⁶ A two-step procedure is typically **used**, whereby **firm** efficiency is estimated using one of the techniques described above and is then regressed **on**, or tested for correlation **with**, a set of variables describing the characteristics being **investigated**.¹⁷

Some econometric issues make such analyses suggestive but not **conclusive**. **First**, the dependent variable in the **regressions, efficiency**, is an **estimate**, but the standard error of this estimate is not accounted for in the subsequent regression or correlation **analysis**. **Second**, none of the variables used in the regressions is completely **exogenous**, and the **endogeneity** of any regressor can bias the coefficient estimates on **all the regressors**. Even a characteristic like the identity of the bank's primary federal regulator is somewhat **endogenous**, since banks can change their **charters**. **Endogeneity** makes conclusions about causation **problematic**. As an alternative to regression **analysis**, simple correlations are provided in some papers to underscore the fact that causation may run in both **directions**.

¹⁶Bank studies include Aly, Grabowski, Pasurka, and Rangan (1990), Berger, Hancock, and Humphrey (1993), Pi and Timme (1993), Kaparakis, Miller, and Noulas (1994), Berger and Hannan (1996), Kwan and Eisenbeis (1995), Spong, Sullivan, and DeYoung (1995), Hughes, Lang, Mester, and Moon (1996a,b), and Mester (1996); savings and loan studies include Cebenoyan, Cooperman, Register, and Hudgins (1993), Mester (1993), and Hermalin and Wallace (1994).

¹⁷The regressions are usually **linear**, but Mester (1993,1996) used the logistic **functional form**, as the stochastic frontier inefficiency estimates varied between zero and **one**.

The different measurement techniques **and** *efficiency* concepts used **and** time periods and samples studied make it difficult to compare the results of the regression analyses across **studies**. The potential correlates used in the second-stage regressions also vary substantially across **studies**, sometimes because each study has a particular **focus**—**e. g.**, market **structure**, geographic **diversification**, or corporate **control**.

Most studies included the asset size of the **institution**, but no consistent picture emerges of its relationship with **efficiency**.¹⁸ Evidence on organizational form was also **mixed**.¹⁹ There is weak evidence that banks in holding companies are more efficient than independent **banks**.²⁰ The relationship between the size of the CEO's stock ownership and efficiency varies across **studies**.²¹ There is limited evidence that banks operating in more concentrated markets are less **efficient**, supporting the “**quiet life**” theory that inefficiency has been sustainable in banking because competition has not been **robust**.²²

Most of the studies have found that well-capitalized banks and **S&Ls** are more **efficient**. This is consistent with moral hazard theory that suggests managers of institutions closer to bankruptcy might be inclined to pursue their own **interests**. But causation could run the other way—**less** efficient institutions have lower **profits**, leading to lower capital **ratios**. Another fairly general finding among the bank studies is that more efficient banks have lower levels of **nonperforming loans**, but as described **above**, **nonperforming loans** likely have exogenous and **endogenous components**.²³ As this summary **suggests**, more work is needed before

¹⁸Hermalin and Wallace (1994) and Kaparakis, Miller, and Noulas (1994) found a significant negative relationship; Berger, Hancock, and Humphrey (1993) found a significant positive relationship; and Aly, Grabowski, Pasurka, and Rangan (1990), Berger and Hannan (1996), Cebenoyan, Cooperman, Register, and Hudgins (1993), Mester (1993 and 1996), and Pi and Timme (1993) found an insignificant relationship.

¹⁹Cebenoyan, Cooperman, Register, and Hudgins (1993), and Hermalin and Wallace (1994) found stock **S&Ls** more efficient than mutual **S&Ls**, while Mester (1993) found the **reverse**, likely because a later sample period was **examined**.

²⁰Mester (1996) found a significant **correlation**, but Spong, Sullivan, and DeYoung (1995) did not.

²¹Pi and Timme (1993) found a significant negative relationship, Berger and Hannan (1996) found an insignificant negative relationship, and Spong, Sullivan, and DeYoung (1995) found a positive relationship.

²² See Berger and Hannan (1996).

²³We do not include financial capital and nonperforming loans in our analysis of correlates described below, since we control for these in the cost and profit models from which our **efficiency** measures are

a complete picture of financial institution efficiency **emerges**, and this paper tries to help complete the **picture**.

5. Empirical Design for Efficiency Estimation

This section outlines and compares the different econometric models used in the estimations below and the assumptions that these models impose on the **data**. To facilitate exposition and keep the number of comparisons under **control**, we choose a “**preferred**” model and measure the effects of deviations from this model one at a **time**. That is, we choose what we believe to be the best set of **variables**, best cost and profit function **specification**, and best frontier efficiency technique within our data and computational constraints and then estimate the effects of making alternative choices one by **one**, in a controlled **experiment**. Note that our “**preferred**” model would not be preferred by most or even necessarily many **researchers**. There is still substantial disagreement over the best methods of **estimation**, but they do seem to be **converging**.

We estimate the efficiency of almost **6,000** U.S. commercial banks that were in continuous existence with **complete**, accurate data over the six-year period **1990-95**.²⁴ We will discuss here the **variables**, **specification**, and **estimation** method of the preferred **model**, then briefly mention the alternatives that will be explored in the empirical analysis **below**.

5.1 Variables Included in the Preferred Specifications of the Cost and Profit **Functions**. Table 1 gives the definitions of all the variables specified in the **cost**, standard **profit**, and alternative profit functions, as well as their sample means and standard deviations for the most recent year of **data**, 1995. The variable input prices, **w**, include the interest rates on purchased **funds** and core deposits as well as the price of **labor**. Expenditures on these inputs **comprise** the vast majority of **all** banking **costs**. The variable **outputs**, **y**, include consumer **loans**, business **loans**, and **securities**, the latter category being measured simply as gross total assets less loans and physical **capital**, so that all financial assets are considered to be **outputs**. This specification of financial assets as outputs and financial liabilities and physical factors as inputs is consistent with the

derived.

²⁴Between **8,378** and **11,077** banks were used in estimating the cost and profit **functions** each year 1990-95, and the restrictions that all the cost and profit **function** data be complete for **all** years **left** **5,949** banks for which we report **efficiencies**. **These banks had about** half of the assets of the U.S. banking industry as of December 1995.

“intermediation” approach or “asset approach” to modeling bank production (Sealey and Lindley, 1977).²⁵

We specify risk-weighted off-balance-sheet **guarantees**, physical **capital**, and financial equity capital as fixed **netputs**, **z**. Off-balance-sheet guarantees are included in the model because they are often effective substitutes for directly issued **loans**, requiring similar information-gathering costs of origination and ongoing monitoring and control of the **counterparties**, and presumably similar revenues if these guarantees are competitive substitutes for direct **loans**. The use of the **Basle Accord** risk weights implies that these guarantees have approximately the same perceived (**according to the Accord**) credit risk **and, therefore**, approximately the same **origination, monitoring**, and control costs as loans to these same **parties**. These guarantees are also concentrated in large **banks**. As a **consequence**, a scale bias might be present if no account were taken of these **items**, as larger banks would have disproportionately higher costs relative to their measured **outputs**. We specify these guarantees as fixed instead of variable primarily because of the difficulty of obtaining accurate output price information for use in **specifying** the standard profit **function**.²⁶

The treatment of physical capital as a fixed input is relatively standard in efficiency **estimation**, but specification of equity is **not**. The reasons for including equity were discussed in section 3.4. As discussed further in section 5.2 below, the specification of equity as fixed helps resolve several estimation **problems**.

Finally, the environmental **variables**, **v**, are limited to the **nonperforming** loan to total loan ratio either for the bank (**NPL**) or for the state in which the bank is located (**STNPL**). In our preferred **specification**, we use **STNPL**, since it is almost entirely exogenous and controls for bad luck in the bank’s **environment**. We are not aware of any previous research in which **STNPL** has been **specified**. In **principle**, **v** could include other measures of the economic conditions faced by the **bank**, such as the growth or unemployment rate of

²⁵In cost function **models**, deposits are specified as **inputs, outputs**, or as having both input and output **attributes**. However, we cannot **specify** deposits as outputs **here**, since it would be too difficult to measure an output price for deposits for use in the standard profit **function**. This is because deposit services are often paid for by paying below-market rates on deposits rather than charging a positive price or fee for **services**.

²⁶A prior study that specified a number of off-balance-sheet activities found that these activities had little effect on cost scale and product mix economies (**Jagtiani, Nathan, and Sick, 1995**). However, we are unaware of any frontier **efficiency** studies of either costs or profits that have taken these activities into **account**.

the state where the bank is located, but these variables are closely related to the state's nonperforming loan record and would make interpretation of the coefficients on NPL and STNPL more difficult. Additionally, we could have included regulatory environmental variables such as state restrictions on branching or on bank holding company expansion. We exclude regulatory information from the efficiency estimates because one of our goals is to test how efficiency is related to these laws by treating them as potential correlates of efficiency.

5.2 Functional Form of the Preferred Specifications. Our preferred model for estimating efficiency specifies the Fourier-flexible fictional form, which is a global approximation that includes a standard translog plus Fourier trigonometric terms. For the cost function we specify:

$$\begin{aligned}
\ln(C/w_3z_3) = & \alpha + \sum_{i=1}^2 \beta_i \ln(w_i/w_3) + \frac{1}{2} \sum_{i=1}^2 \sum_{j=1}^2 \beta_{ij} \ln(w_i/w_3) \ln(w_j/w_3) + \sum_{k=1}^3 \gamma_k \ln(y_k/z_3) \\
& + \frac{1}{2} \sum_{k=1}^3 \sum_{m=1}^3 \gamma_{km} \ln(y_k/z_3) \ln(y_m/z_3) + \sum_{r=1}^2 \delta_r \ln(z_r/z_3) + \frac{1}{2} \sum_{r=1}^2 \sum_{s=1}^2 \delta_{rs} \ln(z_r/z_3) \ln(z_s/z_3) \\
& + \sum_{i=1}^2 \sum_{k=1}^3 \eta_{ik} \ln(w_i/w_3) \ln(y_k/z_3) + \sum_{i=1}^2 \sum_{r=1}^2 \rho_{ir} \ln(w_i/w_3) \ln(z_r/z_3) \\
& + \sum_{k=1}^3 \sum_{r=1}^2 \tau_{kr} \ln(y_k/z_3) \ln(z_r/z_3) + \sum_{n=1}^7 [\phi_n \cos(x_n) + \omega_n \sin(x_n)] \\
& + \sum_{n=1}^7 \sum_{q=n}^7 [\phi_{nq} \cos(x_n + x_q) + \omega_{nq} \sin(x_n + x_q)] \\
& + \sum_{n=1}^7 [\phi_{nnn} \cos(x_n + x_n + x_n) + \omega_{nnn} \sin(x_n + x_n + x_n)] \\
& + v_1 \ln(\text{STNPL}) + \frac{1}{2} v_{11} [\ln(\text{STNPL})]^2 + \ln u_C + \ln \epsilon_C,
\end{aligned} \tag{8}$$

where (y_k/z_3) , (z_r/z_3) , and the STNPL variables have 1 added for every firm in order to avoid taking the natural log of zero, the x_n terms, $n=1, \dots, 7$ are rescaled values of the $\ln(w_i/w_3)$, $i=1, 2$, $\ln(y_k/z_3)$, $k=1, 2, 3$, and $\ln(z_r/z_3)$, $r=1, 2$, such that each of the x_n is in the interval $[0, 2\pi]$, and π refers to the number of radians here (not profits), and the standard symmetry restrictions apply to the translog portion of the function (i.e.,

$$\beta_{ij} = \beta_{ji}, \gamma_{km} = \gamma_{mk}, \delta_{rs} = \delta_{sr}.^{27}$$

The standard and alternative profit functions use essentially the same specification with a few changes. First, the dependent variable for the profit functions replace $\ln(C/w_3z_3)$ with $\ln[(\pi/w_3z_3) + |(\pi/w_3z_3)^{\min}| + 1]$, where $|(\pi/w_3z_3)^{\min}|$ indicates the absolute value of the minimum value of (π/w_3z_3) over all banks for the same year. Thus, the constant $\theta = |(\pi/w_3z_3)^{\min}| + 1$ is added to every firm's dependent variable in the profit function so that the natural log is taken of a positive number, since the minimum profits are typically negative. Thus, for the firm with the lowest value of (π/w_3z_3) for that year, the dependent variable will be $\ln(1) = 0$. For the alternative profit function, this is the only change in specification (other than relabelling the composite error term as $\ln u_{a\pi} + \ln \epsilon_{a\pi}$), since the exogenous variables are identical to those for the cost function. For the standard profit function, the terms containing the variable output quantities, $\ln(y_k/z_3)$, and their trigonometric x_n terms are replaced by the corresponding output prices, $\ln(p_k/w_3)$, and their x_n trigonometric terms.

The Fourier-flexible form is a global approximation because the $\cos x_n, \sin x_n, \cos 2x_n, \sin 2x_n, \text{etc.}$, terms are mutually orthogonal over the $[0, 2\pi]$ interval, so that each additional term can make the approximating function closer to the true path of the data wherever it is most needed.²⁸ A good fit of the data for the estimated efficient frontier is important in estimating efficiency, because inefficiencies are measured as deviations from this frontier.

As shown in equation (8), all of the cost, profit, input price, and output price terms—including the Fourier terms for prices before transformation—are normalized by the last input price, w_3 , in order to impose linear homogeneity on the model. That is, on the efficient frontier, a doubling of all input prices exactly

²⁷We cut 10% off each end of the $[0, 2\pi]$ interval so that the x_n span $[0.1 \times 2\pi, 0.9 \times 2\pi]$ to reduce approximation problems near the endpoints. The formula for x_n is $0.2\pi - \mu \times a + \mu \times \text{variable}$, where $[a, b]$ is the range of the variable being transformed, and $\mu \equiv (0.9 \times 2\pi - 0.1 \times 2\pi) / (b - a)$. We limit the third-order Fourier terms to include just the interactions of the own terms because of computational limitations in applying the stochastic frontier approach below. The model as shown includes 122 net free parameters after imposing symmetry. We exclude consideration of factor share equations embodying Shephard's Lemma or Hotelling's Lemma restrictions because this would impose the undesirable assumption of no allocative inefficiencies.

²⁸The orthogonality is perfect only if the data are evenly distributed over the $[0, 2\pi]$ interval, but in practice the Fourier terms have improved the fit of the data in every application of which we are aware.

doubles costs, and a doubling of all input and output prices doubles standard profits.²⁹ This normalization is the only way to impose homogeneity on the Fourier-flexible specification, since unlike the translog terms, the Fourier terms are not multiplicative.

We specify all of the cost, profit, variable output quantities, and other fixed netput quantities as ratios to the fixed equity capital input, z_3 , to control for heteroskedasticity, to help control for scale biases in estimation, and to give the models more economic interpretation. Since the costs and profits of the largest firms are many times larger than those of the smallest firms, large firms undoubtedly would have random errors with much larger variances in the absence of the normalization. In contrast, firms of different sizes have ratios of costs or profits to equity that typically vary only by a few-fold. This is particularly important because the inefficiency terms in \hat{u}_c , in \hat{u}_n , and in \hat{u}_{nn} are derived from the composite residuals, which might make the variance of the efficiencies dependent on bank size in the absence of normalization. Similarly, the normalization of the variable output and fixed netput quantities keep these variables from being very skewed for the large banks, so that the dependent and independent variables are roughly of the same order of magnitude.

Normalization by equity also reduces the scale bias discussed in section 2.3 that is likely to be present, particularly in the standard profit function. Large banks will tend to have higher profits for a given set of prices, primarily because they were able to gain size over a period of decades, a feat that small banks cannot achieve in the short run. However, the profits per dollar of equity and assets per dollar of equity of large banks are well within the achievable range for small banks. Moreover, even in the short run, equity is often the variable that limits bank size. Regulators and market participants generally tie the allowable size of the bank, especially its loan portfolio, to its quantity of equity capital available to absorb loan losses. Normalization by equity makes the dependent variable reasonably equally achievable for all banks.

Normalization by equity also has a particular economic meaning. The dependent variable in the profit functions is essentially the return on equity, or ROE, achieved by the bank (normalized by prices and with

²⁹The homogeneity restriction does not have to be imposed on the alternative profit function, but it is imposed to keep the functional forms equivalent.

a constant added), or a measure of how well the bank is using its scarce financial **capital**.³⁰ This measure may be closer to the goal of the bank than maximizing the level of **profits**, particularly in **banking**, which is one of the most highly financially levered **industries**. Shareholders are interested in their rate of return on **equity**, which is approximated by **ROE**, and most **debtholders** do not put much pressure on banks to earn profits because their returns are guaranteed by deposit **insurance**.

5.3 Preferred Frontier Efficiency Estimation Technique. Our preferred method of estimating efficiency is the distribution-free **approach**, which disentangles the inefficiency **term**, $\ln u$, from the random error **term**, $\ln \epsilon$, in equations (2), (4), and (6) by assuming that inefficiencies are relatively stable over time and random errors tend to average out over **time**.

We briefly sketch the procedure as it is applied **here**. The **cost**, standard **profit**, and alternative profit equations are estimated separately for each **year**, 1990-95, allowing the coefficients to vary to reflect changes in **technology**, **regulation**, and market **environment**. The average residual for each bank **b** is formed, which is an estimate of $\ln u_c^b$, $\ln u_\pi^b$, or $\ln u_{an}^b$, depending on the **equation**. Despite the assumption that random error averages out to zero over **time**, we realize that the extreme values of these inefficiency estimates may reflect substantial random **components**. Thus, we use truncation to reassign less extreme values to banks with the most extreme values in each of **ten** bank size **categories**. We assign to each bank in the top and bottom 5% of **the** distribution of the average residuals in a size category the value for the bank that is just at **5th** or **95th** percentile, respectively. (Other degrees of truncation are also **tried**, as discussed **below**.) Truncation is performed within size class **deciles** (by gross total **assets**) to reduce the effects of persistently good or bad luck for these banks relative to **firms** of their size (DeYoung and Nolle, 1996). The resulting estimates of the inefficiency **terms**, $\ln \hat{u}_c^b$, $\ln \hat{u}_\pi^b$, and $\ln \hat{u}_{an}^b$, along with their minimum or maximum values $\ln \hat{u}_c^{\min}$, $\ln \hat{u}_\pi^{\max}$, and $\ln \hat{u}_{an}^{\max}$, are then substituted into the formulas (5), (6), and (7) **above**, and the numerators and

³⁰Unfortunately, our accounting measure of equity does not perfectly correspond to the market value of the **bank**, but market values are unavailable for most **banks**.

denominators are summed over the six years to estimate the efficiency ratios.³¹

The distribution-free method gives a single set of **cost**, standard **profit**, and alternative profit efficiency measures for each bank over the entire six-year **period, 1990-95**. Since it is likely that relative efficiencies among the different banks shift somewhat over time because of changes in **management**, technical **change**, regulatory **reform**, the interest rate **cycle**, and other **influences**, this method describes the average deviation of each firm from the best-average-practice **frontier**. That is, our core efficiency estimates how well a bank tends to do relative to its competitors over a range of conditions over **time**, rather than a firm's relative efficiency at any one point in **time**. Besides the fact that this method uses less arbitrary assumptions to disentangle inefficiencies from random **error**, we believe that by averaging over a number of **conditions**, this method gives a better indication of a bank's **longer-term performance** and how it is likely to **perform** in the **future** than any method that relies on a bank's performance under a single set of **circumstances**.

5.4 Deviations from our Preferred Efficiency Measurement Methods. We measure the effects of several deviations from our preferred methods for measuring **efficiency** to **determine** the effects of some of the assumptions commonly employed in the efficiency **literature**. By changing just one assumption at a **time**, but leaving the data set and all other assumptions **unchanged**, we aim to isolate the individual **effects**. The deviations we try **are**: (1) **specifying** the **translog** functional form in place of the preferred Fourier-flexible specification, (2) trying several different specifications of the **nonperforming** loan ratios (**NPL** and **STNPL**), (3) removing equity capital from the **model**, and (4) using the stochastic frontier approach in place of the distribution-free **approach**.

6. The Empirical Results Pertaining to the Efficiency Concepts and Measurement Methods

Table 2 shows the means and standard deviations of the efficiencies estimated in the preferred model and in each **variation**, along with the rank-order **correlations** of the efficiencies from each variation with those

³¹ **Because** the costs and profits in the dependent variables **are expressed** in terms of ratios to w_3z_3 , the $\exp[\hat{f}(\cdot)]$ terms in the efficiency ratios are replaced by $w_3z_3 \times \exp[\hat{f}(\cdot)]$, where $\hat{f}(\cdot)$ is the predicted part of the cost or profit **function**. In order to offset the **nonlinearities** introduced by **exponentiating** and including the **θ terms**, all the predicted costs and profits are **multiplicatively** adjusted so that the average predicted cost or profit for each year equals the average actual cost or profit for the same **year**.

from the preferred **model**. The means and standard deviations are weighted by the denominators of the efficiency ratios (**estimated** cost or potential **profits**) to represent the proportion of the entire sample's resources that are used efficiently or potential profits that are **earned**.³²

6.1 Efficiency Estimates from the Preferred Model. The mean cost efficiency from the preferred model of **0.868** suggests that about 13.2% of costs are wasted on average relative to a best-practice **firm**. The **0.868** figure is within the range found in the **literature**, but is slightly higher than the most typical finding of about 80% cost **efficiency**. The slightly higher figure might be explained by the fact that we are examining data from the first six years of the **1990s**, rather than the **1980s**, the period of study for most earlier **work**.³³

The mean efficiencies for the standard and alternative profit **functions** are similar to each other, both showing that about half of the potential profits that could be earned by a best-practice **firm** are lost to **inefficiency**. These figures are also well within the observed range from the few other profit efficiency **studies**. The standard deviations of the profit efficiencies are **about 20** percentage **points**, suggesting that these efficiencies are quite **dispersed**, with many **firms** earning considerably more or less than the average **figure**. By **contrast**, the cost efficiencies are more tightly distributed with a standard deviation of **6.2** percentage **points**.

We also note that the alternative profit **function** does not **fit** the data nearly as well as the standard profit **function**. The average adjusted **R²** (**not shown**) of the cost, standard **profit**, and alternative profit **functions** across the six years were **0.931, 0.607, and 0.329, respectively**. **Apparently**, the measured prices of the loan and security **outputs** are more closely related to the profit dependent variable than are the quantities of these **outputs**. While a **full** investigation is beyond the scope of this **paper**, it seems likely that at least part

³² **The cost**, standard **profit**, and alternative profit **function** coefficient estimates are available upon request **from the authors**.

³³ **The** reported efficiency estimates are based on 5% truncation of the average **residuals**, but other degrees of truncation were also **tried**. The average measured cost efficiencies at the 0%, 1%, 5%, and 10% truncation levels were **0.689, 0.784, 0.868, and 0.901, respectively**. **Thus**, measured efficiency increases considerably when the degree of truncation rises up to 5%, but the increase tapers off **after** this **point**. This suggests that 5% truncation removes most of the random error not already eliminated by averaging over **time**. **Moreover, further** truncation would not change the efficiency estimates by any economically meaningful **amount**. **Similar** results obtain for the measured profit efficiencies.

of the explanation may lie in differing degrees of service quality or market power. That is, if some banks are providing service qualities that are more in demand and, therefore, are able to charge higher prices, or if some banks are able to exercise market power to raise profits substantially through higher loan prices, this would yield higher explanatory power for the standard profit function.

It is also noteworthy that the alternative profit efficiency ratios are lower on average than the standard profit efficiency ratios. This finding again could be explained by service quality or market power considerations. If, on average, banks are making poor service quality choices relative to the best-practice banks, and these choices are reflected in lower output prices and revenues, the alternative profit efficiency measures would correctly capture this source of inefficiency. Standard profit efficiency is less able to capture the effects of service quality because it takes output prices as given (although they are imperfectly measured). Similarly, if market power in setting output prices tends to explain profitability, the average bank may be further from the alternative profit frontier than from the standard profit frontier, because the alternative frontier does not control for output prices whereas the standard frontier does. Some evidence in favor of these explanations is that the alternative profit efficiency ratio is much more highly correlated with output prices than the standard profit efficiency ratio.³⁴ Thus, the firms measured as alternative profit inefficient receive relatively low prices for their outputs, perhaps reflecting either low service quality or lack of market power.

6.2 Efficiency Estimates from Variations in Measurement Technique. In the first variation on our preferred model, the translog fictional form is substituted for the preferred Fourier-flexible specification by restricting the coefficients of all the trigonometric terms (the x 's in equation (8) above) to be zero.³⁵ The results here suggest only a small difference in average efficiencies and very little difference in efficiency dispersion or rank from using the more restricted specification. The average efficiencies are lower by about

³⁴ Specifically, the correlations of Alt π EFF with p_1 , p_2 , and p_3 are 0.288, 0.528, and 0.593, respectively, whereas the corresponding correlations for Std π EFF are 0.198, 0.325, and 0.260, respectively. All are statistically significant at the 1% level.

³⁵ If one of the specifications fits the data better than the other, it does not necessarily imply that measured efficiency will either increase or decrease. See Berger and DeYoung (1996) for more discussion. They found that the Fourier-flexible specification fit the data better and registered higher measured efficiency, but the efficiencies from both specifications were highly correlated.

1% of costs or potential profits in each case, with about the same degree of dispersion, and rank order correlations of 0.979 or higher with the preferred specification.

Formal statistical tests indicate that the coefficients on the Fourier terms are jointly significant at the 1% level in all 18 cases—the cost, standard profit, and alternative profit functions in all six years. However, the average improvement in goodness of fit or adjusted R^2 is relatively small. Thus, while the null hypothesis of the translog form is rejected from a statistical viewpoint and the Fourier-flexible efficiency estimates are likely more accurate, the improvement in fit is not significant from an economic viewpoint. Both functional forms yield essentially the same average level and dispersion of measured efficiency, and both rank the individual banks in almost the same order.

The next three variations in the table contain alternative specifications of nonperforming loans. In contrast to our preferred model, which specifies the state's nonperforming loan ratio in first- and second-order logged terms [\ln STNPL and $\frac{1}{2}(\ln \text{STNPL})^2$], the next three specifications: (1) replace these terms with the bank's own \ln NPL and $\frac{1}{2}(\ln \text{NPL})^2$; (2) include all of the STNPL and NPL terms; and (3) include none of the STNPL or NPL terms. The efficiency estimates are strikingly similar across the four specifications (including the preferred specification). The average efficiencies are all within 1 percentage point of each other, the measured dispersion is virtually identical, and rank-order correlations are all over 99%. Apparently, given the rest of our specification, the treatment of nonperforming loans is not materially important to the efficiency estimates.

Nonetheless, the coefficients of the STNPL and NPL variables in the cost and profit functions (not shown) did yield some insights as to which of the main hypotheses about the effects of nonperforming loans—"bad luck," "bad management," or "skimping"—is most consistent with the data. For each of the cost and profit equations, we formed the derivatives of the dependent variable with respect to STNPL and/or NPL evaluated at the mean values of the data (not shown). The data primarily supported the "bad management" hypothesis—i.e., that firms that are inefficient at managing their operations are also poor at managing their loan portfolios. In almost every case, the derivative with respect to NPL was unfavorable (positive for costs,

negative for **profits**) and statistically significant at the 1% level. That is, firms with loan performance problems also tended to have high costs and low **profits**, consistent with the “**bad management**” hypothesis. This occurred whether or not **STNPL** was specified in the same **equation**, which **should** remove much of any “**bad luck**” effect. The derivative with respect to **STNPL** was **often** statistically significant in the predicted direction at the 1% or 5% level, **but** was not as consistent as the results for **NPL**. Thus, the “**bad luck**” hypothesis—under which exogenous conditions cause loan performance problems that raise costs—received more limited support than the “**bad management**” hypothesis. The “**skimping**” hypothesis—under which **nonperforming** loans may be associated with **low** costs from choosing to put less effort into loan monitoring and control—was generally not supported by the data or its consequences were overwhelmed by “**bad management**” effects. These results support our choice of **specifying STNPL** in the cost and profit functions and excluding **NPL**. **STNPL** appears to be a **useful control** variable for the bank’s economic environment and is almost completely **exogenous**, whereas the inclusion of **NPL** likely adds an **endogenous** efficiency factor that should not be controlled for when estimating **efficiency**.

In the next **variation**, the equity capital fixed input z_3 is eliminated from the cost and profit functions. There is little **effect** on the average level or dispersion of cost **efficiency**, although the **firms** are ranked slightly **differently**, with a rank order correlation of **0.834** with the preferred **model**. More **important**, the average profit efficiencies fell from means of about **50%** of potential profits earned on average to about **10%**, with a much higher standard deviation and much lower rank-order correlation with the estimates from the preferred **specification**. This is not **unexpected**. As discussed **above**, the specification of equity as a fixed input in the preferred model reduces the scale bias that may be created by the fact that the equity capital of small banks cannot be expanded to match that of large banks and allow them to expand their asset portfolios greatly except after a period of **decades**. The dependent variable in this variation depends on the level of **profits**, which can be much higher for large **banks**, as opposed to our preferred **specification**, where the dependent variable is a **function** of the rate of return on **equity**, which is more comparable across size **classes**.

A breakdown of the measured profit efficiencies by size class when equity is removed (**not shown**)

is consistent with these **arguments**. Banks with gross total assets below \$50 million had mean measured standard and alternative profit efficiencies of -0.068 and 0.020 , **respectively**, whereas the corresponding efficiencies for banks with over \$10 billion were 0.768 and 0.783 . **Clearly**, the removal of the equity control variable rewards large banks that have high **levels** of profits by virtue of their equity positions that have been built up over **time**, but these **firms** generally do not have particularly high rates of return on their **equity**. The evidence from this variation strongly supports our specification of equity capital as fixed in the preferred **model**.

The final variation shown in Table 2 uses the stochastic frontier approach where the inefficiencies are assumed to be half-normally **distributed**. The **data, however**, do not appear to fit that distribution very **well**. As described in the **table**, the skew of the data was not consistent with the half-normal assumptions in a **number** of **cases**. As a **result**, we do not have any standard profit efficiency **estimates**, and the cost and alternative efficiencies must be based on partial **samples**.

Despite **these difficulties**, the efficiencies estimated by the stochastic frontier approach are reasonably consistent with those of the preferred distribution-free **approach**. The average cost efficiency is somewhat higher with less **dispersion**, and the average alternative profit efficiency is somewhat lower with more **dispersion**, but in both **cases**, the rank-order correlations with the distribution-free method are over **90%**.

Overall, the results of Table 2 suggest that variations in methodology usually do not affect measured efficiency **substantially**, except that profit efficiencies may be significantly scale biased when equity capital is **excluded**. For the most **part**, the findings support the choices made in our preferred approach and give us confidence to proceed from this point forward only with the estimates derived **from** the preferred **model**.

6.3 Cost Scale Economies in the Preferred Model. Table 3 shows cost ray scale efficiency by size class and breaks out the X-efficiency by size class as **well**. Scale efficiency is defined as the ratio of predicted minimum average costs to actual average **costs**, both adjusted to be on the X-efficient **frontier**, (*i.e.*, setting $\ln u_c$ to the minimum in the sample and $\ln \epsilon_c$ to **zero**). Total cost efficiency is the product of the scale and

X-efficiency ratios.³⁶ The variable t^* is the ratio of efficient scale to actual scale.

The basic result shown in Table 3 is that in every size class, the typical bank shows unexploited ray scale economies—i.e., that the bank's product mix could be produced at lower average cost by increasing the scale of output. The mean scale efficiencies are around 80%, suggesting that approximately equal amounts of resources are lost because of scale and X-inefficiencies. In every size class more than 90% of firms are operating below efficient scale, and the mean t^* is between 2 and 3 for each size class, suggesting that the typical bank would have to be 2 to 3 times larger in order to maximize cost scale efficiency for its product mix and input prices.³⁷

To ensure that our scale economies estimates reflect the shape of the frontier and are not simply the consequence of correlation between the X-inefficiencies and scale, we reestimated the Fourier-flexible cost model using only relatively efficient banks. We divided the banks into asset size deciles, chose the top 25% of the distribution in terms of efficiency scores in each size class, reestimated the cost frontier model using these banks, and then recomputed the scale measures. We got very similar results to those shown in Table 3.³⁸

These findings differ from most of those found using 1980s data, in which large banks were typically found to be operating at constant returns to scale or with slight cost diseconomies of scale. In almost all cases, cost scale economies were exhausted well below \$10 billion in assets.³⁹ The difference could have occurred because of some of the differences in specification between our cost function and those typically employed in the literature. One candidate is our use of the Fourier-flexible function form in place of the more common

³⁶The standard profit efficiencies are already inclusive of scale efficiency. We do not compute scale efficiencies for the alternative profit function because they would include economies on the consumer side, and would not be comparable (see Berger, Humphrey, and Pulley, 1996).

³⁷As shown in Table 3, unexploited scale economies are actually somewhat larger for banks in the larger size classes. This would be consistent with the hypothesis that larger banks choose product mixes that are more conducive to large scale.

³⁸The weighted average scale efficiency across all banks in this estimation was 0.815, the weighted average t^* was 1.854 (significantly greater than 1), and a weighted average of 93.5% of bank costs were incurred by banks that were operating below efficient scale.

³⁹Exceptions include Hunter and Timme (1986), Shaffer and David (1991), Shaffer (1994), Hughes, Lang, Mester, and Moon (1995, 1996a), and Hughes and Mester (1996).

translog specification. The **translog forces** a symmetric U-shape in logs on the ray average cost **frontier**, which could force measured scale **diseconomies** on the large banks as the imposed reflection of the scale **economies** found for small **banks.** **However,** this does not appear to be the case **here.** We reestimated the scale economies using the **translog (not shown)** and found **that, if anything,** the measured scale economies for the larger banks were even **greater.** Another candidate is our use of equity **capital.** Failure to control for equity could give a bias toward finding **cost scale diseconomies,** because large banks tend to have lower equity ratios and pay interest on higher portions of their **funds.** **Reestimation** without **specifying** equity capital (**not shown**) did reduce our measured scale economies for large **banks,** consistent with the expected **bias,** but it did not eliminate **them.** The last column of Table 3 reports the results of another robustness check of these scale economy findings. We examined the raw data without imposing a **specification.** The ratio C/GTA, average cost per dollar of **assets,** falls consistently when moving into larger size **classes.** This simple measure is, **if anything,** biased against the larger **banks,** which typically have more off-balance-sheet guarantees and more loans per dollar of **assets,** which should raise average **costs.** The finding of declining cost per dollar of assets by size class strongly supports our scale economy **findings.** **Moreover,** an examination of the ratio C/GTA for banks over the **1980s** reveals mild scale economies for asset levels below **\$1 billion** and **diseconomies** for larger **banks,** which is consistent with the prior scale economies **literature.** This suggests that the **1990s** are indeed **different,** and that our methodology has not created the **result.**

An important caveat to the scale efficiency findings is that they may not hold for the very largest **banks.** We group the data from all banks with **GTA** greater than **\$10 billion** into a single size class in Table 3 because there are too few very large banks in the **U.S.** to form credible size subclasses of this largest size **class,** and our data exclusion rules exacerbated the problem by dropping several of these **banks.** To try to ameliorate this **problem,** we recalculated the C/GTA ratio in the last column of Table 3 including all **U.S.** banks (**regardless** of our data exclusion **rules**), and segmented **the** largest size class into **\$10 billion - \$25 billion, \$25 billion - \$50 billion,** and above **\$50 billion ranges.** We find average costs to be decreasing in **all** size classes up through **\$25 billion,** with an increase in average costs **thereafter.** **Thus,** we still find relatively

robust evidence of scale economies **well** beyond the region usually found in studies using the **1980s data**. Serious estimates of scale economies for U.S. banks over **\$25 billion** will likely have to wait for the consolidation of the industry to create enough of these large banks to yield reasonable **estimates**.

Our scale economy results suggest that some conditions changed between the **1980s** and **1990s** that substantially raised the cost-efficient **scale** of U.S. banks. **While** a complete investigation is beyond the scope of this **paper**, three explanations seem **plausible**. **First**, open-market interest rates have been relatively low recently—the one-year U.S. Treasury rate averaged **9.74%** in the **1980s** and **5.39%** over our sample period of **1990-1995**. It is quite likely that these low rates reduced interest rate expenses (**which** account for most of **costs**) proportionally more for large banks than small **banks**, because a greater proportion of large **banks'** liabilities tend to be **market-sensitive**. Large banks often rely on wholesale purchased **funds** that pay market **rates**, whereas small banks typically rely more on core deposits with rates that do not vary one-for-one with open-market **rates**. Under this **explanation**, the scale economies of the early **1990s** may be a temporary phenomenon that will disappear if and when market rates rise **substantially**. **To partially check this explanation**, we reevaluated each bank's scale economies as if interest rates were at their levels in the **1980s**.⁴⁰ We **still find** scale economies (**although** they are slightly **lower**), suggesting that a rise in interest rates back to the higher levels of the **1980s** would not eliminate the scale **economies**. We **acknowledge**, however, that our interest-rate **experiment** is subject to the Lucas **critique**. **Namely**, the cost **function** was estimated for the low interest rate environment of the **1990s**. Because rates are **low**, banks might be paying less attention to optimizing with respect to interest **rates**. As interest rates **rise**, the parameters of the cost **function** could change in a way that affects scale economies **significantly**.

A second possible explanation for our scale economies result is that recent regulatory changes may have tended to favor large banks relative to small **banks**. **In particular**, the elimination of geographic

⁴⁰**In particular**, for each bank in the sample that had at least nine years of data for the **1980s**, we calculated the average interest rate the bank paid on purchased **funds** and core deposits in the **1980s** and the average **interest** rates it paid for these funding sources in the **1990s**, and found the differences in average rates **paid**. We then **added** each bank's difference to its core deposit rate in each year in the **1990s** and recalculated the bank's scale economies at this new evaluation **point**. **On average**, this added **2.55%** to the purchased **funds** rate and **2.50%** to the core deposit **rate**.

restrictions on bank branching and holding company expansion during the 1980s and into the early 1990s may have removed some **scale diseconomies** and made it less costly to become **large**. For **example**, in the extreme case of unit **banking**, there are very severe **diseconomies** to becoming **large** without being able to have **any** branch offices to collect **deposits**, and such **diseconomies** would be removed by allowing statewide **branching**.⁴¹ Similarly, the removal of interest rate **ceilings** on core deposits during the 1980s likely raised costs more for small **banks**, which rely more on core deposits for their **funding**.

Finally, improvements in technology and applied finance may have reduced costs more for large banks than for small **banks**. Improvements in information processing and credit scoring may have reduced the costs of extending small business loans and credit card loans more for larger **banks**. **Similarly**, improved automation may have allowed large banks to expand **faster** and at lower cost by setting up ATM machines in place of adding more expensive brick-and-mortar branch **offices**. Large banks may have also been better positioned to take advantage of the new tools of financial **engineering**, such as derivative contracts and other **off-balance-sheet activities**.

6.4 Comparison of Efficiency Across Concepts. Table 4 shows the rank-order correlations among the different X-efficiency measures and some other commonly used financial ratios that may be considered raw-data measures of **efficiency**. Standard and alternative profit **efficiency** are highly positively and statistically significantly correlated with each other ($\rho = 0.794$), as **expected**. Perhaps **surprisingly, however**, measured cost efficiency is essentially **uncorrelated** with standard profit efficiency and it is negatively correlated with alternative profit **efficiency**.

One possible explanation is that cost and revenue inefficiencies may be negatively **related**, so that **firms** with low cost efficiency tend to have high revenue efficiency that offsets **it**. This could occur because of competitive pressures **if, for example**, firms with highly valued product mixes or high revenue efficiency feel less market discipline to control their **costs**.

⁴¹ **Jayaratne and Strahan (1996)** found that bank **performance** measured several different ways improved after within-state branching restrictions were **removed**, although they did not separate the improvement into scale and X-efficiency **effects**.

An alternative explanation is that much of what are measured as cost inefficiencies are actually unmeasured differences in product quality that required additional costs to **create**. As discussed **above**, the alternative profit function and to a lesser extent the standard profit **function** tend to control for product quality implicitly by letting revenues **received** for higher quality offset the extra costs of creating the **quality**. We will explore this possibility more in the next **table**, where we compare cost and profit **inefficiencies**.

The correlations between the efficiencies and each of the raw-data measures follow the expected **pattern**—**efficiency** by any definition is negatively and significantly correlated with the standard average cost ratio **C/GTA** and positively and significantly correlated with the standard profitability ratios **ROA** and **ROE**. These findings suggest that our efficiency measures are robust and are not simply the consequences of our specifications or **methods**.

As **measured**, the cost and profit efficiency ratios **are** not directly comparable because they are reported in terms of different denominators (**predicted** actual costs versus potential **profits**). In Table 5, we report the dollar values of the **cost**, standard **profit**, and alternative profit **inefficiencies** divided by the same denominators—potential **profits**, gross total assets, and **equity**. The meanings of these ratios are the proportions of potential profits **lost**, the loss of **ROA**, and the loss of **ROE**, **respectively**, because of **inefficiency**. These ratios may provide evidence on the extent to which the measured cost inefficiencies incorporate unmeasured differences in product **quality**. If markets are competitive so that differences in product quality are rewarded with higher revenues that cover the **costs**, the alternative profit inefficiency essentially just improves on cost efficiency by offsetting the extra costs of producing higher quality with higher **revenues**. **In this event**, the alternative profit inefficiency ratios measured here would be expected to be smaller than the cost inefficiency **ratios**. **If instead**, the effects of market power in pricing bank outputs are more **important**, alternative profit inefficiency **may be** larger than both cost inefficiency and standard profit **inefficiency**, as **firms** with the most market power are measured as much more alternative-profit **efficient** than the average **bank**.

The empirical results suggest that this market power paradigm appears to dominate any effects of

unmeasured differences in product quality on measured **efficiency**. Alternative profit **inefficiency** is larger than **are both cost and standard profit inefficiencies**. **This does not** suggest that unmeasured differences in product quality are **unimportant**, just perhaps less important than market power considerations in determining bank profits. These results also suggest that the standard assumption of perfect competition in setting output prices maintained for measuring standard **profit efficiency** may be violated by the **data**.

7. Empirical Investigation of the Potential Correlates of Efficiency

The last part of our analysis relates our efficiency estimates to various aspects of the **banks**, their **markets**, and their regulation that are potential correlates of **efficiency**, **i.e.**, factors that are at least partially exogenous and may explain some of the efficiency differences that remain **after** controlling for **efficiency** concept and measurement **method**. **Here**, we use the three distribution-free X-efficiency measures estimated for the 1990-95 period and the average values of the **bank, market**, and regulatory characteristics over 1990-95. As we did when estimating **efficiency**, we also investigate a **few** alternative specifications of the potential correlates to check robustness.

The characteristics we investigate are given in Table 6, where we show their **definitions**, means and standard deviations over 1990-95. These variables fall into six broad **categories**: **bank size, organizational form and corporate governance, other bank characteristics, market characteristics, state geographic restrictions on competition, and primary federal regulator.**

We **performed** both multiple regressions and single variable **regressions**. Including an **endogenous** variable in a multiple regression can bias the coefficients even on the exogenous **variables**, and perhaps all of our variables are partly **endogenous** and partly **exogenous**. **Thus**, in addition to the multiple **regressions**, we also ran regressions that each included a constant term and a single explanatory **variable**. These **single-variable** regression coefficients are proportional to correlation **coefficients**. A disadvantage of these single variable regressions is that any significant **correlation** found might be **spurious**, with both efficiency and the included variable being significantly related to a **third, omitted factor**. Because the multiple and single regression analyses each has advantages and **disadvantages**, we will be conservative and tend to draw

conclusions only when the **coefficients** in both are statistically significant and of the **same sign**. These results are shown in Table 7.

7.1 Bank Size. The bank size variables (**SMLBANK, MEDBANK, LARBANK, HUGBANK**) are **measured** with dummy variables to allow for **nonmonotonicity** and **nonlinearities** in the relationship between bank size and **efficiency**. We specified our multiple regression equation without a constant term and included **all four** of these size **variables**.⁴² As shown in Table 7, the cost efficiency estimates do not vary much across size classes-holding all else **equal**, the cost efficiency is about 2.5% higher at the largest banks (**with assets over \$10 billion**) than the smallest banks (**with assets under \$100 million**). But in terms of profit efficiency (**both standard and alternative**), small banks show the greatest level of **efficiency**. This result suggests that our profit efficiency measures display very **little** of the potential scale biases favoring larger firms discussed above (**as long as equity capital is specified**). The cost and profit efficiency results together seem to imply that as banks grow **larger**, they are equally able to control **costs**, but it becomes harder to efficiently create **revenues**. This is consistent with conventional wisdom and the historical fact that **small banks** typically have higher profitability **ratios**. It also helps explain the lack of a positive correlation between cost efficiency and profit efficiency discussed **above**.

7.2 Organizational Form and Corporate Governance. The banking industry is consolidating at a rapid **pace**, so it is important to determine the efficiency effects of bank mergers and **acquisitions**. Our results indicate **that**, all else **equal**, banks that have survived at least one merger over our sample period (**MERGED**) have higher standard and alternative profit **efficiency** than other **banks**, which is consistent with prior findings discussed **above**. This result is not confined, **however**, in the single variable **regressions**, where alternative profit **efficiency** is significantly lower for banks that have been **involved in mergers**. This is perhaps because being involved in a merger is correlated with bank **size**, and size is negatively related to alternative profit **efficiency**. On the other **hand**, being acquired by another holding company (**ACQUIRED**) does not appear to be associated with profit **efficiency**, but is associated with higher cost **efficiency**. All in

⁴²We excluded one of the state branching dummy variables (**STATEB**) and one of the primary federal regulator dummy variables (**OCC**) to avoid perfect collinearity in the **regressions**.

all, these results are fairly **mixed**.

Banks with implicated organizational forms or internal management structures could be less **efficient**, but a holding **company structure** might also impose some discipline on **banks**, so we explored the relationships between efficiency and whether the bank is in a bank holding company (**INBHC**), whether the holding company is multilayered (**MUL_LAY**), and whether the top-tier holding company is located out of state (**OUTST**), which could make control more **difficult**. Banks in holding companies tend to have higher levels of profit **efficiency** (**both** standard and alternative) than independent **banks**, and their cost efficiency is significantly greater as **well**, consistent with some previous cost efficiency **studies**. If the holding company has multiple **layers**, this means even higher levels of profit and cost **efficiency**. **Thus**, the more complex structure of multilayered holding companies does not appear to be **harming** bank **efficiency**. Having the highest holding company owner from out of state also is associated with **higher**, not **lower**, cost **efficiency**. A potential explanation for these results may be a form of the efficient structure hypothesis (**Demsetz, 1973**)—**more** efficient banking organizations may tend to acquire other **banks**, and the **multilayer**, multistate holding company is the vehicle that allows them to do it.

We **also** included a variable indicating whether the bank's highest holder is registered with the SEC for public trading (**PUB_TRADED**). To the extent that outside shareholders can exert control over bank **management**, we might expect publicly traded banks to be more **efficient**, all else **equal**, and this is indeed what our results **indicate**. Publicly traded **firms** tend to have both higher cost and standard profit **efficiencies**.

For 126 of the banks we have information from **1987-88** on the proportion of stock owned by **insiders**, i.e., board members and their relatives (**INSIDE**) and the proportion of stock owned by outsiders who had more than 5% of the outstanding shares (**OUTSIDE**).⁴³ So in an alternative specification with the more limited number of observations (**not** shown in Table 7), we also included the **first-** and second-order terms of these two variables [**INSIDE**, $\frac{1}{2}$ **INSIDE**², **OUTSIDE**, and $\frac{1}{2}$ **OUTSIDE**²]. We included the second-order terms because **Gorton** and Rosen (**1995**) predict a U-shaped relationship between **insiders'** stock holdings and

⁴³We thank Gary **Gorton** and Rich Rosen for providing these **data**.

efficiency. At low levels of inside ownership, a negative relationship would be consistent with managers who have greater control pursuing their own interests, which may involve inefficiencies. However, at higher stakes, an increase in insider ownership may serve to align management's objectives with those of owners, yielding greater efficiency. We include the OUTSIDE variables, since outside investors can be a controlling influence, and the more stock in the hands of large, outside investors, the more control these investors can be expected to exert and the more efficient the bank might become. However, in none of our regressions are any of these governance variables significantly related to efficiency.

7.3 Other Bank Characteristics. We also explored the effects of other characteristics of the bank. A bank's age (AGE) might be related to efficiency since bank production might involve "learning by doing" (Mester, 1996). While significantly different from zero in our profit efficiency regressions, the coefficient on AGE is very small in all the regressions.

We included several variables to control for the strategic niche of the bank, including proxies for the amount of risk the bank is taking on. Banks with higher loan-to-asset ratios (LOAN/GTA) tend to have higher profit efficiency. This might reflect that banks' loan product is more highly valued than securities, or it could reflect higher market power that exists in loan markets compared to the other product markets in which banks operate. Whether a bank is heavily using derivative contracts, such as swaps, forwards, and futures (SUBDER), does not appear to be consistently related to its efficiency. This might be because of heterogeneity in the uses of these instruments, which can be used for both hedging and speculative purposes. Reliance on purchased funds (PF/GTA) could also be related to efficiency, since the cost of purchased funds differs from that of core deposits over the business cycle. We find that banks that use more of these funds tend to have lower profit efficiencies than other banks.

As a direct measure of bank risk, we included the standard deviation of return on assets (SDROA). To the extent that we are not adequately controlling for risk taking in our profit models, riskier banks may be more profit efficient if they are trading off between risk and return. Alternatively, banks that are poor at operations might also be poor at risk management, which would imply a positive relationship between profit

and/or cost efficiency and **risk**. The evidence suggests that banks with more variable returns tend to have lower profit efficiencies (in the multiple **regressions**) and also lower cost **efficiencies**, consistent with the notion that bad managers are poor at both operations and risk **management**. A negative relationship with cost efficiency was also found when we replaced **SDROA** with the **standard** deviation of the return on book equity (**SDROE**) as a robustness **check**.

7.4 Market Characteristics. The next set of variables characterizes the competitive conditions of the markets in which the banks operate. The **Herfindahl** index (**HERF**) measures the degree of local deposit market concentration and proxies for the bank's market **power**. As might be **expected**, market power is negatively related to cost efficiency but positively related to alternative profit **efficiency**. Banks in less competitive markets can charge higher prices for their services but might feel less pressure to keep costs down (i.e., enjoy the "**quiet life**").⁴⁴ We included two other variables related to market **competition**. **INMSA** indicates whether the bank is located in a metropolitan **area**, which may be more competitive than a rural **area**. The results are not consistent across the multiple and single variable **regressions**, because **INMSA** is likely correlated with other aspects of the **bank**, like its **size**, merger **activity**, etc. State income growth (**STGROW**) proxies for the growth of market demand for banking **services**. Greater demand might allow for less cost efficient **production**, at least in the short run before new competitors **enter**, but more profit **efficiency**, since it means greater opportunity to make **profit**. This is what our estimates **show**.⁴⁵

7.5 State Geographic Restrictions on Competition. Geographic restrictions on bank **expansion**, which differ across **states**, can also limit the competitive forces banks **face**. We included variables to control for the degree of branching restrictions (**UNITB**, **LIMITB**, **STATEB**), the degree of in-state holding company expansion permitted (**LIMITBHC**), whether out-of-state holding company expansion is allowed or not

⁴⁴However, this result is not robust to replacing **HERF** with **SHARE**, the bank's share of local market deposits, as **SHARE** is significantly positively related to cost **efficiency**.

⁴⁵As a robustness check we replaced **STGROW** with the state unemployment rate (**STUNEMP**), which is negatively related to market **demand**. Here the results are much **weaker**, and the signs on **STUNEMP** in the profit regressions are **positive**, indicating a negative relationship **between** market demand and profit **efficiency**.

(NOINTST), and the **proportion** of the banking industry's assets held in any states that are allowed to enter (ACCESS). These variables are **meant** to control for the degree of competition or contestability of the bank's **market**. Perhaps the most surprising finding here is that the relationship between branching restrictions and efficiency does not appear to be monotonic in the severity of the **restrictions**. We find some support that banks in states with limited branching restrictions have higher cost efficiency and lower profit efficiency than banks in either unit banking states or states without branching **restrictions**; banks in unit banking states appear to be the least cost efficient but most profit **efficient**. The other variables included to measure geographic restrictions produce no consistently significant **results**, except that banks in states that prohibit interstate expansions (NOINTST) appear to be less cost efficient than banks in states that permit such **expansions**. In **summary**, efficiency does seem to be related to limits on geographic **expansion**, but the findings are somewhat **inconsistent**.

7.6 Federal Bank Regulator. Our last group of **variables**—the identity of the bank's primary federal regulator—helps account for some control for the regulatory regime banks are **facing**. The **regulator**, like the **market**, exerts some control over the bank and thus might be related to bank **efficiency**. Also, the bank's primary federal regulator (FED, OCC, or FDIC) varies depending on the type of charter the bank **has**; thus, the variables might reflect differences in banks with different **charters**. We find only weak relationships between regulator identity and our three efficiency **measures**, with banks overseen by the Federal Reserve tending to be more cost efficient than banks overseen by the OCC or FDIC.

7.7 Fit of the Correlates Equations. A final observation from Table 7 is that the adjusted R^2 s suggest that we have not explained most of the variance in measured **efficiency**. Our 25 explanatory variables are **able** to explain about 7% of the variance of measured cost efficiency and about 35% of the variance of the two types of measured profit **efficiency**. We make no judgment as to whether these figures are high or low, but simply note that most of the variance in measured efficiency **after** controlling for efficiency concept and measurement methods remains **unexplained**. It may be due to essentially unmeasurable **factors**, such as differences in managerial **ability**, to potential correlates of efficiency that we have could have included but

failed to do so, or to measurement error in the **dependent** variable due to the many difficulties in measuring **efficiency**. Further investigation is beyond the scope of this **paper**.

8. Conclusion

Despite the very significant research effort that has been mounted over the last few years examining the efficiency of financial **institutions**, there is as yet **little** information and no consensus on the sources of the substantial variation in measured **efficiency**, i.e., these sources remain a “**black box**.” **Here**, we focus on getting inside the box by **examining** a number of **sources**, holding the data set **constant**. We examine three types of **sources**: (1) differences in the **efficiency** concept **used**, (2) differences in efficiency measurement methodology within the context of these **concepts**, and (3) the potential correlates of efficiency that may explain some of the efficiency differences that remain **after** controlling for efficiency concept and measurement **method**. We review the literature on the sources of efficiency at commercial banks and provide new evidence using a large data set of almost **6,000** U.S. commercial banks that were in continuous operation over the six-year period 1990-95.

We examine three economic efficiency **concepts**—**cost**, standard **profit**, and alternative profit **efficiencies**. Each corresponds to how well a **firm performs** relative to a different economic optimization **program**, and so each may provide different insights about firm **efficiency**. Consistent with this **expectation**, we **find** that measurement of each of the **efficiency** concepts does add some independent **informational value**. **In fact**, the measures of profit efficiency are not positively correlated with cost **efficiency**, even though all three efficiency measures are positively related to some raw-data measures of **performance**. As **well**, a number of the potential correlates had different relationships with the three different **efficiency measures**, again suggesting that each is measuring a different type of **optimization**. These results suggest that **future** researchers might consider **measuring** all three concepts to be sure that any conclusions about which **firms** are most efficient or which potential correlates succeed in “**explaining**” efficiency are robust with respect to **all** three economic **efficiency concepts**.

We explore the effects of a number of different efficiency measurement methods on each of the three efficiency **concepts**. These methods include the use of different measurement **techniques**, different functional

forms, and various treatments of output quality and financial **capital**. The results for each of the efficiency concepts are quite **robust**. We **find that** the choices made concerning measurement **technique, functional form**, and other variables usually make very little difference in terms of either average industry efficiency or the rankings of individual firms in our data **set**. An exception is the treatment of equity **capital**. Failure to account for the equity position of a bank seems to yield a strong scale **bias**, making large banks appear to be more efficient than small banks by virtue of the equity they have built up over **time**.

We also find substantial unexploited cost scale economies for our 1990s data up to bank sizes much larger than typically found in the **past**. This might have occurred because the decline in interest **rates**, regulatory changes such as the liberalization of intrastate and interstate **banking**, and improvements in technology and applied finance since the 1980s may have tended to favor large **banks** over **small banks**.

Our analysis of the potential correlates of bank efficiency cover a number of **bank, market**, and regulatory characteristics using **multiple-** and single-variable **regressions**. The results are quite **mixed**. Some of the potential correlates of efficiency have the predicted sign and statistical **significance**; others have **little** independent influence on **efficiency**; and some have unexpected or mixed **signs**. **Importantly**, most of the variance in measured **efficiency** for each of the efficiency concepts remains **unexplained**, because of unmeasured factors such as differences in managerial **ability**, potential correlates that were inadvertently excluded from the **analysis**, or measurement error in the **efficiency** dependent **variables**. We leave to **future** research the task of better explaining efficiency or determining that not much more can be **explained**.

We close with a caveat that the empirical results of this study should not be taken too seriously unless confined by **future research**. To our **knowledge**, this is the first study of the efficiencies of the first six years of the 1990s, the **first** to compare **cost, standard profit**, and alternative profit **efficiency** of banks using a single data set and consistent **specifications**, the first to evaluate the effects of so many differences in **methodology**, and the **first** to use such a comprehensive set of potential correlates of **efficiency**. It is quite likely that some of these results will differ in **future** studies of these data that use different sets of **assumptions**.

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Table 1

**Variables Employed in the Cost, Standard Profit, and Alternative Profit Functions
Means and Standard Deviations for 1995 only**

**(All financial variables measured in 1000's of constant 1994 dollars,
Prices of financial assets and liabilities are measured as interest rates.)**

<u>Symbol</u>	<u>Definition</u>	<u>Mean</u>	<u>Std Dev</u>
Dependent Variables			
C	Variable operating plus interest costs, includes costs of purchased funds, deposits, and labor	13,466	105,671
π	Variable profits, includes revenues from loans and securities less variable costs	8,628	66,767
Variable Input Prices			
w_1	Price of purchased funds (jumbo CDs, foreign deposits, federal funds purchased, all other liabilities except core deposits).	.0410	.0111
w_2	Price of core deposits (domestic transactions accounts, time and savings)	.0284	.0081
w_3	Price of labor (1000's of constant dollars per employee)	32.5	6.8
Variable Output Quantities (Cost and Alternative Profit Functions Only)			
y_1	Consumer loans (installment and credit card and related plans)	38,179	298,130
y_2	Business loans (all other loans)	164,952	1,489,552
y_3	Securities (all non-loan financial assets, i.e., Gross Total Assets - $y_1 - y_2 - z_2$)	114,916	838,231
Variable Output Prices (Standard Profit Function Only)			
p_1	Price of consumer loans	.0926	.0329
p_2	Price of business loans	.0898	.0126
p_3	Price of securities	.0468	.0087

(Table 1, p. 2)

<u>Symbol</u>	<u>Definition</u>	<u>Mean</u>	<u>Std Dev</u>
Fixed Netput Quantities			
z_1	Off-balance-sheet guarantees (commitments , letters of credit , etc.) measured using Basle Accord risk weights to be risk-equivalent to loans .	26,367	445,427
z_2	Physical capital (premises and other fixed assets)	4,818	38,909
z_3	Financial equity capital	26,686	184,880
Environmental Variables			
NPL	Nonperforming loans (past due at least 90 days or on nonaccrual basis) divided by total loans	.0258	.0217
STNPL	Weighted average of NPL for the state , using proportions of the loans issued by banks in the state as the weights .	.0220	.0043
Num. observations, cost and alternative profit regressions , 1995		9,002	
Num. observations, standard profit regressions , 1995		8,378	

Notes: All stock values are real quantities **as** of the December call report and all prices are flows over the year divided by these **stocks**. Because the price data are subject to error from this **procedure**, we eliminate observations in which the prices on assets and liabilities (**which** are interest **rates**) are more than 2.5 standard deviations from the mean value for that **year**. **Similarly**, we eliminate observations in which liability and asset rates are more than .10 above and more than .50 above the one-year Treasury **rate**, **respectively**. The standard profit **function** uses fewer observations because these procedures eliminated some output price **data**. We also eliminated observations in which equity was below 1% of gross total assets because the data for such banks are **suspicious**. From these **regressions**, efficiency is reported only for the 5,949 observations in which all of these data plus data on other variables in Table 2 are available for every year 1990-1995. All of the continuous variables that can take on the value 0 have 1 added before taking logs in **specifying** the cost and profit **regressions**. This applies to the **y**'s, **z**'s, **NPL**, and **STNPL**. For π , an additional adjustment was made because profits can take on negative values (**see text**).

Table 2

**Measured Bank X-Efficiency
Using Various Econometric Models
U.S. Banks 1990-1995**

(weighted mean efficiencies, standard deviations in parentheses, correlations)

Model Specification	Cost Efficiency	Standard Profit Efficiency	Alternative Profit Efficiency
Preferred Model: Distribution-Free Approach, Fourier-Flexible Specification, Includes State Average Nonperforming Loan Ratios and Equity Capital.	.868 (.062)	.549 (.208)	.463 (.195)
Same as Preferred Model, Except Uses Translog Specification In Place of Fourier-Flexible Specification.	.860 (.063)	.539 (.207)	.452 (.194)
Rank-Order Correlation with Preferred Model:	.979	.995	.995
Same as Preferred Model, Except includes Bank's Own NPL Ratio instead of State Average STNPL.	.866 (.062)	.550 (.209)	.469 (.198)
Rank-Order Correlation with Preferred Model:	.992	.999	.997
Same as Preferred Model, Except includes Bank's Own NPL Ratio in Addition to State Average STNPL.	.866 (.062)	.550 (.208)	.471 (.197)
Rank-Order Correlation with Preferred Model:	.992	.999	.999
Same as Preferred Model, Except Excludes both STNPL and NPL.	.869 (.061)	.546 (.207)	.461 (.196)
Rank-Order Correlation with Preferred Model:	.999	.999	.998
Same as Preferred Model, Except Excludes Equity Capital.	.869 (.062)	.088 (.287)	.106 (.301)
Rank-Order Correlation with Preferred Model:	.834	.215	.425
Same as Preferred Model, Except Stochastic Frontier Approach, Half-Normal Distribution. ^a	.942 (.023)	— —	.351 ^b (.709)
Rank-Order Correlation with Preferred Model:	.988	—	.912
Number of Observations:	5949	5949	5949

^aFor the stochastic frontier approach to yield meaningful efficiency estimates, the cost or profit residuals must have the correct skew, (rightward for cost, leftward for profit). In some cases this did not occur, including standard profit efficiency in all six years, cost efficiency in 1992, and alternative profit efficiency in 1994 and 1995. The stochastic frontier cost efficiency estimate is therefore based on data from 1990, 1991, 1993, 1994 and 1995 only, and alternative profit efficiency is based on data from 1990, 1991, 1992 and 1993. To be consistent with the distribution free approach, the stochastic frontier efficiencies were calculated by comparing firms to the best observed expected value of ln_u so that the best-practice firm has an efficiency of 1.

^bThree banks were eliminated from this calculation because they had negative potential profits, and the profit efficiency ratios are meaningless in these cases. This leaves a sample size of 5946.

Table 3

Cost Scale and **X-Efficiency**
Estimates by Size Class
(Weighted Means)

Bank Size (GTA)	# of Banks	Scale Efficiency	% Below Efficient Scale	t*	X- Efficiency	Total Cost Efficiency	C/GTA
0-\$50M	2218	.856	94.3%	2.200	.851	.728	.0482
\$50M-\$100M	1794	.842	96.5%	2.363	.870	.733	.0473
\$100M-\$300M	1344	.818	97.3%	2.523	.873	.715	.0466
\$300M-\$1B	392	.786	99.8%	2.815	.876	.688	.0453
\$1B-\$10B	171	.782	99.8%	2.986	.860	.671	.0436
> \$10B	30	.782	94.4%	2.673	.872	.680	.0427
Total	5949	.795	97.3%	2.723	.868	.689	.0443

Notes: All figures (except C/GTA, which is weighted by GTA) are weighted by each bank's predicted costs; consequently the efficiencies indicate the proportion of the sample banks' costs that are used efficiently, with respect to scale efficiency, frontier efficiency and total cost efficiency, the product of scale and frontier efficiency.

The percent below efficient scale refers to the percentage of banking costs that are incurred by firms below efficient scale.

t* is the bank's ratio of the cost-efficient size to its actual size, so that t* > 1 indicates unexploited scale economies, and t* < 1 indicates diseconomies of scale.

C/GTA is average cost or total cost divided by gross total assets, is included as a raw-data version of cost efficiency. It has an unweighted mean of .0473 and a standard deviation of .0050.

Because the Fourier-flexible form has numerous local minima and maxima, the scale-efficient point for each bank's product mix was discovered by means of grid search over the interval [0.5, 5.0]. We limit the interval in order to avoid extrapolating too far from the observed data, but this interval should allow for any realistic short-term expansion or contraction prospects. Fortunately the limits on the interval were generally non-binding, as only 3 banks out of 5949 had t* values at one of the endpoints (see Berger, Leusner, and Mingo, 1996 for more details on this method).

Table 4

Correlations Among the Efficiency Measures and Raw-Data Measures of Performance†

	COST EFFICIENCY	STANDARD PROFIT EFFICIENCY	ALTERNATIVE PROFIT EFFICIENCY	C/GTA	ROA
STANDARD PROFIT EFFICIENCY	0.019 (0.145)				
ALTERNATIVE PROFIT EFFICIENCY	-0.167 (0.000)	0.794 (0.000)			
C/GTA	-0.206 (0.000)	-0.119 (0.000)	-0.235 (0.000)		
ROA	0.247 (0.000)	0.122 (0.000)	0.177 (0.000)	-0.279 (0.000)	
ROE	0.205 (0.000)	0.469 (0.000)	0.334 (0.000)	-0.220 (0.000)	0.726 (0.000)

C/GTA is average cost, i.e., total cost divided by gross total assets, a raw-data version of cost efficiency. It has an unweighted mean of 0.047 and a standard deviation of 0.005 over 1990-1995.

ROA is return on assets, i.e., net income divided by gross total assets. It has a mean of 0.011 and a standard deviation of 0.004 over 1990-1995.

ROE is return on equity, i.e., net income divided by equity. It has a mean of 0.016 and a standard deviation of 0.047 over 1990-1995.

†Spearman correlation coefficients, with p-values of the tests for zero correlation in parentheses.

Table 5

Cost, Standard Profit, and Alternative Profit X-Inefficiencies
Relative to Potential Profits,^a Gross Total Assets, and Equity

Bank Size (GTA)	# of Banks	Inefficiency Potential Profits			Inefficiency GTA			Inefficiency Equity		
		Cost ^b	Standard Profit ^c	Alternative Profit ^c	Cost ^b	Standard Profit ^c	Alternative Profit ^c	Cost ^b	Standard Profit ^c	Alternative Profit ^c
0-\$50M	2218	.165 (.085)	.414 (.157)	.412 (.217)	.007 (.003)	.018 (.011)	.018 (.011)	.074 (.039)	.185 (.071)	.184 (.090)
\$50M-\$100M	1794	.143 (.074)	.382 (.140)	.362 (.188)	.006 (.003)	.016 (.009)	.015 (.009)	.065 (.034)	.173 (.065)	.164 (.078)
\$100M-\$300M	1344	.182 (.092)	.472 (.220)	.732 (.276)	.006 (.003)	.015 (.008)	.023 (.010)	.066 (.034)	.172 (.072)	.267 (.102)
\$300M-\$1B	392	.184 (.107)	.449 (.229)	.775 (.311)	.006 (.003)	.013 (.008)	.023 (.009)	.068 (.039)	.167 (.089)	.288 (.101)
\$1B-\$10B	171	.204 (.113)	.456 (.224)	.694 (.276)	.006 (.003)	.013 (.008)	.020 (.009)	.082 (.045)	.182 (.092)	.278 (.104)
> \$10B	30	.184 (.135)	.468 (.200)	.628 (.248)	.005 (.003)	.014 (.005)	.018 (.006)	.078 (.051)	.199 (.073)	.267 (.084)
Total	5949	.185 (.114)	.451 (.208)	.639 (.303)	.006 (.003)	.014 (.008)	.020 (.009)	.075 (.044)	.183 (.081)	.259 (.109)

^aThe potential profits denominator in the first set of comparisons is calculated using the standard profit function. Using the alternative profit function yields similar results.

^bCost inefficiency is predicted cost minus minimum cost.

^cProfit efficiency is potential profits minus predicted profits.

Note: All figures are weighted averages of the values for all banks in the sample. If an individual bank's value is given by x/z , then the figures in the table are $\sum x_i / \sum z_i$.

Numbers in parentheses are standard deviations.

Table 6

Variables Employed as Potential Correlates of Efficiency
(One observation per bank averaged over 1990-1995 unless otherwise indicated)
(All financial variables measured in 1000's of constant 1994 dollars)

<u>Symbol</u>	<u>Definition</u>	<u>Mean</u>	<u>Std Dev</u>
Bank Size Variables			
SMLBANK	Dummy, equals one if bank has GTA below \$100 million. Excluded from the regressions as the base case.	.673	.449
MEDBANK	Dummy, equals one if bank has GTA of \$100 million to \$1 billion.	.293	.432
LARBANK	Dummy, equals one if bank has GTA of \$1 billion to \$10 billion.	.028	.157
HUGBANK	Dummy, equals one if bank has GTA over \$10 billion. over \$10 billion.	.005	.067
Organizational Form/Governance			
MERGED	Dummy, equals one if bank survived one or more bank-level mergers during the period (i.e., absorbed the assets of one or more other banks).	.132	.338
ACQUIRED	Dummy, equals one if bank was acquired by a new high holder bank holding company during the period.	.108	.310
INBHC	Dummy, equals one if bank is owned by a bank holding company.	.761	.407
MUL_LAY	Dummy, equals one if the bank is in a multiple-layered BHC, i.e., the direct holder is not the high holder.	.087	.251
OUTST	Dummy variable, equals one if bank's high holder is located in another state.	.055	.211
PUB-TRADED	Dummy, equals one if the bank's high holder is registered with the SEC for public trading.	.228	.407
INSIDE	Proportion of stock owned by board members and their relatives. Reported only for banks with over 50% of the banking assets of publicly traded organizations (126 observations).	.159	.187
OUTSIDE	Proportion of stock owned by outside owners with share blocks greater than 5%. Same restrictions as INSIDE (126 observations).	.058	.083

(Table 6, p. 3)

<u>Symbol</u>	<u>Definition</u>	<u>Mean</u>	<u>Std Dev</u>
State Geographic Restrictions (con't.)			
NOINTST	Dummy, equals one for states that do not allow interstate expansions of multibank holding companies.	.032	.095
ACCESS	Proportion of nation's banking assets in states that are allowed to enter the state (equals proportion of national assets in the state for states that do not allow interstate banking).	.503	.276
Primary Federal Regulator			
FED	Dummy, equals one if the bank's primary federal regulator is the Federal Reserve.	.085	.268
FDIC	Dummy, equals one if the bank's primary federal regulator is the FDIC.	.608	.481
OCC	Dummy, equals one if the bank's primary federal regulator is the OCC. Excluded from the multiple regressions as the base case.	.307	.455
Raw Data Measures of Performance¹			
C/GTA	Total cost divided by gross total assets, a raw-data version of cost efficiency.	.047	.005
ROA	Return on assets: ratio of net income to gross total assets.	.011	.004
ROE	Return on equity: ratio of net income to equity.	.116	.047
Num. Observations			

¹The raw data measures of performance are included in the analysis as alternative measures of efficiency as robustness checks of the more complicated frontier efficiency estimates. They are included in a separate correlation analysis but are excluded from the regression analysis as being completely endogenous.

Table 7
Regression Analysis of the Potential Correlates of Efficiency[†]

Dep Var	COST EFFICIENCY		STANDARD PROFIT EFFICIENCY	ALTERNATIVE PROFIT EFFICIENCY		
	(1)	(2)	(3)	(4)	(5)	(6)
<u>Bank Size Variables</u>						
SMLBANK	0.883** (137.355)	-0.021** (-12.682)	0.184** (10.929)	0.083** (15.799)	0.375** (19.890)	0.206** (38.908)
MEDBANK	0.902** (132.626)	0.021** (12.118)	0.036* (1.994)	-0.083** (-15.099)	0.117** (5.885)	-0.200** (-35.778)
LARBANK	0.899** (97.130)	0.0123* (2.536)	0.009 (0.358)	-0.038* (-2.444)	0.077** (2.859)	-0.147** (-8.708)
HUGBANK	0.908** (60.940)	0.009 (0.773)	-0.040 (-1.028)	-0.089* (-2.492)	0.093* (2.133)	-0.132** (-3.349)
<u>Organizational Form/Governance</u>						
MERGED	-0.004 (-1.532)	0.007** (3.168)	0.023** (3.606)	0.004 (0.511)	0.031** (4.303)	-0.052** (-6.631)
ACQUIRED	0.006* (2.223)	0.010** (3.989)	-0.002 (-0.335)	0.019* (2.387)	0.007 (1.005)	0.013 (1.508)
INBHC	0.004* (2.062)	0.012** (6.318)	0.055** (10.549)	0.079** (13.609)	0.057** (9.909)	0.039** (5.974)
MUL_LAY	0.011** (3.303)	0.020** (6.709)	0.040** (4.525)	0.032** (3.314)	0.0314** (3.201)	-0.017 (-1.561)
OUTST	0.010* (2.562)	0.021** (5.996)	-0.006 (-0.529)	0.015 (1.273)	-0.011 (-0.960)	-0.046** (-3.687)
PUB-TRADED	0.008** (3.691)	0.017** (9.064)	0.025** (4.433)	0.032** (5.448)	0.013* (2.114)	-0.038** (-5.825)
<u>Other Bank Characteristics</u>						
AGE	0.00003 (0.900)	0.0001** (4.283)	-0.0006** (-9.776)	-0.0008** (-10.734)	-0.0009** (-12.373)	-0.001** (-13.256)
LOAN/GTA	-0.019** (-2.943)	0.005** (0.867)	0.755** (45.731)	0.656** (39.678)	0.426** (23.059)	0.260** (12.860)
SUB_DER	-0.019** (-3.128)	0.004 (0.771)	0.015 (0.930)	-0.013 (-0.856)	0.053** (2.924)	-0.084** (-4.917)
PF/GTA	0.024 (1.771)	0.032** (2.620)	-0.143** (-3.970)	-0.131** (-3.335)	-0.224** (-5.558)	-0.404** (-9.396)
SDROA	-2.517** (-9.120)	-2.905** (-10.788)	-2.89** (-3.995)	0.258 (0.299)	-3.876** (-4.796)	1.718 (1.805)
<u>Market Characteristics</u>						
HERF	-0.015** (-2.610)	-0.018** (-3.614)	0.023 (1.527)	0.035** (2.243)	0.067** (4.039)	0.130** (7.572)
INMSA	-0.007** (-3.368)	0.001 (0.926)	0.003 (0.491)	-0.008 (-1.474)	0.021** (3.665)	-0.042** (-7.405)
STGROW	-1.610** (-3.220)	-1.640** (3.602)	4.172** (3.185)	1.843 (1.274)	6.038** (4.125)	8.967** (5.632)

[†]Columns (1), (3), and (5) report multivariate regression coefficients with t-statistics in parentheses. Note that the OCC and STATEB dummy variables and a constant term are omitted from the multivariate regressions to avoid perfect collinearity. Columns (2), (4), and (6) report univariate regression coefficients, where each regression included the variable and an intercept term, with t-statistics in parentheses.

*Significant at the 5% level. **Significant at the 1% level.

Dep Var	COST EFFICIENCY (1)	(2)	STANDARD PROFIT EFFICIENCY (3)	(4)	ALTERNATIVE PROFIT EFFICIENCY (5)	(6)
<u>State Geographic Restrictions on Competition</u>						
UNITB	-0.058** (-2.768)	-0.059** (-3.106)	0.337** (6.115)	0.450** (7.547)	0.426** (6.922)	0.603** (9.196)
LIMITB	0.008** (4.450)	0.005** (3.146)	-0.013** (-2.641)	-0.020** (-3.912)	-0.041** (-7.449)	-0.006 (-1.131)
STATEB	-----	0.005** (-2.911)	-----	0.017** (3.300)	-----	0.002 (0.349)
LIMITBHC	-0.0008 (-0.462)	-0.004* (-2.380)	0.032** (6.737)	0.007 (1.442)	0.032** (6.064)	0.030** (5.730)
NOINTST	-0.046** (-4.745)	-0.036** (-4.497)	-0.028 (-1.053)	-0.089** (-3.536)	-0.039 (-1.374)	-0.047 (-1.682)
ACCESS	-0.011** (-3.090)	0.0009 (0.315)	0.054** (6.008)	-0.027** (-3.080)	0.079** (7.891)	-0.006 (-0.593)
<u>Primary Federal Regulator</u>						
FED	0.008* (2.559)	0.008** (2.947)	-0.003 (-0.412)	0.002 (0.252)	-0.013 (-1.433)	-0.015 (-1.536)
FDIC	-0.0006 (-0.340)	-0.007** (-4.193)	-0.008 (-1.784)	0.018** (3.514)	-0.019** (-3.808)	0.031 (5.544)
OCC	-----	0.004** (2.696)	-----	0.020** (-3.863)	-----	0.029** (-4.953)
Adj R-sq‡	0.067		0.364		0.348	
No. Banks	5949	5949	5949	5949	5949	5949

†Columns (1), (3), and (5) report multivariate regression coefficients with t-statistics in parentheses. Note that the OCC and STATEB dummy variables and a constant term are omitted from the multivariate regressions to avoid perfect collinearity. Columns (2), (4), and (6) report univariate regression coefficients, where each regression included the variable and an intercept term, with t-statistics in parentheses.

‡The adjusted R-squared is computed as $1 - \frac{(N-1)(1-R^2)}{N-K}$ where N=number of observations, K=number of parameters, R^2 = sum of squared errors from the regression/sum of squared deviations of the dependent variable from its mean. This adjusted R-squared is equivalent to that obtained from the model in which SMLBANK is replaced with an intercept term.

*Significant at the 5% level. **Significant at the 1% level.