Modelling technical inefficiencies in a stochastic frontier profit function: Application to bank mergers

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Abstract

This study modifies the original stochastic frontier estimation approach to incorporate the effects of conditions that may be associated with inefficiency. The alternative profit efficiency concept for cross-sectional data is specified. The study assumes that technical inefficiency effects are independently distributed as truncations of the normal distributions with constant variance, but with means that are a linear function of observable firm-specific variables. The model is applied empirically to data on United States banks in 1997. The null hypotheses that the auxiliary equation (inefficiency-effects model) is not important and should not be incorporated in the frontier function, and that the normal-half normal distribution is an adequate representation of the data given the normal-truncated normal distribution is rejected. The null hypothesis that the flexible translog functional form is not a better representation or does not fit the data well is also not subscribed to. The null hypothesis that the inefficiency effects are not stochastic and do not depend on the bank-specific variables is also rejected. The results of the inefficiency-effects variables were also consistent with the diversification hypothesis. Results also show an improvement in measured bank-profit efficiency.

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1 Introduction

The past several decades have seen considerable changes in the landscape of the banking industry across the globe. These changes were driven mostly by factors such as globalisation, changes in the regulatory structures, consolidations, technological advances, to name but a few. Questions arise as to whether these financial institutions are becoming more or less efficient after all these changes. That is, an efficient institution is believed to lead to better quality services for consumers at reasonable prices, improved safety and soundness of the financial sector that shrugs off possibilities of failures, and institutions that are better able to mediate funds within the financial system at large.

The United States (US) banking industry, in particular, has seen massive consolidation in the past two decades that have resulted in not only a significant decline in the number of banks but have also lead to the formation of some of the world's largest banking organisations. The changing nature of the banking industry also prompted more studies that attempt to measure the efficiency of these financial institutions. However, it is well accepted that studies on the efficiency of financial institutions have not kept pace with developments in the banking industry. There has also been little attention paid on measuring the X-efficiency of these banks as studies mostly measured scale and scope efficiency. Studies that measured the X-efficiency of banks indicated that X-inefficiencies account for about 20 per cent and more of banking costs. In addition, efficiency differences across banks are large, and they dominate scale and scope efficiencies.

These studies also indicated that there is not a best method of estimating X-efficiency. From an econometric perspective, the challenge (as Berger et al. 1993 indicated) lies in distinguishing X-efficiency differences from random errors that may affect institutions' costs levels. Major issues of contention are choices of the efficiency concept to use (cost or profit efficiency), efficiency measurement techniques (parametric or nonparametric), functional forms (Translog, Fourier, etc.), efficiency correlates, etc. Berger and Mester (1997) provide a discussion on these issues.

This paper modifies the basic stochastic frontier estimation approach to incorporate effects of conditions that may be associated with inefficiency. This approach provides a framework for the analysis of the effects of potential determinants of inefficiency and differences in measured efficiency among banks. A stochastic frontier alternative profit function for cross-sectional data in which the technical inefficiency effects are assumed to be a function of firm-specific variables is defined. The main objective is to present and test the theoretical model for inefficiency effects on US banking data.

The rest of the paper is structured as follows: Section 2 provides a brief review of the literature in the banking sector. Section 3 outlines the methodology applied. This section also outlines the basic stochastic frontier model as suggested by Aigner, Lovell, and Schmidt (1977), the alternative profit function to be estimated, and the inefficiency effects model. Section 4 presents the empirical application and results and Section 5 presents conclusions and direction for further research.

2 Literature review

Since the introduction of the concept of efficiency (Farrell 1957 and Leibenstein, 1966), studies have attempted to measure the performance of firms in various industries. In the financial sector, early studies only applied accounting-based efficiency ratios to determine the performance of financial institutions or the impact of such issues as mergers on performance. Recently, frontier studies have extended the analysis by trying to measure the X-efficiency (technical and allocative efficiencies) of financial institutions. These frontier studies produced mixed and different results due to the efficiency concepts applied, efficiency measurement technique used, functional form specified, efficiency correlates hypothesised etc.

X-efficiency studies became a viable alternative to accounting-based efficiency ratios studies. Most financial ratio studies simply measured performance based on improved financial ratios and/or by comparing the pre- and post-merger financial ratios (in the case of mergers evaluation). These studies found that there were no significant cost savings or improvements of these institutions relative to the industry at large. There was also no evidence of a substantial change in cost performance associated with bank mergers [Rhoades 1986, 1990; Linder and Crane 1992; Srinivasan and Wall 1992; Srinivasan, 1992; Cornett and Tehranian 1992; Spindt and Tarhan, 1992].

Berger and Humphrey (1992a) highlighted the following limitations of the ratio studies: Firstly, financial ratios exclude interest expenses that constitute about 70 per cent of the total bank costs. Secondly, operating cost analysis might produce results that are biased towards showing false benefits from mergers as larger bank tend to substitute interest cost-intensive purchased funds for operating costs-intensive core deposits. Also banks' capital structure tends to shift towards purchased funds when core deposits decline more than the assets. This leads to a decline in the operating costs ratio, which can be mistaken as an increase in efficiency.

Thirdly, beyond the traditional banking activities (taking deposits and making loans) different banks sell different products packaged differently depending on the location of the banks (rural, urban, etc.), attitude towards risk, management style, etc. On the contrary, the cost-to-asset ratios assume that a dollar of assets should entail the same costs irrespective of the asset type and cost of doing business in that particular area. Firm efficiency is a concept that cannot be easily captured by mere accounting ratios. Fourthly, cost ratios do not provide a clear distinction between X-efficiency and scale/scope efficiency effects. Fifthly, financial ratios do not take full account of the distinction between within-market and across-market mergers. Lastly, DeYoung (1997a) indicated that extra precautions need to be taken when interpreting the financial ratios. For example, a bank that excessively cuts costs might destroy service quality, earnings, portfolio quality, etc. This might lead to inefficiency.

Frontier studies help solve the methodological shortcomings of the financial ratio studies. These studies estimated the best practice frontier of banks based on the cost and profit efficiency and found mixed results. Studies that applied the cost efficiency concept found no evidence of improved performance or cost savings on the banks. However, studies that applied the profit efficiency found some evidence of improved profit efficiency. (see Berger and Humphrey 1992b; Berger, Hancock, and Humphrey 1993; Berg, et al. 1993; Kaparakis 1994; Kwan and Eisenbeis, 1996; Allen and Rai 1996; Berger and Mester, 1997; Bikker, 2001).

Frontier studies that analysed the cost-efficiency implications of mergers also did not find any efficiency benefits on average following a merger. They could not determine whether the cost changes were greater or less than the revenue changes by looking at the cost analysis alone. These studies were limited because they take output as given and ignored the revenue effects of the merger (see Berger and Humphrey, 1992a; Rhoades, 1993b; Shaffer 1993; Fixler and Zieschang, 1993; Vander Vennet 1996; Peristiani 1997; DeYoung 1997b; Berger 1998; Lang and Welzel, 1999). However, frontier studies that applied the profit-efficiency concept in analysing bank mergers found evidence of improved profit efficiency (Vander Vennet, 1996; Berger 1998; Akhavein 1997; Focarelli et al. 2002; Munyama, 2004).

3 Methodology

3.1 Inefficiency frontier model for cross-sectional data

The stochastic production frontier model was simultaneously introduced by Aigner, Lovell, and Schmidt (1977), and Meeusen and van den Broeck (1977). The model was motivated by the idea that deviations from the production frontier may not be entirely under the control of the production unit under scrutiny. As Kumbhakar and Lovell (2000:72) indicated, "the great virtue of stochastic production frontier models is that the impact on output of shocks due to variation in labour and machinery performance, vagaries of the weather, and just plain luck can at least in principle be separated from the contribution of variation in technical efficiency".

While allowing for technical inefficiency, these models also acknowledge the fact that random shock outside the control of producers can affect output. They account for measurement error and other factors (such as weather and luck) on the value of the output of unspecified input variables in the production process. Following Aigner, Lovell, and Schmidt (1977) a stochastic frontier model can be formulated in terms of a general production function for the ith production unit as,

$$\begin{aligned} y_i &= f\left(x_i, \beta\right) + v_i - u_i \\ &= f\left(x_i, \beta\right) + \varepsilon_i \quad \text{i=1:N} \end{aligned} \tag{3.1}$$

where v_i = two-sided noise component, and $u_i \geq 0$ is the non-negative technical inefficiency component of the error term. The model is such that the possible production, Y_i, is bounded above by the stochastic quantity, $f\left(x_i; \beta\right) \cdot \exp\left(v_i\right)$, (hence, the term stochastic frontier). The noise component v_i is assumed to be independently and identically distributed (iid), symmetric, and distributed independently of u_i. The error term $\varepsilon_i = v_i - u_i$ is, therefore, asymmetric since $u_i \geq 0$.

If we assume that v_i and u_i are distributed independently of x_i, then the estimation of (3.1) by OLS provides consistent estimates of the βs except β_0. That is, $\mathrm{E}(\varepsilon_i) = -\mathrm{E}(u_i) \leq 0$. The OLS estimation also provides a simple test for the presence of technical efficiency in the data. That is, if $u_i > 0$, then $\varepsilon_i = v_i - u_i$ is negatively skewed and there is evidence of technical inefficiency in the data. However, the OLS does not provide estimates of producer-specific technical efficiency, which is the ultimate objective of the estimation process in addition to obtaining estimates of the production technology parameters β in $f(x_i;\beta)$. This requires an extraction of separate estimates of statistical noise v_i and technical inefficiency u_i from the estimates of ε_i for each producer. Therefore, the distributional assumptions of the inefficiency term are required to estimate the technical efficiency of each producer.

3.1.1 Normal-truncated normal stochastic frontier model

The normal-half normal (and the exponential) distributions are the arbitrary choice due to lack of a priori justification for selecting a particular distributional form for the technical inefficiency effects. The normal-half normal model assumes a distribution of u with a mode at u = 0 (u represents the level of inefficiency). This specification outlined by Aigner, Lovell, and Schmidt (1977) is based on the implicit assumption that the likelihood of inefficient behaviour monotonically decreases for increasing levels of inefficiency. Stevenson (1980) argued that economic agents are humans or human institutions such that the possibility of a non-zero mode for the density function of u should seem a more tenable presumption. He then generalised Aigner, Lovell and Schmidt's (1977) specification to permit a non-zero mode for density function of u, and to enable the testing of the special case of a zero mode. His model is reasonably general without regard to the pattern of efficiency distribution throughout the sample (Hence the introduction of the normal-truncated normal formulation).

The following distributional assumptions can be made (Munyama, 2004):

i. $v_i \sim$ iid $N(0,\sigma_v^2)$

ii. $u_i \sim$ iid $N^+(\mu,\sigma_u^2)$

iii. v_i and u_i are distributed independently of each other, and of the regressors.

Stevenson's (1980) model (normal-truncated normal distribution) differs from the one-parameter half-normal distribution in that it allows the latter to have a non-zero mode. Kumbhakar and Lovell (2000) pointed out that the truncated normal distribution contains an additional parameter μ to be estimated. Therefore, the truncated-normal model is a more flexible representation of the pattern of efficiency in the data.

The density functions for u and v are:

$$f(u) = \frac{1}{\sqrt{2\pi}\sigma_u \Phi\left(\frac{\mu}{\sigma_u}\right)} \cdot e^{\left\{-\frac{1}{2}\left(\frac{u-\mu}{\sigma_u}\right)^2\right\}} \quad \text{for } u \geq 0 \qquad (3.2)$$

$$= 0 \qquad \text{otherwise}$$

$$f(v) = \frac{1}{\sqrt{2\pi}\sigma_v} \cdot e^{\left\{-\frac{1}{2}\left(\frac{v}{\sigma_v}\right)^2\right\}} \quad \text{for all } v \qquad (3.3)$$

where v is assumed to be normally distributed with zero mean and variance σ_v^2, u is assumed to be distributed as a truncated normal with mode μ, and $\Phi(\cdot)$ is the cumulative distribution function for a standard normal random variable. f(u) is the density of a normally distributed variable with possibly non-zero mean μ, truncated below at zero. If $\mu = 0$, the density function in equation (3.2) collapses to the half-normal density function. The truncated normal distribution, as specified by Stevenson (1980) is a two-parameter distribution, which depends on the placement and spread parameters μ and σ_u. The joint density function of $\varepsilon = u - v$ is given as:

$$f(u,v) = \frac{1}{2\pi\sigma_u\sigma_v\Phi\left(\frac{\mu}{\sigma_u}\right)} \cdot e^{\left\{-\frac{1}{2}\left[\left(\frac{u-\mu}{\sigma_u}\right)^2 + \left(\frac{v}{\sigma_v}\right)^2\right]\right\}} \qquad (3.4)$$

The joint density of u and ε is

$$f(u,\varepsilon)=\frac{1}{2\pi\sigma_u\sigma_v\Phi\left(\frac{\mu}{\sigma_u}\right)}\cdot e^{\left\{-\frac{1}{2}\left[\left(\frac{u-\mu}{\sigma_u}\right)^2+\left(\frac{\varepsilon+u}{\sigma_v}\right)^2\right]\right\}} \tag{3.5}$$

which after integration we get the marginal density of ε as

$$\begin{aligned}
\mathrm{f}(\varepsilon)&=\int_0^\infty f(u,\varepsilon)\,du\\
&=\int_0^\infty \frac{1}{\sqrt{2\pi}\sigma_u\sigma_v\Phi\left(\frac{\mu}{\sigma_u}\right)}\cdot e^{\left\{-\frac{1}{2}\left[\left(\frac{u-\mu}{\sigma_u}\right)^2+\left(\frac{\varepsilon+u}{\sigma_v}\right)^2\right]\right\}}du\\
&=\frac{1}{\sqrt{2\pi}\sigma\Phi\left(\frac{\mu}{\sigma_\mathrm{u}}\right)}\cdot\Phi\left(\frac{\mu}{\sigma\lambda}-\frac{\varepsilon\lambda}{\sigma}\right)\cdot e^{\left\{-\frac{1}{2}\left(\frac{\varepsilon+\mu}{\sigma}\right)^2\right\}}\\
&=\frac{1}{\sigma}\phi\left(\frac{\varepsilon+\mu}{\sigma}\right)\cdot\Phi\left(\frac{\mu}{\sigma\lambda}-\frac{\varepsilon\lambda}{\sigma}\right)\cdot\left[\Phi\left(\frac{\mu}{\sigma_u}\right)\right]^{-1}
\end{aligned} \tag{3.6}$$

where $\sigma=\left(\sigma_u^2+\sigma_v^2\right)^{\frac{1}{2}}$ and $\lambda=\frac{\sigma_\mathrm{u}}{\sigma_\mathrm{v}}$, ϕ is the standard normal density function evaluated at $\left(\frac{\varepsilon+\mu}{\sigma}\right)$. Note that f(ε) collapses to the half-normal marginal density function if μ = 0 (similar to Aigner, Lovell, and Schmidt, 1977). f(ε) is asymmetrically distributed, and its mean and variance are respectively given as:

$$\begin{aligned}
\mathrm{E}(\varepsilon)&=-\,\mathrm{E}(\mathrm{u})\\
&=-\,\frac{\mu\mathrm{a}}{2}-\frac{\sigma_u a}{\sqrt{2\pi}}\cdot e^{\left\{-\frac{1}{2}\left(\frac{\mu}{\sigma_u}\right)^2\right\}}\\
V(\varepsilon)&=\mathrm{V}(\mathrm{u})+V(v)\\
&=\mu^2\frac{a}{2}\left(1-\frac{a}{2}\right)+\sigma_u^2\frac{a}{2}\left(\frac{\pi-a}{\pi}\right)+\sigma_v^2
\end{aligned} \tag{3.7}$$

where $a=\left[\Phi\left(\frac{\mu}{\sigma_u}\right)\right]^{-1}$.

This normal-truncated normal distribution has three parameters: A placement parameter μ and two-spread parameters, σ_u and σ_v. The log likelihood function for a sample of N producers can be represented as:

$$\ln \mathrm{L} = \text{constant - N} \ln\sigma - N\ln\Phi\left(\frac{\mu}{\sigma_u}\right) + \sum_i \ln\Phi\left(\frac{\mu}{\sigma\lambda} - \frac{\varepsilon_i\lambda}{\sigma}\right) - \frac{1}{2}\left(\frac{\varepsilon_i + \mu}{\sigma}\right)^2 \quad (3.8)$$

where we write σ_u as $\sigma\left(\lambda^{-2}+1\right)^{-\frac{1}{2}}$. Maximising the log likelihood function with respect to the parameters β, λ, σ^2, and u will yield the maximum likelihood estimates.

The normal-half normal distribution, which has a mode at zero, implies that there is the highest probability that the inefficiency effects are in the neighbourhood of zero. As such, technical efficiency is high, which might not be evident in practice. The normal-truncated normal (and the gamma) model presented above addresses these shortfalls. That is, the normal-truncated normal and the gamma distributions allow for a wider range of distributional shapes, which include ones with non-zero modes. Therefore, this study adopts the normal-truncated normal model because of its flexible representation of the pattern of efficiency in the data.

3.2 Specification of the alternative profit function

We express the deterministic portion of the frontier alternative profit function as a flexible trans-logarithmic function of output quantities, input prices, and fixed netput quantities. The alternative profit function is given by:

$$\ln\left(\pi+\theta\right) = f_{a\pi}\left(X_{\pi}\right) + \ln\xi_{a\pi} + \ln v_{a\pi} \quad (3.9)$$

where $X_{a\pi} \equiv \left(\ln w, \ln y, \ln z, \ln r\right)$.

Following this formulation, the estimated stochastic frontier alternative profit function is given by[2]:

[2] Firms do not actually take their outputs as given and maximize profits as implied by the alternative profit specification. However, we use the alternative profit maximization concept if the assumptions behind cost minimization and standard profit maximization do not hold precisely. Berger and Mester (1997) identified four violations of these assumptions under which the alternative profit concept may provide useful information in efficiency measurement.

$$
\begin{aligned}
\ln\left[\frac{\pi}{z_2}+\theta\right] = {} & \alpha_0+\sum_{i=1}^{4}\alpha_i \ln\left(\frac{y_i}{z_2}\right)+\frac{1}{2}\sum_{i=1}^{4}\sum_{r=1}^{4}\delta_{ir}\ln\left(\frac{y_i}{z_2}\right)\ln\left(\frac{y_r}{z_2}\right) \\
& + \sum_{j=1}^{4}\beta_j \ln\left(w_j\right)+ \frac{1}{2}\sum_{j=1}^{4}\sum_{k=1}^{4}\gamma_{jk}\ln\left(w_j\right)\ln\left(w_k\right) \\
& +\sum_{i=1}^{4}\sum_{j=1}^{4}\rho_{ij}\ln\left(\frac{y_i}{z_2}\right)\ln\left(w_j\right) \\
& +\varphi_0 \ln R+\frac{1}{2}\varphi_1\left(\ln R\right)^2 \\
& +\sum_{i=1}^{4}\kappa_i \ln\left(\frac{y_i}{z_2}\right)\ln R+\sum_{j=1}^{4}\mu_j \ln\left(w_j\right)\ln R \\
& +\omega_0 \ln\left(\frac{z_1}{z_2}\right)+\frac{1}{2}\omega_1 \ln\left(\frac{z_1}{z_2}\right)^2 \\
& +\sum_{i=1}^{4}\phi_i \ln\left(\frac{y_i}{z_2}\right)\ln\left(\frac{z_1}{z_2}\right)+\sum_{j=1}^{4}\eta_j \ln\left(w_j\right)\ln\left(\frac{z_1}{z_2}\right) \\
& +\varepsilon_i \qquad\qquad (3.10)
\end{aligned}
$$

where π = the profits of the firm; θ = constant added to every firm's profit so that the natural log is taken of a positive number; y = vector of variable outputs; w = vector of variable input prices; r = Altman Z-score or measure of bank risk; z = fixed netput quantities; $\varepsilon = v + \xi$, where V's are assumed to be iid $\sim N(0,\sigma^2_\pi)$ incorporated in the model to reflect the random disturbance that is independent of the explanatory variable and the ξs. The ξs are the random disturbances that capture the degree of technical inefficiency in production.

The alternative profit function uses the same dependent variable as the standard profit function, but the same explanatory variables as the cost function. This functional form, however, lacks some of the advantages of the standard profit function. Unlike the standard profit function, the alternative profit function requires choosing whether deposits are inputs or outputs. As such, we adopt the "value-added" approach (Berger and Humphrey 1992b) in defining and measuring bank outputs. The value-added approach defines output as those activities that have substantial value added as judged by using an external source of operating cost allocations. That is, activities that have large expenditure on labour and physical capital. It considers all liability and asset categories to have some output characteristics rather than distinguishing inputs from outputs in a mutually exclusive way.

The value-added approach also explicitly uses operating cost data as part of the return or cost not accounted for by the difference between measured financial flows and marginal opportunity costs. Therefore, this approach is considered the best for accurately estimating changes in bank technology and efficiency over time. The value-added approach, as applied in this study, identifies the major categories of produced deposits (demand, time and savings) and loans (real estate, commercial, and instalment) as important outputs because they are responsible for the great majority of value added.

The alternative profit concept not only bridges the gap between the standard cost and profit function, but also becomes more relevant if one or more assumptions underlying the cost efficiency and the standard profit efficiency do not hold. Berger and Mester (1997) identified some violations of these assumptions such that the alternative profit concept becomes more useful and provides valuable information in efficiency measurement. Therefore, the alternative profit efficiency is appropriate if one or more of the following conditions hold: There is the presence of substantial unmeasured differences in the quality of banking services; variable outputs are not completely variable, which might lead to scale bias; banks having some market power over the prices they charge (i.e. output markets are not perfectly competitive); and output prices not being accurately measured.

Berger and Mester (1997) stated that one of the drawbacks with studies on bank efficiency before the introduction of the Fourier-flexible form was the reliance on the translog frontier functions following Bauer and Ferrier's (1996) claim that the Fourier-flexible form is the global approximation capable of providing a better fit to bank data.[3] Most studies have since indicated that the translog function does not fit the data well especially if the data are far from the mean in terms of output size or mix. McAllister and McManus (1993), and Mitchell and Onvural (1996) pointed out that variation or differences in results on scale economies across studies might be due to

[3] Other studies include McAllister and McManus (1993), Berger, Cummins, and Weiss (1997), Berger and DeYoung (1997), Berger and Mester (1997), Berger and Humphrey (1997).

the ill fit of the translog function across a wide range of bank sizes. Therefore, the Fourier-flexible form was considered more flexible than the translog, and a global approximation to virtually any cost and profit function. Berger and DeYoung (1997) found that measured inefficiencies were about twice as large when the translog was specified in place of the Fourier-flexible form.

Shaffer (1998) indicated that the translog functional form cannot incorporate zero quantities of any output and typically exhibits substantial multicollinearity among the various terms and their squares and cross products. The translog functional form also tends to impose a spurious U-shaped average cost structure in the face of monotonically declining true average cost data. That is, the translog form generally cannot portray monotonically declining average costs in practice. However, Shaffer (1998) also indicated that the translog form has the theoretical advantage of being able to fit exactly the level, first and second derivatives of an arbitrary function at a point.

Altunbas and Chakravarty (2001) argued that the goodness of fit criterion is not necessarily an indication of goodness in prediction or a reliable indicator of the claim that the Fourier-flexible functional form is a global approximation to any cost or profit function, and that it fits the data for financial institutions better than the translog. They urge some caution on the growing use of the Fourier-flexible specification of the frontier function to investigate bank efficiency. In their analysis of the Fourier-flexible form as a better fit to the data compared to the translog function, they found that the translog functional form does a better job in the prediction and forecasting of the largest 5 per cent of the banks in their sample.

Furthermore, the optimal number of estimated coefficients in a flexible Fourier form is equal to the number of sample observations to the 2/3 power. In this study, there were 347 observations. According to the standard requirement of the Fourier flexible form, about $(347)^{2/3} \approx 49$ estimated coefficients are needed. The translog flexible form, as specified in equation (3.10) has 65 coefficients, which is more than what is required by the Fourier flexible form. Therefore, a properly specified Fourier form would be no more flexible (in terms of the number of estimated coefficients) than the specified translog.

In equation (3.10) the dependent variable of the alternative profit function is specified as

$$\ln\left[\frac{\pi}{z_2}+\left|\left(\frac{\pi}{z_2}\right)^{\min}\right|+1\right] \qquad (3.11)$$

where $\left|\left(\frac{\pi}{z_2}\right)^{\min}\right|$ is the absolute value of the minimum value of $\left(\frac{\pi}{z_2}\right)$ over all banks during the same period. Thus, we add a constant $\theta=\left|\left(\frac{\pi}{z_2}\right)^{\min}\right|+1$ to the dependent variable in every firm so that we can take natural logs of a positive number.

Following Berger and Mester (1997), this study also specifies all of the profit, variable output quantities and fixed input quantities as ratios to the fixed equity capital input, z_2. This helps address various shortfalls. For example, the smallest firms have profits many times smaller than those of the largest firms and vice versa. As such, large firms would have random errors with much larger variances than small firms would in the absence of normalisation. Therefore, normalisation helps alleviate this heteroscedasticity problem. It should also be noted that the inefficiency term $\ln\xi_\pi$ is derived from the composite residuals and this might make the variance of the efficiencies dependent on the size of the bank in the absence of normalisation.

Normalising the variable output, the dependent and the independent variables becomes of the same order of magnitude rather than being skewed towards large banks. Therefore, scale bias is reduced as we can now express profits or asset per dollar of equity, which alleviate differences in profits and asset sizes between large and small banks. Berger and Mester (1997) also indicated that normalisation by equity capital has economic meaning. That is, the dependent variable becomes the return on equity (ROE) or a measure of how well banks are using their scarce financial capital. That is, banking is the most highly financially leveraged industry. Shareholders are mostly interested in their rate of return on equity (ROE), which is a measure closer to the goal of the bank than maximising the level of profits.

Normalisation by the financial equity capital also follows from the choice of equity capital as a fixed input quantity. That is, equity capital is very difficult and costly to change substantially except over the long run. Although we specify physical capital (premises and equipment) and equity capital as fixed input quantities, fixed assets are very small in banking, they are only about 20 per cent (Akhavein et al. 1997) as large as equity, and can be increased much more quickly and easily than equity. Therefore, equity capital is preferred as a normalisation variable besides being the fixed input quantity. Furthermore, if equity was not specified as fixed, the largest banks may be measured as the most profit efficient simply because their higher capital levels allow them to have the most loans.

We can predict the technical efficiency of individual firms on the basis of cross-sectional or panel data on these firms. However, few theoretical stochastic frontier functions have explicitly formulated models for the inefficiency effects, and in few banking studies (e.g. Munyama 2004) are the determinants of technical inefficiency used jointly with the other variables of the model. This study models the error term, ε_i, as a two-component error structure, $\varepsilon_i = V_i + \xi_i$. The symmetric random error component V_i is assumed to be $\text{iid}\,\mathrm{N}\left(0,\sigma_V^2\right)$, independently distributed of the ξ_is. The inefficiency error component, ξ_i, is assumed to be independently distributed, such that ξ_i is obtained by truncation (at zero) of the normal distribution with mean $z_i\delta$ and variance σ^2; z_i is a (1xM) vector of firm-specific variables; and δ is an (Mx1) vector of unknown coefficients of the firm-specific inefficiency variables.

If ξ_i and V_i are independent, the joint density functions of $\varepsilon_i = V_i + \xi_i$ is

$$f\left(\varepsilon_i \mid \sigma^2, \lambda\right) = \sqrt{\frac{2}{\pi}} \cdot \frac{1}{\sigma} \cdot e^{\frac{1}{2}\left(\frac{-\varepsilon_i}{\sigma}\right)^2 \left[1 - F^*\left(\frac{-\varepsilon_i \lambda}{\sigma}\right)\right]} \tag{3.12}$$

where $\sigma^2 = \sigma_v^2 + \sigma_\xi^2 ; \lambda = \sigma_\xi / \sigma_V$; f* and F* are the standard normal and standard normal cumulative density functions respectively.[4] Given the p.d.f. of ε_i, the log-likelihood functions of the observed random variable $\ln\left[\frac{\pi}{z_2} + \theta\right]$ can be expressed as

[4] Meeusen and Van Den Broeck (1977), and Stevenson (1980) provide the derivations for this expression.

$$\ln L\left[\ln\left(\frac{\pi}{z_2}+\theta\right) \mid \text{parameters}, \sigma_\xi^2, \lambda\right]$$

$$= \frac{n}{2}\ln\frac{2}{\pi} - n\ln\sigma - \frac{1}{2}\left(\frac{\sum \varepsilon_i}{\sigma}\right)^2 + \sum_1^n\left[\ln\left(1-F^*\left(-\frac{\varepsilon_i\lambda}{\sigma}\right)\right)\right] \tag{3.13}$$

where $\varepsilon_i = \ln\left[\frac{\pi}{z_2}+\theta\right] - \underset{\sim}{X}_i{}'\beta$, and $\underset{\sim}{X}_i$ is a vector of the right hand side variables in (3.10). In equation (3.13) above, as λ goes to zero, the frontier approaches the OLS estimation.

3.3 Inefficiency effects model

We specify the technical inefficiency effects, ξ_i, in the stochastic frontier model (3.10) as

$$\xi_i = z_i\delta + \tau_i \tag{3.14}$$

where ξ_i is the composite inefficiency level, Z_i is a vector of firm-specific inefficiency explanatory variables, and the random error, τ_i, has the same general distribution as previously assumed for ξ_i. That is, τ_i is defined as truncation of the normal distribution with zero mean and variance σ^2 such that the point of truncation is $-z_i\delta$, i.e., $\tau_i \geq -z_i\delta$. These assumptions are consistent with the ξ_is being non-negative truncations of the $N(z_i\delta, \sigma^2)$-distribution (Battese and Coelli (1995).

From the model in equation (3.10), technical inefficiency of production for the i^th firm is defined by

$$TE_i = \exp(-\xi_i) = \exp(-z_i\delta - \tau_i) \tag{3.15}$$

In this inefficiency frontier function (3.10) - (3.14), the τ-random variables are not identically distributed. They could be negative if $-z_i\delta > 0$, i.e., $\tau i \geq -z_i\delta$, but are independent truncations of the normal distributions with zero mean and variance σ^2. From the inefficiency model (3.14), the explanatory variables may include some input variables in the stochastic frontier, provided the inefficiency effects are stochastic. If the first z-variable has value one and the coefficients of all other z-variables are zero, the model represents that specified by Stevenson (1980) and Battese and Coelli (1988, 1992). If all elements of the δ-vector are equal to zero, then the technical inefficiency effects are not related to the z-variables. We, therefore, obtain Aigner, Lovell, and Schmidt's (1977) model. If we include any interaction between firm-specific variables and input variables such as the z-variables, we obtain the non-neutral stochastic frontier model proposed by Huang and Liu (1994). The empirical analysis is carried out through a method of maximum likelihood that simultaneously estimates the parameters of the stochastic frontier and the model for the technical inefficiency effects. The technical efficiencies are predicted using the conditional expectation of $\exp[-\xi_i]$ given the composed error term of the stochastic frontier.

4 Empirical Application

4.1 Data

We apply the specified models to data on US banks that participated in a merger and acquisition in 1997. The choice of the period followed that of Munyama (2004), which was motivated by the enactment of the Riegle-Neal Interstate Banking and Branching Efficiency Act of 1994. There were 762-recorded mergers in 1997. As the majority of mergers reported were merely corporate reorganisations and will have less meaning in this study, only bank mergers that consolidated under common ownership operating banks formerly independent of one another are analysed. That is, corporate reorganisations are excluded. As a result, the number of merger cases decline to 347. Data was collected from the Federal Reserve's Annual Report of Condition and Income (Call Report) during 1997. Software STATA v8 and FRONTIER 4.1 (Coelli 1992, 1994) were used to estimate the models.

4.2 Empirical results

The maximum likelihood estimates for some of the parameters of the model together with the standard errors are given in Table 1 below[5]. Almost all variables estimated in the alternative profit function were significant at 5 per cent level of significance. Of the specified variable outputs, the demand deposits (DDEPOSIT) and the consumer loans (CLOAN) are positively and significantly related to the alternative profit (as expected) at the 0,05 level of significance. Therefore, a bank that is issuing more consumer loans in this case should improve its alternative profit. Since the analysis is done on a sample of merged banks, this is consistent with the diversification hypothesis under which merged banks tend to shift away from securities into consumer loans as they have more diversification opportunities. An evaluation of the proportion of consumer loans to total assets or equity capital should provide a complete picture. Furthermore, banks that are taking more demand deposits improve their alternative profit as demand deposits are positive and statistically

[5] The descriptive statistics for variables employed in measuring the profit function is presented in the appendix.

significant in determining alternative profit. The coefficients for real estate loans (RLOAN) and business loans (commercial and industrial loans – BLOAN) are negative and significantly different from zero at 0,05 level of significance. This implies that banks that increase their real estates and business loans portfolios experience a decline in their alternative profit.

Table 1 Maximum-likelihood estimates of some parameters of the stochastic frontier alternative profit function

Variable	Parameter	Coefficient	Variance Parameters	
DDEPOSIT	β_1	1,2801 (0,0374)*	σ^2	0,0159 (0,0043)
RLOAN	β_2	-0,2062 (0,0294)*	γ	1,0000 (0,0000)
CLOAN	β_3	0,2256 (0,0150)*	σ^2_v	0,0000 (0,0000)
BLOAN	β_4	-0,3781 (0,0567)*	σ^2_ξ	0,0159 (0,0043)
UFUNDS	β_5	-49,7530	Mu	-0.4195 (0,1317)
UCDEP	β_6	0.0998 (0,0424)*	ILGTγ	23,7003 (10,9548)
UCAP	β_7	-1,1907 (0,0422)*	lnσ^2	-4.1445 (0,2683)
ULAB	β_8	01434 (0,1168)*		
RISK	β_9	0,4008 (0,0462)*		
Z_1	β_{10}	-0,2625 (0,0126)*		
Log-likelihood function		**829.516**		
N = 347				
H_0: No inefficiency component: Z = -1.974 Prob <= 0.024				

- *Significant at 0,05 level of significance; the significance is tested based on the Z-statistics reported by STATA v8.
- Asymptotic standard errors in parenthesis.

These results can also be interpreted in line with the "value added approach" (Berger and Humphrey 1992b) used to define and measure bank outputs in this study. The value added approach employs, as important outputs, categories of the bank's financial statements that have substantial value added (as judged using an external source of operating cost allocations). Those identified as major categories include produced deposits (demand, time and savings) and loans (real estate, commercial, and installment). The results of this study confirm that demand deposits and consumer loans do add value on average to the firm, as they are positive and statistically significant in determining alternative profit. On the contrary, real estate loans and business loans do not add value on average to the banks as expected. An increase in the portfolio of real estate loans and business loans leads to a decrease in alternative profit.

The coefficients for the unit price of core deposits (UCDEP) and the unit price of labour (ULAB) are positive and statistically significant (at 0,05 level of significance) in determining alternative profit. That is, an increase in these costs is associated with more activities that add value to the firm, thus leading to an increase in alternative profit. These results on the unit price of labour are contrary to what is asserted by most bank analysts who measure efficiency in terms of spending on overhead (e.g. physical plant and bank personnel) relative to the amount of financial services produced. From the bank analysts' perspective, the unit price of labour should be inversely related to bank profit. That is, the banking industry is expected to not only improve its profits but also record some impressive efficiency gains because reducing overhead is a stated goal in many bank mergers and bank holding company reorganisations.

The results of this study also allude to the misleading nature of the accounting-based ratio analysis widely employed by bank analysts in assessing bank efficiencies and cost structures. The US banking industry experience shows that even though the number of banks continued to decline since the 1980s due to mergers, the number of branch offices continued to increase. The result on the unit price of labor should, however, be interpreted with caution. That is, the unit price of labour is calculated as the ratio of salaries and benefits to the number of people employed in the banking industry during the period in question. An increase in the unit price of labour might be a result of an increase in the salaries and benefits while the number of people employed is constant or declining. Therefore, an increase in expenditure on labour might not necessarily mean that banks are hiring more employees. Humphrey (1994) reported that the number of bank locations (main offices, branches, and Automatic Teller Machines - ATMs) per person in the US tripled between 1973 and 1992. DeYoung (1997a) indicated that from the mid-1980s to the mid-1990s total employment in commercial banks fell by about 5 per cent (about 13 per cent per dollar of assets). However, this was offset by a 19 per cent increase in real salaries and benefits per employee. This implies that the unit price of labour (the way we measure it) should increase.

An increase in the cost of labour might be associated with value added in the banking industry. That is, higher wages might lead to the production of more financial services per worker. However, higher wages might also be a result of the production of more financial services. DeYoung (1997a) indicated that a large employee turnover might make a bank healthier if additional workers are monitoring loans. The study should also indicate to bank analysts that efficiency and cost cutting might not necessarily be one and the same thing. Therefore, industry-wide expenditures on labour can be expected to increase at a time when the most inefficient banks are exiting the industry.

The coefficient for the unit price of physical capital (UCAP) is negative and statistically significant (at 0,05 level of significance) in determining alternative profit. That is, an increase in the unit costs associated with physical capital depletes value on average, thereby leading to a decline in the alternative profit. In this case, reducing the physical overhead should add value on average into the bank in line with what most bank analysts infer. This result is also confirmed by the coefficient of the input fixed quantity (physical capital – Z_1), which is also negative and statistically significant in determining alternative profit (at 0,05 level of significance).

Another variable of importance is the Altman Z-score (RISK), which measures the bank's probability of bankruptcy. From the public-policy perspective, the risk of failure of banks is of primary concern regarding banks' product-line expansion. Merged banks are expected to not only increase their geographic reach, but to also expand their product line. Boyd and Graham (1989) indicated that one of the views of proponents of bank-holding company expansion is that increases in volatility on rates of return (as represented by the standard deviation of ROA) would be offset by increases in rates of return, thereby resulting in lowered risk of failure. The measure of risk, Z-score, offers an opportunity to directly test their view in this study.

The coefficient for the measure of risk (RISK) is positive and statistically significant (at 0,05 level of significance) in determining the alternative profit. This measure of risk is expected to decrease with the volatility of assets returns. That is, losses push a firm towards insolvency but these losses are cushioned by the firm's equity capital. Therefore, the Z-score accounts for both the mean level of bank profits and mean equity ratio such that a higher coefficient of RISK indicates an improved risk-adjusted performance in the bank. This will in turn lead to an improvement in alternative profit.

Table 1 also reports the estimates for the parameters $\sigma_v^2, \sigma_\xi^2, \gamma, \mu$, etc. Gamma is the estimate of $\gamma = \sigma_\xi^2 / \sigma_s^2$ and σ^2 is the estimate of $\sigma_s^2 = \sigma_v^2 + \sigma_\xi^2$. Since γ must be between 0 and 1, the optimisation is parameterised in terms of the inverse logit of γ, and this estimate is reported as ILGTγ. Also, since σ_s^2 must be positive, the optimisation is parameterised in terms of $\ln\left(\sigma_s^2\right)$ whose estimate is reported as $\ln\sigma^2$. Mu (μ) is the mean of the truncated-normal distribution.

From Table 1, the generalised log-likelihood ratio test for the presence of the inefficiency term has been replaced with a test based on the third moment of the OLS residuals. That is, if $\mu = 0$ and $\sigma_\xi = 0$, then the truncated-normal model reduces to a linear regression model with normally distributed errors. However, in this case, the distribution of the test statistic under the null hypothesis is not well established as it becomes impossible to reliably evaluate the log-likelihood as σ_ξ approaches zero. Therefore, we cannot use the likelihood-ratio test in this case (Munyama 2004:137).

Coelli (1995) noted that the presence of an inefficiency term would cause the residuals from an OLS regression to be negatively skewed. Therefore, by identifying the negative skewness in the residuals with the presence of an inefficiency term, he defined a one-sided test for the presence of the inefficiency term. The result is presented at the bottom of Table 1. This result affords an opportunity to test the hypothesis that determines if the inefficiency component should be incorporated in the frontier model (i.e. is there evidence of inefficiency in the model?). From the results presented at the bottom of Table 1, we can reject the null hypothesis (no inefficiency component in the model) at 0,05 level of significance. Therefore, the auxiliary equation (inefficiency component) needs to be incorporated into the frontier model. This hypothesis will be re-tested after estimating both the stochastic frontier and the inefficiency effects models.

Finally, to confirm the presence of inefficiencies or inefficiency component in the model, Table 1 also reports the results of γ. It is observed that the estimated gamma is 1,0000 and its standard error is 0,0000. This result indicates that the vast majority of the residual variation is due to the inefficiency effect (ξ_i), and that the random error, V_i, is approximately zero. The same model was estimated using FRONTIER 4.1 and the results show that based on the likelihood-ratio (LR) test, the stochastic frontier is statistically different from the OLS estimation. That is, the estimated γ is significantly different from zero, suggesting that the auxiliary equation (the technical inefficiency equation) plays an important role in the estimation of the profit frontier. Most previous studies on bank efficiency employed the OLS in estimating the parameters of the frontier function. These studies obtained the inefficiency residuals that are then regressed against some firm-specific variables or potential efficiency correlates. However, results in this study indicate that the maximum likelihood estimation, and not OLS, should be the focus when estimating the parameters of the frontier function.

4.2.1 **Hypotheses testing on the estimates and structure of the model**

The model for inefficiency effects can only be estimated if the inefficiency effects are stochastic and have a particular distributional specification. Hence, there is growing interest to test the null hypotheses that the inefficiency effects are not stochastic; the inefficiency effects are not present; and the coefficients of the variables in the model for the inefficiency effects are zero. These and other null hypotheses are of interest in this study and they are tested using the generalised likelihood-ratio statistic, λ, and the Wald test (Green 2003, Gallant 1997).[6] Table 2 presents the tests for these hypotheses. Table 2 also presents the results for a test of the presence of

[6] The generalised likelihood-ratio test statistic, λ, is calculated as $\lambda = -2\ln\left[\frac{L(H_0)}{L(H_1)}\right] = -2\left\{\ln\left[L(H_0)\right] - \ln\left[L(H_1)\right]\right\}$. If the null hypothesis, H_0, is true, then λ is asymptotically distributed as a Chi-square (or mixed Chi-square) random variable with parameters equal to the number of parameters assumed to be equal to zero in the null hypothesis, H_0.

inefficiencies. We know that banks are not perfectly efficient such that some level of inefficiencies exist. We, however, present the results and procedures followed in administering the test.

Table 2 Tests of hypotheses for coefficients of the explanatory variables for the technical inefficiency effects in the stochastic frontier profit function

Null hypothesis	Log-likelihood function	Test statistic λ	Critical value	Decision
H_0: $\gamma = \delta_0 = \ldots = \delta_{25} = 0$	764	3,64	2,706	Reject
H_0: $\beta_{ij} = 0$, $i \leq j = 1{:}54$	676,61	175,54	75,35	Reject
H_0: $\delta_1 = \ldots = \delta_{20} = 0$	829	191,9	37,57	Reject
H_0: $\mu = 0$	764,38	3,65	2,706	Reject

- The critical values for the tests involving $\gamma = 0$ are obtained from Table 1 of Kodde and Palm (1986) where the degrees of freedom are q + 1, where q is the number of parameters which are specified to be zero but which are not boundary values.
- If the null hypothesis involves $\gamma = 0$, then λ has mixed Chi-square distribution because $\gamma = 0$ is a value on the boundary of the parameter space for γ (Coelli, 1995, provides more details).

The first null hypothesis (Table 2) specifies that the inefficiency effects are absent from the model (all banks are efficient) against the alternative hypothesis that inefficiencies are present. This null hypothesis (no technical inefficiency effects in the model) can be conducted by testing the null and alternative hypothesis, H_0: $\sigma^2 = 0$ vs. H_A: $\sigma^2 > 0$. In this case, σ^2 is the variance of the normal distribution, which is truncated at zero to obtain the distribution of ξ_i. If this variance is zero, then all the ξ_is are zero, which implies that all firms are fully efficient. To test this null hypothesis, we can use the Wald statistic, which involves the ratio of the maximum likelihood estimator of σ^2 to its estimated standard error.

Coelli et al. (1998) pointed out that another set of hypotheses, H_0: $\lambda = 0$; vs. H_A: $\lambda > 0$; or H_0: $\gamma = 0$ vs. H_A: $\gamma > 0$ can be considered depending upon the parameterisation used in the estimation of the stochastic frontier model. This study adopted Battese and Corra (1977) parameterisation such that the hypotheses involving γ are considered. Considering the Wald test, we calculate the ratio of the estimate for γ to its estimated standard error. If H_0: $\gamma = 0$ is true, this statistic is asymptotically distributed as a standard normal random variable. Coelli et al. (1998) also indicated that this test must be performed as a one-sided test because γ cannot take negative values. However, following footnote 6, under H_0: $\gamma = 0$, the model is equivalent to the traditional average response function without the technical inefficiency effects. Coelli (1995) pointed out that the difficulties arise in testing H_0: $\gamma = 0$ because $\gamma = 0$ lies on the boundary of the parameter space γ. Therefore if, H_0: $\gamma = 0$ is true, the generalised likelihood-ratio statistic, LR, has asymptotic distribution, which is a mixture of chi-square distributions,

viz. $\frac{1}{2}\chi_0^2 + \frac{1}{2}\chi_1^2$ where χ_0^2 is the unit mass at zero.

Table 2 shows that the log-likelihood function for the full stochastic frontier model and the inefficiency effects model is 764,38 and the value for the OLS fit of the profit function is 762,56, which is less than that for the full frontier model. This implies that the generalised likelihood-ratio statistic for testing the absence of the technical inefficiency effects from the frontier is calculated to be:

$$LR = -2\{762{,}56 - 764{,}38\} = 3{,}64$$

This value is calculated by FRONTIER 4.1 and reported as the "LR test of the one-sided error". This value is also significant, as it exceeds 2,706, which is the critical value obtained from Table 1 of Kodde and Palm (1986) for the degrees of freedom equal to 1. Hence, the null hypothesis of no technical inefficiency is rejected. Therefore, there is evidence of inefficiencies in these banks. It should be noted that we are only measuring efficiency at a point in time (cross-sectional data). Therefore, one should also draw a comparison of the estimated efficiency scores/rank with those of other previous bank efficiency studies. The rest of the hypotheses in Table 2 test the structural properties of the model.

The second null hypothesis (Table 2), H_0: $\beta_{ij} = 0$, $i \leq j = 1{:}54$, state that the 2^{nd} order coefficients of the translog frontier are simultaneously equal to zero. That is, the study tests whether the Cobb-Douglas functional form is an adequate representation of the data, given the specifications of the translog model. The estimated value of the log-likelihood function is 676,61. Hence the value of the generalised likelihood-ratio statistic for testing the null hypothesis, H_0: $\beta_{ij} = 0$, is calculated to be

$$LR = -2\{676,61 - 764,38\} = 175,54$$

This value is compared with the upper one percent point for the χ^2_{54} distribution, which is 75,35. Thus, the null hypothesis that the Cobb-Douglas frontier is an adequate representation of the data, given the specifications of the translog function is rejected. However, this result is not surprising as the translog offers more flexibility than the Cobb-Douglas functional form.

The third null hypothesis (table 2), H_0: $\delta_1 = \ldots = \delta_{20} = 0$, specifies that all the coefficients of the explanatory variables in the model for the technical inefficiency are equal to zero (and hence that the technical inefficiency effects have the same truncated normal distribution). That is, the inefficiency effects are not a linear function of the δ_is. The calculated generalised likelihood ratio test is 191,9. This value is compared with the upper one percent point of the χ^2_{20} distribution, thus rejecting the null hypothesis that the inefficiency effects are not a linear function of the δ_is. This implies that the joint effects of these variables on inefficiencies are significant although the individual effects of one or more variables may not be statistically significant.

The fourth null hypothesis (table 2), H_0: $\mu = 0$, specifies the distributional assumption of the model. This hypothesis tests whether the simpler half-normal model is an adequate representation of the data, given the specification of the generalised truncated normal model. That is, we test whether the technical inefficiency effects have a half-normal distribution or follow the normal-truncated normal distribution. The value of the likelihood-ratio statistic for testing this null hypothesis is 3,65. This value is compared with the upper ten percent points for the χ^2_1 distribution, which is 2,706. Thus, the null hypothesis that the normal-half normal distribution is an adequate representation of the inefficiency effects given the normal-truncated normal distribution is rejected.

This result shows that, contrary to other bank efficiency studies, other distributional assumptions than the simpler normal-half normal that is an arbitrary choice should be specified. As indicated in the previous sections, the normal-half normal distribution implies that there is the highest probability that the inefficiency effects are in the neighbourhood of zero, such that technical efficiency could be unnecessarily high. This might not be the case in practice. The normal-truncated normal distribution (like the gamma distribution) addresses this shortfall by allowing for a wider range of distributional shapes, which include ones with non-zero modes. Berger and Mester (1997) used the stochastic frontier approach where the inefficiencies were assumed to be half-normally distributed. The data, however, did not appear to fit that distribution very well. They indicated that the skew of the data was not consistent with the half-normal assumptions in a number of cases.

4.2.2 **Predicted technical efficiencies**

This section presents the results of the predicted technical efficiencies of the sampled banks during 1997. This affords an opportunity to compare the predicted efficiencies in this study with other previous studies in bank efficiency. As indicated, previous studies established that banks on average are very inefficient with respect to profit. These results should be surprising as studies that incorporated the revenue or output effects of banks showed that there were some improvements in profit efficiency. Since this study also incorporated a measure of risk in the model, the intention is to find out whether that leads to improvements in measured efficiencies.

Table 3 presents the summary statistics of the predicted technical efficiencies of the sampled banks during 1997, together with results from Berger and Humphrey's (1997) survey of bank efficiency studies. In this study, all banks have predicted technical efficiencies greater than 0,90 (and some very close to 1,0). From the combined model (the frontier model and the inefficiency effects model) the mean efficiency was 0,9809 (median = 0,9818). This implies that the average inefficiency was (1 – 0,98)/0,98 = 0,02. That is, if the average firm was producing on the frontier instead of the current location, then only 98 per cent of the resources currently being used would be necessary to produce the same output. The last column indicates the summary statistics of the predicted technical efficiencies as summarised by Berger and Humphrey (1997).

Table 3 Summary statistics of predicted technical efficiencies

Statistics	Combined Model♣	Cobb-Douglas	U.S. EFF.*
Mean	0,9809	0,9633	0,72 (0,84)
Median	0,9818	0,9656	0,74 (0,85)
Std. Deviation	0,0084	0,2313	0,17(0,06)
Skewness	-2,1235	-2,2893	
Minimum	0,9358	0,8288	0,31(0,61)
Maximum	0,9946	0,9930	0,97(0,95)
Mode	0,9816	0,9656	

*Berger and Humphrey 1997; Parametric estimates in parenthesis.

♣Average Inefficiency ~ (1 – 0.98)/0.98 = 2,0 per cent. That is, If the average firm was producing on the frontier instead of the current location, then only 98 per cent of the resources currently being used would be necessary to produce the same output.

Berger and Humphrey (1997) noted that efficiency estimates from nonparametric techniques were slightly lower and seemed to have greater dispersion than those from the parametric techniques (as indicated in the last column of table 3). The authors' analysis further indicated that from the parametric studies, those that applied the stochastic frontier approach had mean efficiencies that ranged from 0,81 to 0,95.

As this study applies the parametric technique (stochastic frontier approach) in analysing the profit efficiency of banks, the predicted technical efficiencies is expected to be higher as evident from Table 3 above. However, it should be noted that most of the studies surveyed by Berger and Humphrey (1997) estimated the cost efficiency of banks. This study presents technical efficiencies of banks estimated from the profit function. The profit efficiency is measured in terms of best-practice profits, which are typically much smaller than costs, inputs, or output levels used in conventional studies. Therefore, the predicted technical efficiencies of this study cannot be easily compared with those surveyed in Berger and Humphrey (1997). To give a better indication of the distribution of the individual efficiencies, the frequency distributions of these efficiencies is plotted in Figure 1 below.

Figure 1 Frequency distribution of predicted technical efficiencies

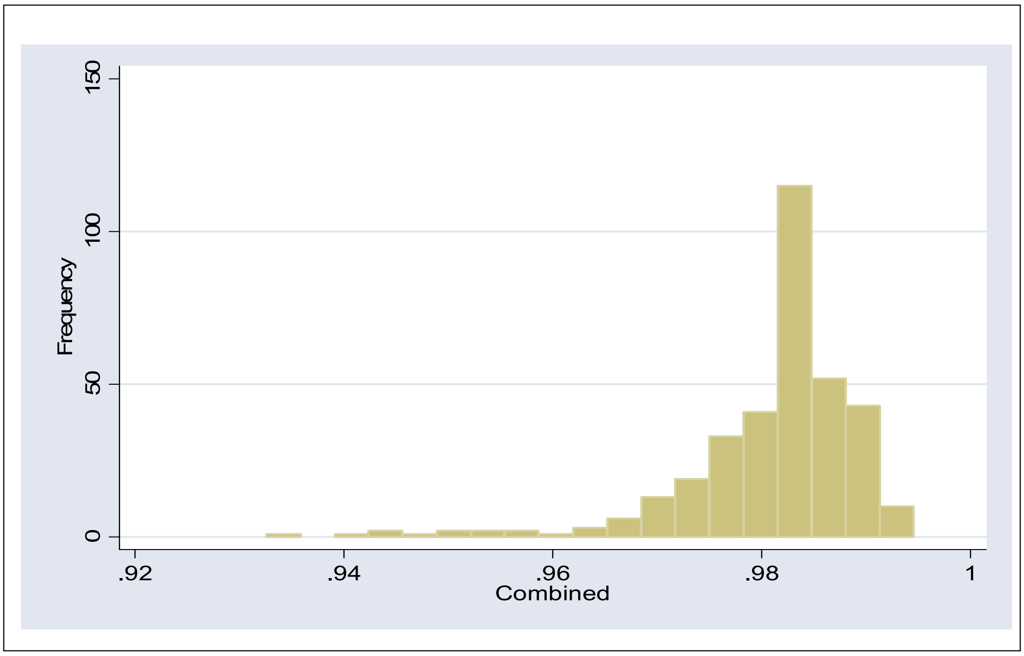

Figure 5.1: Frequency Distribution of Predicted Efficiencies

The graph also shows a thin tail that gradually rises to a maximum in the 0,97 to 0,98 interval and then drops sharply in the 0,99 to 1,0 interval. The fact that the mode of the distribution is not in the final interval offers support for the use of a more general distribution (rather than the normal-half normal distribution) like the normal-truncated normal distribution applied in this study.

4.2.3 Empirical investigation of the potential efficiency correlates

This section relates efficiency estimates to variables that define various aspects of the banks and their markets[7]. These factors are at least partially exogenous and may explain some of the differences in measured efficiencies. We also test the diversification hypothesis that as the banking organisation increases in size (through merger), its risk-return trade-offs should improve because of better diversification of portfolio risk. That is, improved diversification of the loan portfolio owing to a broader coverage of geographic areas, industries, loan types, or maturity structures might allow consolidated banks to shift their output mixes from lower-yielding securities towards higher-yielding loans without raising their costs of funding.

In support of the diversification hypothesis, the coefficient HHI_{NON} (an index that measure a bank's ability to diversify within non-traditional banking activities) is positive and statistically significant in determining banks' technical inefficiencies as expected. That is, a higher value of HHI_{NON} indicates an increase in concentration and less diversification. Therefore, a bank that increased its HHI_{NON} becomes more technically inefficient. On the contrary, the coefficients HHI_{LOAN} (an index that measures a bank's ability to diversify within lending activities), HHI_{REV} (an index that measures the bank's ability to diversify within each of the bank's major activities) were negatively related to technical inefficiency. That is, banks that increased their HHI_{LOAN} and HHI_{REV} experienced increased efficiency. However, these coefficients were not statistically different from zero.

Table 4 also indicates that the coefficients of the ratio of gross total assets to equity (GTAEQUITY), the ratio of purchased funds to equity (FUNDSEQUITY), and the ratio of business loans to gross total assets (BLOANGTA) were negatively related to technical inefficiency. The coefficient of the ratio of purchased funds to gross total assets (FUNDSGTA) was positively related to technical inefficiency. All these coefficients were statistically different from zero, and consistent with the diversification hypothesis.

The results for the coefficients of the ratio of total loans to gross total assets (LOANGTA), the ratio of total loans to equity (LOANEQUITY), and the ratio of consumer loans to gross total assets (CLOAN/GTA) did not support the diversification hypothesis. However, these coefficients were not statistically different from zero. Overall, it can be deduced that a bank that increases in size (especially through a merger) should experience an improved risk-return trade-off that could improve its alternative profit and thereby reducing its technical inefficiencies.

From Table 4, the coefficient for the measure of risk (Altman Z-score that measures the probability of bankruptcy) is negative and statistically different from zero at 0,05 level of significance. This implies that as the Z-score increases, technical inefficiency declines. That is, a higher Z-score indicates an improved risk-adjusted performance

[7] The variables descriptive statistics is presented in the appendix.

of the bank, which also implies improved profit efficiency. Therefore, as we correct for variations in bank risk, the average degree of measured efficiency should improve. The variable RISK is also the only variable in the study that is included as an explanatory variable in both the profit frontier model and the inefficiency effects model. Previous studies did not incorporate risk within the frontier measure as they only incorporated risk as a potential efficiency correlate in the second-stage regression.

Table 4 Maximum-likelihood estimates of the parameters of the inefficiency effects model

Variable	**Parameter**	**Coefficient**	**Variable**	**Parameter**	**Coefficient**
Loan/GTA	δ_1	0,1504 (0,1788)	Large	δ_{11}	0,0558 (0,0223)*
GTA/Equity	δ_2	-0,0112 (0,0040)*	Mega	δ_{12}	0,0035 (0,0095)
Loan/Equity	δ_3	-0,0046 (0,0206)	$HHI_{R\ EV}$	δ_{13}	0,0102 (0,0677)
Cloan/GTA	δ_4	-0,0067 (0,7625)	HHI_{NON}	δ_{14}	0,0965 (0,0373)*
Bloan/GTA	δ_5	-0,2903 (0,1736)**	HHI_{LOAN}	δ_{15}	-0,0896 (0,1076)
Cloan/Equity	δ_6	-0,0310 (0,0522)	Risk	δ_{16}	-0,1041 (0,0476)**
Bloan/Equity	δ_7	-0,0201 (0,0771)	ROA	δ_{17}	-9,7262 (0,4161)*
Funds/GTA	δ_8	0,2960 (0,1624) **	HERF	δ_{18}	-0,0411 (0,0682)
Funds/Equity	δ_9	-0,0242 (0,0142) **	Share	δ_{19}	0,0084 (0,0391)
Medium	δ_{10}	0,0098 (0,0187)			
Variance parameters					
σ^2	0,0027 (0,0008)				
γ	0,9999 (0,0000)				
σ_v^2	0,0000 (0,0000)				
σ_ξ^2	0,0026 (0,0008)				
Log-likelihood function	**925,48202**				

* Significant at 0,05 level of significance, ** significant at 0,10 level of significance. Variable Small was dropped due to collinearity. Asymptotic standard errors are in parenthesis.

The coefficient of return on assets (ROA) is negative and statistically significant (at 0,05 level of significance), which implies that banks with high return on assets are more technically efficient or experience less technical inefficiency. This also alludes to the banks’ ability to diversify into various aspects of their operations owing to such issues as broader coverage of geographic areas, and their ability to shift their output mix from lower to higher-yielding products without raising costs

5 Conclusion

Despite all the research effort in examining the efficiencies of financial institutions, there are still varying opinions about the differences in measured efficiencies. Research has mostly concentrated on measuring the cost efficiencies of banks rather than profit efficiencies. There is still lack of research in examining the effects of mergers on bank efficiencies from a profit function perspective. Banking efficiency studies have also failed to explicitly present a model for inefficiency effects. Most studies on bank efficiencies also concentrated on evaluating performance during the 1980s rather than the 1990s. This study attempted to address these issues.

The study presented a model for technical inefficiency effects for cross-sectional data applied on the US banks the engaged in a merger during 1997. In deviating from previous studies that estimated a frontier function and then regress the estimated inefficiency effects against a set of explanatory variables, this study simultaneously estimated the profit frontier and the inefficiency effects model. The inefficiency effects term,ξ_i, is assumed to follow a normal-truncated normal distribution rather than the normal-half normal distribution adopted by other bank efficiency studies.

The results show that the estimated efficiencies are higher on average than efficiencies presented in other studies. It was also established that the auxiliary equation (the inefficiency effects model) is an important component and should be incorporated in the stochastic frontier profit function. The analysis also indicated that the normal-truncated normal distribution is an adequate representation of the data than the normal-half normal distribution. In addition, the flexible translog functional form, as specified, is a better representation of the data than the Cobb-Douglas functional form, and should perform as good as the Fourier-flexible functional form.

The efficiency correlates variables also support the diversification hypothesis. The study also incorporated a measure of risk (the Altman Z-score that measures the probability of bankruptcy) in both the profit frontier and the inefficiency effects model. This measure of risk indicated that when we measure bank efficiency correcting for variation in risk, banks showed a decrease in technical inefficiencies, thereby improving their alternative profit. Further analysis (theoretical or empirical) is required to improve the application of the stochastic frontier model in bank efficiency. Research also needs to measure efficiency on panel data, test other functional forms, and specify other distributional assumptions.

Appendix A1: Variables employed in measuring the alternative profit efficiency

Symbol	Definitions	Mean	Median	Std. Dev.
Dependent Variable ($1000)				
π	Profits	355,072	14.545	706,202
Variable output quantities ($1000)				
Y_1	Demand Deposits	2,921,078	143,075	5,610,506
Y_2	Real Estate Loans	8,528,412	471,123	16,556,212
Y_3	Consumer loans	2,007,645	94,117	3,495424
Y_4	Business loans (C&I)	5,778,665	137,968	11,947,830
Variable input prices				
W_1	Unit price of Purchased Funds	1,010702	1,010102	0,00421
W_2	Unit price of Core Deposits	0,025028	0,025023	0,00624
W_3	Unit price of Physical Capital	0,32146	0,26722	0,64981
W_4	Unit price of Labour	37,16756	37,51563	9,30837
Fixed input quantities ($1000)				
Z_1	Physical Capital	395,317	21,140	778,050
Z_2	Financial Equity Capital	3,006,808	126,553	625,8621
R	Z-Score: Measure of Insolvency risk	20,27502	18,68850	9,05659

- All stock values are real quantities as of December Call Reports and all prices are flows over the year divided by these stocks. All of the continuous variables that can take on the value 0 have 1 added before taking logs. This applies to the y's. For π, an additional adjustment was made because profits can take a negative value.
- R is the Altman Z-score.

Appendix A2: Diversification hypotheses ratios

Variables	Descriptions	Mean	Std. Dev	Expected signs♣
Loans/GTA	Total Loans Divided by Gross Total Assets	0,60495	0,12921	Positive
GTA/Equity	Gross Total Assets Divided by Equity	11,6472	2,35704	Positive
Loans/Equity	Total Loans Divided by Equity	7,09835	2,13003	Positive
CLoans/GTA	Consumer Loans Divided by Gross Total Assets	0,08863	0,06784	Positive
BLoans/GTA	Business Loans Divided by Gross Total Assets	0,12491	0,06486	Positive
CLoans/Equity	Consumer Loans Divided by Equity	1,05106	0,84210	Positive
BLoans/Equity	Business Loans Divided by Equity	1,47600	0,86372	Positive
PF/GTA	Purchased Funds Divided by Gross Total Assets	0,07709	0,08814	Negative
PF/Equity	Purchased Funds Divided by Equity	0,92221	1,03325	Positive

♣These variables are expected to have opposite signs when measured with respect to technical inefficiency

Appendix A3: Variables employed as determinants of technical inefficiency

Variables	Description	Mean	Std. dev	Expected sign
Bank Size variables				
Small	Dummy equals one if bank has GTA below $100 million	58,696	25,191	Positive
Medium	Dummy equals one if bank has GTA of $100 million to $1 billion	443,457	293,936	Positive
Large	Dummy equal one if bank has GTA of $1 billion to $10 billion	4,132,751	2,388,090	Positive
Mega	Dummy equals one if bank has GTA over $10 billion	125,419,926	87,434,046	Negative
Bank Characteristics				
HHI_{Rev}	Revenue HHI Index	0,67217	0,09091	Positive
HHI_{non}	Noninterest Income HHI Index	0,76249	0,19442	Positive
HHI_{loan}	Loan Portfolio HHI index	0,41187	0,13514	Positive
ROA	Return on Asset	0,0112	0,0055	Negative
HERF	Herfindahl-Hirschman Index	0,3780	2,9101	Negative
SHARE	Local Market Concentration	0,5293	3,1180	Negative
RISK	Altman Z-scores: Measure of Bank Insolvency Risk	2,9616	0,2676	Negative

- GTA is the Gross Total Assets. The GTA equals to total assets plus loan and lease loss reserves and allocated risk reserve (reserve for certain foreign loans). It does not depend on the performance status of the assets, and is therefore a superior measure of bank size to total assets.
- HERF is the weighted-average Herfindahl index of local deposit market concentration across the bank's markets, where each weight is the bank's deposit share in the market. Let d^{jk} = bank j's deposits in market k, then HERF for bank j

$$HERF^{j} = \sum_{market=k} SHARE^{jk} \times MKTHERF^{k}$$

  is:

$$\text{where SHARE}^{jk} = \frac{d^{jk}}{\sum_{bank=i} d^{ik}} \text{ and MKTHERF}^{k} = \sum_{\text{bank i}} \left(SHARE^{ik}\right)^{2}$$

- HERF is calculated at state levels

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