ELSEVIER Journal of Banking & Finance 24 (2000) 1605–1628

Journal of BANKING & FINANCE

www.elsevier.com/locate/econbase

Efficiency and risk in Japanese banking

Yener Altunbas [a], Ming-Hau Liu [b], Philip Molyneux [c,*], Rama Seth [d,1]

[a] The Business School, South Bank University, Southwark Campus, 103 Borough Road, London, SE1 0AA, UK

[b] Nanyang Business School, NTU, Singapore 639798, Singapore

[c] School of Accounting, Banking and Economics, University of Wales Bangor, Gwynedd, Bangor, LL57 2DG, UK

[d] Federal Reserve Bank of New York, New York, NY 10045, USA

Received 18 April 1997; accepted 27 July 1999

Abstract

This paper investigates the impact of risk and quality factors on banks' cost by using the stochastic cost frontier methodology to evaluate scale and *X*-inefficiencies, as well as technical change for a sample of Japanese commercial banks between 1993 and 1996. Loan-loss provisions are included in the cost frontier model to control for output quality, with a financial capital and a liquidity ratio included to control risk. Following the approach suggested in Mester (1996) we show that if risk and quality factors are not taken into account optimal bank size tends to be overstated. That is, optimal bank size is considerably smaller when risk and quality factors are taken into account when modelling the cost characteristics of Japanese banks. We also find that the level of financial capital has the biggest influence on the scale efficiency estimates. *X*-inefficiency estimates, in contrast, appear less sensitive to risk and quality factors. Our results also suggest that scale inefficiencies dominate *X*-inefficiencies. These are important findings because they contrast with the results of previous studies on Japanese banking. In particular, the results indicate an alternative policy prescription, namely, that the largest banks should

* Corresponding author. Tel.: +44-1248-382170; fax: +44-1248-364760.
E-mail address: p.molyneux@bangor.ac.uk (P. Molyneux).

[1] The views expressed are those of the author and do not necessarily reflect those of the Federal Reserve Bank of New York or the Federal Reserve System.

PII: S0378-4266(99)00095-3

shrink to benefit from scale advantages. It also seems that financial capital has the largest influence on optimal bank size.

JEL classification: G21; D21; G23

Keywords: Japanese banks; Cost functions; Economies of scale; Inefficiencies; Technical change

---

1. Introduction

Studies of the Japanese banking industry have typically found strong evidence of scale economies across a broad range of bank sizes (see for example, Kasuya, 1986; Yoshioka and Nakajima, 1987; Tachibanaki et al., 1991; Fukuyama, 1993; McKillop et al., 1996). The aforementioned studies provide an indication of the cost characteristics of the Japanese banking industry, however, they may be limited because they do not take into account the risks associated with banks' operations. This is a particularly relevant issue in Japanese banking given that the system has experienced substantial asset quality problems and low levels of capitalisation since the early 1990s (see Bank of Japan, 1995, 1996). Recent studies such as those Hughes and Mester (1993), Hughes et al. (1995), McAllister and McManus (1993), Mester (1996) and Clark (1996) have drawn attention to the fact that bank efficiency studies typically ignore the impact of risk on banks' costs or profits and they suggest that risk characteristics need to be incorporated in the underlying industry cost or profit functions because, 'unless quality and risk are controlled for, one might easily miscalculate a bank's level of inefficiency' (Mester, 1996, p. 1026). For instance, Hughes et al. (1995) in their study on 1989–90 US banks which exceed $1 billion in asset size, find that when they control for risk, inexhaustible economies of scale that increase with size are prevalent. When risk neutrality is imposed on the estimation, the large scale economies disappear and constant returns to scale are obtained. McAllister and McManus (1993) also show that for larger US banks estimates of scale economies are increased when they control for risk. (This tends to be more prevalent for banks up to $1 billion in asset size.) In contrast, Hughes and Mester (1993) find that estimates of increasing returns to scale for a wide range of bank sizes become constant returns when asset quality, financial capital and risk are taken into account. Clark (1996) also re-emphasises the influence of risk factors in the cost characteristics of US banks and shows how risk can statistically influence efficiency levels – in particular, he shows how *X*-inefficiency estimates tend to become smaller (about 3% from 9%) when risk factors are incorporated in frontier estimations.

In order to advance the aforementioned literature, this paper evaluates cost efficiency and technical change for Japanese commercial banks by comparing results obtained from two cost functions specifications. First we use the stochastic cost frontier methodology to estimate scale economies, scale efficiencies and X-inefficiency, as well as technical change, for a sample of Japanese commercial banks between 1993 and 1996 using a three input–three output Fourier-flexible cost function specification. The three outputs include total loans, total securities and total off-balance sheet items (nominal value). We then compare these results with those generated by a similar cost function which also includes variables controlling for risk and quality factors. In addition, we also evaluate the sensitivity of scale economy and X-inefficiency estimates to various risk and quality variables.

Our results show that when the underlying cost function specification does not control for risk and quality factors, scale economies are prevalent for all but the largest Japanese banks. Those larger than Yen 10,000 billion exhibit significant diseconomies. Overall, Japanese banks appear to be relatively scale efficient. When risk and quality factors are taken into account, however, only the very smallest banks exhibit significant economies with the majority of banks experiencing significant diseconomies of scale which appear to get larger with asset size. Estimates derived from the model including risk and quality variables suggested that there are widespread scale inefficiencies in the Japanese banking market. These results suggest that bank minimum efficient scale becomes smaller after controlling for risk, a finding similar to that of Hughes and Mester (1993). This contrasts with the results of Hughes et al. (1995) and McAllister and McManus (1993) who find either minimum efficient scale is increased or scale economies are never exhausted after controlling for risk. Our results also point to the limitations of previous studies on the cost characteristics of Japanese banking and also suggest different policy conclusions, namely, that the largest banks should reduce their size if they wish to benefit from scale economies. In contrast to the scale estimates and Clark's (1996) findings on US banking, X-inefficiency scores appear to be less sensitive to the inclusion of risk and quality variables. The mean level of X-inefficiency for the largest banks range between 5% and 7%. This also indicates that the largest Japanese banks should focus on reducing managerial and other inefficiencies, as well as reducing their size if they are to generate cost savings. Finally, this study also finds that technical change has reduced bank cost, but at a declining rate, between 1993 and 1996.

2. Methodology

Following Mester (1996), Cebenoyan et al. (1993) and Allen and Rai (1996) we use the stochastic cost frontier methodology. This approach labels a bank as inefficient if its costs are higher than those predicted for an efficient bank producing the same input/output configuration and the difference cannot be explained by statistical noise. The cost frontier is obtained by estimating a Fourier Flexible cost function with a composite error term, the sum of a two-sided error representing random fluctuations in cost and a one-sided positive error term representing inefficiency.

The single-equation stochastic cost function model can be given as

$$\mathrm{TC} = \mathrm{TC}(Q_i, P_i) + \varepsilon_i, \tag{1}$$

where TC is observed total cost, Q_i is a vector of outputs, and P_i is an input price vector. Following Aigner et al. (1977), we assume that the error term of the cost function is

$$\varepsilon = u + v, \tag{2}$$

where u and v are independently distributed. u is usually assumed to be distributed as half-normal, that is, a one-sided positive disturbance capturing the effects of inefficiency, and v is assumed to be distributed as two-sided normal with zero mean and variance σ^2, capturing the effects of the statistical noise.

Observation-specific estimates of technical inefficiency, u, can be calculated by using the distribution of the inefficiency term conditional on the estimate of the composed error term, as proposed by Jondrow et al. (1982). The mean of this conditional distribution for the half-normal model is shown as

$$E(u_i|\varepsilon_i) = \frac{\sigma\lambda}{1+\lambda^2}\left[\frac{f(\varepsilon_i\lambda/\sigma)}{1-F(\varepsilon_i\lambda/\sigma)} + \left(\frac{\varepsilon_i\lambda}{\sigma}\right)\right], \tag{3}$$

where $F(\cdot)$ and $f(\cdot)$ are the standard normal distribution and the standard normal density function, respectively. $E(u|\varepsilon)$ is an unbiased but inconsistent estimator of u_i, since regardless of N, the variance of the estimator remains non-zero (see Greene, 1993a, pp. 80–82). Jondrow et al. (1982) have shown that the ratio of the variability (standard deviation, σ) for u and v can be used to measure a bank's relative inefficiency, where $\lambda = \sigma_u/\sigma_v$, is a measure of the amount of variation stemming from inefficiency relative to noise for the sample. Estimates of this model can be computed by maximising the likelihood function directly (see Olson et al., 1980). Kaparakis et al. (1994), Allen and Rai (1996) and Mester (1996) all use the half-normal specification to test for inefficiency differences between financial institutions mainly in the US market. [2]

[2] See Bauer (1990) for an excellent review of the frontier literature and how different stochastic assumptions can be made. Cebenoyan et al. (1993) and Berger and DeYoung (1997), for example, use the truncated normal model. Mester (1993) in common with many (non-banking) studies uses the half-normal distribution. Stevenson (1980) and Greene (1990) have used normal-gamma model. Altunbas and Molyneux (1994) find that efficiency estimates are relatively insensitive to different distributional assumptions when testing the half normal, truncated normal, normal-exponential and gamma efficiency distributions, as all distributions yield similar inefficiency levels for the German banking markets.

The Fourier-flexible cost function used to calculate X-inefficiencies (as well as scale economies and technical change) incorporates a two-component error structure and is estimated using the maximum likelihood procedure. [3] First we estimate a cost function that controls for risk and quality factors and then we compare the results with those derived from the same cost function excluding all and then individual risk and quality variables (because we use three risk and quality variables there are five cost functions estimates in total). The cost function is given as

$$\begin{aligned}\ln \mathrm{TC} = {} & \alpha_0 + \sum_{i=1}^{3} \alpha_i \ln Q_i + \sum_{i=1}^{3} \beta i \ \ln P_i + \tau_1 \ln E + \lambda_1 \ln \mathrm{NPL/L} \\ & + \lambda_2 \ln \mathrm{L/TA} + t_1 T + \frac{1}{2} \left[\sum_{i=1}^{3} \sum_{j=1}^{3} \delta_{ij} \ln Q_i \ \ln Q_j \right. \\ & \left. + \sum_{i=1}^{3} \sum_{j=1}^{3} \gamma_{ij} \ln P_i \ \ln P_j + \phi_1 \ln E \ \ln E + t_{11} T^2 \right] \\ & + \sum_{i=1}^{3} \sum_{i=1}^{3} \rho_{ij} \ln P_i \ln Q_j + \sum_{i=1}^{3} \psi_{i\tau} \ln P_i \ \ln E + \sum_{i=1}^{3} \theta_{i\tau} \ln Q_j \ \ln E \\ & + \sum_{i=1}^{3} [a_i \cos(z_i) + b_i \sin(z_i)] + \sum_{i=1}^{3} \sum_{j=1}^{3} [a_{ij} \cos(z_i + z_j) \\ & + b_{ij} \sin(z_i + z_j)] + \varepsilon, \end{aligned} \tag{4}$$

where ln TC the natural logarithm of total costs (operating and financial cost); ln Q_i the natural logarithm of ith bank outputs; ln P_i the natural logarithm of ith input prices; ln E the natural logarithm of financial capital; [4] ln NPL/L the

[3] Spong et al. (1995), Berger et al. (1997) and Mitchell and Onvural (1996) have suggested that the Fourier-flexible functional form should be preferred over the translog because the former better approximates the underlying cost function across a broad range of outputs. The semi-non-parametric Fourier functional form has desirable mathematical and statistical properties because an (infinite) Fourier series is capable of representing any function exactly and even truncated Fourier series can approximate a function reasonably well throughout its entire range. In contrast, when using parametric methods like the translog, one holds the maintained hypothesis that the bank industry's true cost function has the translog form. If this maintained hypothesis is false misspecification error occurs. When using the Fourier functional form, one avoids holding any maintained hypothesis by allowing the data to reveal the true cost function through a large value of fitted parameters. For ease of exposition, however, we choose to use the translog functional form to illustrate the impact risk and quality factors have on Japanese commercial banks' cost efficiencies.

[4] Note that the financial capital variable (E) is fully interactive with the output (Q) and input price (P) variables but NPL/L and L/TA are not. This is because the inclusion of more than one of the risk/quality variables would significantly reduce the degrees of freedom, due to the expansion of Fourier terms and the limited number of observations.

natural logarithm of the ratio of non-performing loans to total loans; ln L/TA the natural logarithm of the ratio liquid assets to total assets; T time trend; Z_i the adjusted values of the log output ln Q_i such that they span the interval $[0, 2\pi]$; α, β, δ, γ, λ, ϕ, θ, ψ, ρ, λ, a, b and t are coefficients to be estimated.

Since the duality theorem requires that the cost function must be linearly homogeneous in input prices, the following restrictions have to be imposed on the parameters in Eq. (4):

$$\begin{aligned} &\sum_{i=1}^{3}\beta_i = 1; \quad \sum_{i=1}^{3}\gamma_{ij} = 0 \quad \text{for all } j; \\ &\sum_{i=1}^{3}\rho_{ij} = 0; \quad \sum_{i=1}^{3}\Psi_{ij} = 0 \quad \text{for all } j. \end{aligned} \tag{5}$$

Furthermore, the second order parameters of the cost function in Eq. (4) must be symmetric, that is,

$$\begin{aligned} &\delta_{ij} = \delta_{ji} \quad \text{for all } i, j, \\ &\gamma_{ij} = \gamma_{ji} \quad \text{for all } i, j. \end{aligned} \tag{6}$$

For the definition of inputs and outputs we use a variation of the intermediation approach proposed by Sealey and Lindley (1977) where the inputs, labour, physical capital and deposits are used to produce earning assets. Two of our outputs, total loans and total securities are earning assets and we also include total off-balance sheet items (measured in nominal terms) as a third output. Although the latter are technically not earning assets, this type of business constitutes an increasing source of income for banks and therefore should be included when modelling banks' cost characteristics, otherwise, total output would tend to be understated (Jagtiani and Khanthavit, 1996).

Following Mester (1996) we use loan-loss provisions as a proportion of total loans as the output quality proxy. [5] We also use a variable to account for liquidity risks because liquidity holdings (particularly those imposed by the authorities) represent a cost to bank that hold a higher proportion of cash and liquid assets have higher costs. As suggested in Hughes and Mester (1993) and Mester (1996) the level of equity capital, rather than the equity-to-assets ratio is included to control for differences in risk preferences. [6] We also include a time

[5] Berger and DeYoung (1997) argue that this variable may be a function of management efficiency, efficient banks will be better underwriters and monitors and hence will have lower losses, and hence it is endogenous, not exogenous. One referee also pointed out that a similar argument could be made for the liquidity risk variable, efficient mangers will hold only low levels of liquid assets, while inefficient mangers will hold excess amount of these low-yield assets.

[6] As Mester (1996, p. 1026) states, "Financial capital should be accounted for in the cost function and the level rather than the price of financial capital should be included since there is good reason to believe that cost-minimisation does not fully explain a bank's capital level – e.g., regulations set minimum capital-to-assets ratios, and bank managers may be risk averse".

trend in our cost frontier to capture the missing time dimension of inputs or other dynamics that are not modelled explicitly. [7]

The cost frontiers are estimated using the random effects panel data approach (as in Lang and Welzel, 1996). We use the panel data approach because technical efficiency is better studied and modelled with panels (See Baltagi and Griffin, 1988; Cornwell et al., 1990; Kumbhakar, 1993). The random effects model is preferred over the fixed effects model because the latter is considered to be the more appropriate specification if we are focusing on a specific set of N firms. Moreover, and if N is large, a fixed effects model would also lead to a substantial loss of degrees of freedom (See Baltagi, 1995).

Within sample scale economies are calculated as in Mester (1996) and are evaluated at the mean output, input price, quality and financial capital levels for the respective size quartiles. A measure of overall economies of scale (SE) is given by the following cost elasticity by differentiating the cost function in Eq. (4) with respect to output. [8] This gives us:

$$\begin{aligned}\mathrm{SE} &= \sum_{i=1}^{3} \frac{\partial \ln \mathrm{TC}}{\partial \ln Q_i} \\ &= \sum_{i=1}^{3} \alpha_i + \frac{1}{2} \sum_{i=1}^{3} \sum_{j=1}^{3} \delta_{ij} \ln Q_j + \sum_{i=1}^{3} \sum_{j=1}^{3} \rho_{ij} \ln P_i + \sum_{i=1}^{3} \theta_{i\tau} \ln E \\ &\quad + \mu_i \sum_{i=1}^{3} [-a_i \sin(Z_i) + b_i \cos(Z_i)] + 2\mu_i \sum_{i=1}^{3} \sum_{j=1}^{3} [-a_{ij} \sin(Z_i + Z_j) \\ &\quad + b_i \cos(Z_i + Z_j)]. \end{aligned} \tag{7}$$

If $\mathrm{SE} < 1$ then increasing returns to scale, implying economies of scale.
If $\mathrm{SE} = 1$ then constant returns to scale.
If $\mathrm{SE} > 1$ then decreasing returns to scale, implying diseconomies of scale.

Following McKillop et al. (1996) and Lang and Welzel (1996) the rate of technical progress may be inferred from changes in a firm's cost function over time. A time trend variable, T, serves as a proxy for disembodied technical change. The time-trend is a 'catch-all' variable that captures the effects of

[7] One referee suggested that because annual economic conditions are not controlled for in the cost function specifications the time trend will capture more than just technological factors. Ideally one should control for exogenous conditions that change over time (e.g. economic indicators, competition, financial regulations). To this end a method suggested by DeYoung and Hasan (1998) was recommended where non-performing loans were decomposed into two components, exogenous and internal. Unfortunately data limitations did not allow us to undertake such a breakdown.

[8] Evanoff and Israilevich (1995) make the distinction between scale elasticity and scale efficiency where the former is measured as in Eq. (7), and the latter measures the change in output required to produce at minimum efficient scale. Throughout this paper references to economies and diseconomies of scale relate to scale elasticities.

technological factors: i.e. learning by doing and organisational changes allowing for the more efficient use of existing inputs, together with the effects of other factors, such as changing environmental regulations (see Baltagi and Griffin, 1988; Nelson, 1984). Technical progress allows the firm to produce a given output, Q, at lower levels of total cost over time, holding input prices and regulatory effects constant. In order to estimate the impact of technical change we calculate the variation in the total cost due to a given change in technology. This can be measured by the partial derivative of the estimated cost function with respect to the time trend (T) and can be shown as follows:

$$T_C = \frac{\partial \ln \mathrm{TC}}{\partial T} = t_1 + t_{11} T. \tag{8}$$

The parameters on Eq. (8) capture the pure effect of technical change, that is the decline in costs, keeping constant input proportions. [9]

3. Data and results

Our data comprise the population of Japanese commercial banks listed in the London based IBCA bank credit rating agencies Bankscope (1997) database for the years 1993–1996, and consists of 139 banks for each year from 1993 to1995 and 136 in 1996. [10] The median asset size of banks included was Yen 1.6 trillion and the average asset size was Yen 5 trillion (see Appendix A for more details). Table 1 provides the descriptive statistics for the input, output and control variables for 1996.This shows that for 1996 the median bank had Yen 1.19 trillion in loans, Yen 334 billion in securities and Yen 41 billion of off-balance sheet items. Non-performing loans as a proportion of gross loans ranged between 0.29% and 9.5%, the latter figure perhaps suggesting that some banks faced substantial credit quality problems.

Various structural tests were undertaken to test for data poolability and heteroscedasticity and the results of these are shown in Table 2. Homoscedasticity, which implies the disturbance variance is constant across observations, is not rejected at the one percent level for the whole sample applying the Goldfeld and Quandt, (1965) test. [11] The question of whether to pool the data

[9] As in Lang and Welzel (1996), we do not include the interactive terms of outputs and input prices. Hence we are not able to measure the technical change associated with changes in output (scale augmenting in our estimates of technical change) and the technical change with the use of inputs due to changes in input prices.

[10] The data set includes commercial bank only and excludes long-term credit banks and trust bank.

[11] White's (1980) test was also undertaken to investigate cross-sectional heteroscedasticity and we could not reject the hypothesis of homoscedasticity at the 1% level of significance.

Table 1
Descriptive statistics of the outputs, inputs and control variables used in the model, 1996[a]

Variable	Description	Mean	Median	St. Dev.	Min	Max
TC	Total cost (YEN bil)	165.7	40.8	506.9	4.1	4291.5
P_1	Price of labour (YEN bil) (total personnel expenses/total asset)	0.0089	0.0091	0.0023	0.0001	0.0142
P_2	Price of funds (%) (total interest expenses/total funds)	0.0118	0.0101	0.0067	0.0051	0.0579
P_3	price of physical capital (%) (total depreciation and other capital expenses/total fixed assets)	0.3247	0.2720	0.2014	0.1842	0.9419
Q_1	Total loans (domestic loans, foreign loans and trust a/c loans)(YEN bil)	3373.0	1186.0	7903.0	98.0	46,887.0
Q_2	total securities (trading securities, Japanese public bonds, other investments and equity investments) (YEN bil)	1189.0	334.0	3005.0	32.0	23,098.0
Q_3	Off balance sheet Items (contingent liabilities, acceptances, guarantees and L/Cs) (YEN bil)	297.9	41.1	1029.9	1.5	5820.4
E	total equity (YEN bil)	179.1	58.7	417.3	4.6	2855.0
NPL/L	Non-performing loans/total loans (%)	2.40	1.89	1.78	0.29	9.54
L/TA	Cash and due from banks/total assets (%)	4.29	3.62	2.63	0.83	15.22
T	Time trend	–	–	–	1993	1996

[a] Number of observed banks: 136.

Table 2
Structural test results

Test performed	Test statistics	Degrees of freedom	Critical value	Decision
Goldfeld–Quandt Test Hetroscedasticity	1.110	$n_1 = 382$, $n_2 = 170$	$F_{0.01(n1-k,n2-k)} \cong 1.250$	Rejected
Poolability	1.002	$3k = 150$, $N - 4k = 353$	$F_{0.01(150,353)} \cong 1.00$	Not-rejected
Translog form	55.689	$k = 18$	$\chi^2_{0.05} = 28.869$	Rejected
No risk and quality variables	91.144	$k = 9$	$\chi^2_{0.05} = 16.916$	Rejected
No equity variables	87.288	$k = 7$	$\chi^2_{0.05} = 14.067$	Rejected
No NPL/L variables	15.510	$k = 1$	$\chi^2_{0.05} = 3.842$	Rejected
No L/TA variables	3.333	$k = 1$	$\chi^2_{0.05} = 3.842$	Not-rejected
No technical progress	41.022	$k = 2$	$\chi^2_{0.05} = 5.991$	Rejected

or not naturally appears with panel data. In the econometric model, we assume that estimated parameters are the same over time. However, this assumption can be tested using Chow's (1960) test. Table 2 shows that Chow's test for poolability over time yields an F-value of 1.002 which is distributed as $F(150, 353)$ under the null hypothesis: $H_0 : \beta_t = \beta$ for $t = 1, \ldots, T$, and this test does not reject poolability across time periods.

We also undertake likelihood ratio tests, as an alternative to the F-statistic for testing hypotheses about τ, λ_1 and λ_2 (see Greene, 1993b), to see if the cost function that included the risk and quality variables (RQCF) differed significantly from the standard model (CF). The likelihood ratio test rejects the hypothesis that the two models CF and RQCF are not significantly different. Similar tests were also undertaken to see whether the inclusion of individual risk and quality variables as well as the time trend significantly altered the model. Table 2 shows the likelihood ratio statistics indicating that all but the L/TA variables have a significant influence on model specification. This suggests that the equity and non-performing loans variables provide the bulk of information relating to quality and risk factors.

Table 3 shows the estimated scale, X-inefficiencies and technical change results (parameter estimates are given in Appendix A). The findings from the RQCF model which controls for risk and quality factors conflict with the results from previous studies on Japanese banking in that we find scale economies to be much smaller. For instance, McKillop et al. (1996) find evidence of 'appreciable' scale economies in their study using data from the five largest Japanese banks, and their results support the earlier findings of Kasuya (1986), Tachibanaki et al. (1991) and Fukuyama (1993). Our results show that diseconomies of scale become much more widespread and optimal bank size falls from around Yen 5–10 trillion to Yen 1–2 trillion when risk and quality factors are taken into account. Estimates of scale economies for the largest Japanese commercial banks tend to be overstated when the underlying cost function specification does not control for these factors. This finding also contrasts with the studies by Hughes et al. (1995) and McAllister and McManus (1993) on US banks which find that either optimal bank size increases or scale economies are never exhausted when risk and quality variable included. The conflicting results could be related to a variety of factors including: different institutional structures, the decline in capital strength of Japanese banks during the 1990s; the different time frame covered and growth variation in the output/input mix of Japanese compared with US banks.

Unlike Clark (1996) who finds that risk variables significantly alter X-inefficiency estimates for US banks, we find that in the case of Japanese banks the inefficiency results from both models are similar. Mean levels of inefficiency range between 5% and 7%, with no discernible trend across size classes. This suggests that if the average bank in each size class used its inputs as efficiently as possible it could decrease its costs somewhere in the region of 5–7%. These X-inefficiency scores are similar to the results found in recent US studies (see Berger and DeYoung (1997) and Berger and Humphrey (1997)). Overall the results from the model which controls for risk and quality factors (RQCF)

Table 3
Scale economies, inefficiencies and technical change for Japanese commercial banks 1993–1996[a]

Total assets sizes (Yen bil)	1993		1994		1995		1996	
	RQCF	CF	RQCF	CF	RQCF	CF	RQCF	CF
Scale economies[b]								
1–500	0.773*	0.981	0.774*	0.983	0.769*	0.990	0.774*	0.991
500–1000	0.889*	0.949*	0.885*	0.944*	0.879*	0.945*	0.875*	0.947*
1000–2000	0.981	0.946*	0.978	0.946*	0.978	0.949*	0.977	0.948*
2000–3000	1.050**	0.965**	1.050**	0.967**	1.044	0.961**	1.044	0.964*
3000–5000	1.091*	0.934*	1.093*	0.938*	1.090*	0.936*	1.086*	0.932*
5000–10,000	1.212*	1.008	1.210*	1.000	1.204*	0.995	1.196*	0.999
>10,000	1.457*	1.063**	1.455*	1.063**	1.455*	1.072*	1.456*	1.081*
Scale inefficiency[c]								
1–500	0.223	0.078	0.263	0.097	0.233	0.083	0.194	0.029
500–1000	0.166	0.171	0.150	0.193	0.150	0.202	0.151	0.166
1000–2000	0.000	0.153	0.000	0.172	0.000	0.134	0.000	0.125
2000–3000	0.045	0.168	0.067	0.145	0.065	0.083	0.078	0.081
3000–5000	0.069	0.204	0.080	0.164	0.072	0.169	0.072	0.102
5000–10,000	0.234	0.000	0.215	0.000	0.175	0.000	0.134	0.000
>10,000	0.297	0.229	0.254	0.225	0.249	0.240	0.259	0.251
Inefficiency scores								
1–500	0.073	0.065	0.072	0.065	0.069	0.063	0.074	0.070
500–1000	0.055	0.046	0.056	0.047	0.053	0.041	0.071	0.053
1000–2000	0.047	0.043	0.050	0.050	0.053	0.047	0.060	0.055
2000–3000	0.049	0.045	0.060	0.058	0.064	0.055	0.068	0.064
3000–5000	0.051	0.046	0.064	0.058	0.061	0.051	0.076	0.059
5000–10,000	0.056	0.067	0.070	0.081	0.053	0.053	0.037	0.045
>10,000	0.076	0.060	0.085	0.069	0.061	0.049	0.093	0.086
All	0.056	0.050	0.061	0.057	0.058	0.050	0.068	0.060
Overall technical progress[d]	−0.040*	−0.046*	−0.026*	−0.031*	−0.012*	−0.016*	0.002	−0.001

*For the scale economy estimates, statistically different from one at the one percent level for two-tailed test for the scale results, for the technical progress estimates statistically different from zero at the one percent level.

**For values significantly different from one at the 10% level.

[a] Results reported in the table are derived from estimated coefficients for a single equation panel data model 1993–1996. Estimates calculated for the mean values within each size category.

[b] The scale economies measure is $SE = (\partial \ln TC/\partial \ln Q_1) + (\partial \ln TC/\partial \ln Q_2) + (\partial \ln TC/\partial \ln Q_3)$ where TC is the actual cost of producing the average output bundle at the average input prices, financial capital and quality factors; Q_i is the volume of output i. $SE < 1$ indicates increasing returns to scale; $SE > 1$ indicates decreasing returns to scale; $SE = 1$ indicates constant returns to scale.

[c] The scale inefficiency measure is derived from the methodology suggested by Evanoff and Israilevich (1995).

[d] Overall technical progress can be measured as the elasticity of total cost TC with respect to time t, i.e., $T_C = \partial \ln TC/\partial T$.

show that scale economies are exhausted at lower levels of output compared with the case where risk and quality factors are not taken into account. Because the scale economy measure is a cost elasticity (the percent change in cost with respect to a percent increase in scale) while X-efficiency is (approximately) a percentage of total cost (the percent change in cost if the bank moved to the efficient cost frontier) we cannot directly compare the scale economy and X-inefficiency results. Therefore we have to transform the scale economy measure into a scale efficiency measure. Using the approach suggested by Evanoff and Israilevich (1995) the scale efficiency results, which measure the percentage that cost would decline if banks were to move to minimum efficient scale, are also reported in Table 3. [12] The scale efficiency results show that both the smallest and largest banks are the most scale inefficient when one controls for risk and quality factors. In contrast, estimates derived from the traditional cost function suggest that relatively large Japanese banks (those in the Yen 5–10 billion asset size category) are the most scale efficient. Overall, these results strongly suggest that optimal bank size tends to be overstated when the underlying cost function specification does not control for risk and quality factors. The scale efficiency results show that for the model that includes risk and quality factors the smallest Japanese banks as well as the largest (with assets over Yen 5000 billion) have substantial scale inefficiencies. This means that, on average, the largest banks would have to substantially reduce their size to reach optimal scale. In contrast, the estimates derived from the frontier which does not control for risk and quality suggest that all Japanese banks, apart from the largest size category, should grow to achieve optimal scale. Finally, our results also suggest that scale inefficiencies in the Japanese banking market are larger than X-inefficiencies, a finding that contrasts with earlier US studies (for instance see Berger and Humphrey (1991) and Mester (1996)). Overall these results show that for the largest banks greater cost savings are to be had through reducing output size rather than from improving X-efficiency. Table 3 also shows estimates of technical change. The technical progress results obtained from the RQCF model indicates that technical change in nominal terms,

[12] Thanks to one referee for pointing out the issues associated with comparing scale economies and X-inefficiencies. Evanoff and Israilevich (1995) demonstrate how scale elasticity measures are inappropriate for approximating the extent of scale efficiency in an industry. This is because, 'elasticity is related to incremental changes in output, and inefficiency to the change in output required to produce at the minimum efficient scale' (p. 1037). Evanoff and Israilevich (1995) calculate scale efficiency as follows: Percent change in unit costs = [estcost(j)/assets(j) − estcost(es)/assets(es)]/[estcost(j)/assets(j)], where, estcost(j) = estimated cost frontier evaluated for average bank in size category j, estcost(es) = estimated cost frontier evaluated for average bank in efficient scale size category, assets(j) = asset size of average bank in size category j, assets(es) = asset size of average bank in efficient scale size category. The percent change in unit costs is an approximate measure of scale inefficiency and will be positive for all categories "j" and it will equal zero for category "es."

has reduced the cost of production by 4.0% in 1993, 2.6% in 1994, 1.2% in 1995 and 0.2% in 1996. (The CF model also suggests that technical change has reduced bank costs.) These estimates, however, should be treated with caution given the problems associated with using a time trend to measure technical change (see Hunter and Timme, 1991).

Table 4 shows the influence different risk and quality variables have on scale economies and *X*-efficiency estimates. The scale economy and *X*-inefficiency values are calculated using different cost function specifications where individual risk and quality variables are excluded. Table 4 reveals that financial capital has the most noticeable influence on the scale economy and scale efficiency results. If one excludes it from the estimation the scale economy and scale efficiency estimates are similar (across) years as the cost function which has no risk and quality variables. Non-performing loans and the liquidity ratio appear to have little effect on the results. The result, however, should be treated with caution given that the influence of the financial capital variable (E) may be overstated because this variable is fully interactive with the output and input price variables in the cost function but the non-performing loan ratios and the liquidity ratio are not (see footnote 3). [13] It could be the case that the inclusion of financial capital impacts the results most because Japanese banks experienced a decline in their capital strength over the period of study whereas changes in provisioning levels were more modest.

To further investigate the determinants of Japanese commercial bank *X*-inefficiency we use a logistic regression model as suggested in Mester (1993 and 1996). Since the values of estimated inefficiencies range between zero and one the logistic functional form is preferred over the linear regression model. We regress the *X*-inefficiency values against various firm-specific characteristics. The independent variables used include: D-CITY = a binary variable to distinguish between city banks and other commercial banks, TASSET = total assets measured in billions of Yen, CRATIO = equity/total assets, ROAA = return on average assets, NL/TASSET = net loans/total assets, OBS/TASSET = off-balance sheet items (nominal value)/total assets, C&SF/TFUND = customer and short-term funds/total funds, L/TA = liquid assets/total assets, and finally, NPL/L = non-performing loans/total loans. TASSET controls for the overall size of the bank. NPL/L and L/TA are included to account for output quality and liquidity risk, respectively. CRATIO is the financial capital

[13] Following a referees suggestion we re-estimated the model using only NPL/L (non-performing loans to total loans) and then L/TA (liquid assets to total assets) as fully interactive variables. The inclusion of NPL/L as an interactive term influenced the scale and inefficiency measures having a smaller influence but more in-line with the model which included the equity variable. The L/TA variable had little impact on the overall results. In general, the inclusion of the equity term fully interacted had the biggest impact on scale measures, followed by the NPL/L with the L/TA having only a marginal impact. Results are available from the authors on request.

Table 4
Estimates of scale economies, inefficiencies and technical change for Japanese commercial banks 1993–1996 after excluding risk and quality variables[a,b]

	1993			1994			1995			1996		
	Excluded variables			Excluded variables			Excluded variables			Excluded variables		
	E	NPL/L	L/TA	*E*	NPL/L	L/TA	*E*	NPL/L	L/TA	*E*	NPL/L	L/TA
Scale economies[c]												
1–500	0.974	0.802*	0.833*	0.976	0.802*	0.832*	0.982	0.802*	0.833*	0.988	0.805*	0.835*
500–1000	0.952*	0.861*	0.880*	0.947*	0.856*	0.877*	0.957*	0.852*	0.871*	0.957*	0.848*	0.868*
1000–2000	0.947*	0.954*	0.959*	0.945*	0.952*	0.957*	0.948*	0.951*	0.957*	0.950*	0.950*	0.956*
2000–3000	0.958*	1.029	1.021	0.960**	1.030	1.022	0.957*	1.023	1.016	0.960**	1.024	1.015
3000–5000	0.960*	1.070*	1.056*	0.962**	1.072*	1.057*	0.960**	1.068*	1.055*	0.957*	1.064*	1.051*
5000–10,000	1.004	1.200*	1.169*	0.999	1.197*	1.167*	0.996	1.191*	1.162*	1.000	1.186*	1.155*
>10,000	1.073*	1.463*	1.390*	1.075*	1.460*	1.388*	1.080*	1.463*	1.388*	1.086*	1.461*	1.390*
Scale inefficiency[d]												
1–500	0.102	0.204	0.187	0.101	0.205	0.186	0.097	0.198	0.180	0.039	0.200	0.174
500–1000	0.130	0.168	0.137	0.125	0.170	0.143	0.120	0.177	0.156	0.119	0.172	0.137
1000–2000	0.169	0.092	0.085	0.146	0.093	0.088	0.151	0.094	0.086	0.143	0.091	0.086
2000–3000	0.152	0.000	0.000	0.144	0.000	0.000	0.122	0.000	0.000	0.131	0.000	0.000
3000–5000	0.146	0.102	0.112	0.137	0.108	0.119	0.133	0.103	0.097	0.127	0.104	0.108
5000–10,000	0.000	0.162	0.145	0.000	0.157	0.146	0.000	0.165	0.157	0.000	0.158	0.147
>10,000	0.200	0.226	0.219	0.204	0.230	0.222	0.228	0.245	0.236	0.236	0.247	0.234
Inefficiency scores												
1–500	0.065	0.073	0.079	0.063	0.072	0.073	0.064	0.066	0.070	0.069	0.073	0.072
500–1000	0.048	0.046	0.050	0.047	0.049	0.049	0.043	0.044	0.050	0.052	0.065	0.069

1000–2000	0.044	0.047	0.050	0.049	0.054	0.053	0.050	0.053	0.059	0.056	0.064	0.068
2000–3000	0.043	0.044	0.042	0.055	0.056	0.051	0.058	0.055	0.059	0.065	0.064	0.069
3000–5000	0.045	0.046	0.043	0.054	0.061	0.055	0.052	0.050	0.053	0.058	0.063	0.067
5000–10,000	0.066	0.061	0.060	0.077	0.077	0.075	0.054	0.058	0.062	0.044	0.048	0.051
>10,000	0.063	0.067	0.073	0.069	0.076	0.079	0.049	0.052	0.054	0.085	0.091	0.092
All	0.051	0.052	0.055	0.055	0.059	0.058	0.052	0.053	0.058	0.060	0.066	0.069
Overall technical progress[e]	−0.041*	−0.046*	−0.040*	−0.026*	−0.032*	−0.027*	−0.011*	−0.017*	−0.013*	0.005	−0.003	0.001

[a] E = Financial capital; NPL/L = Non-performing/Total Loans; L/TA = Liquid assets/Total Assets. Estimates derived by excluding E, NPL/L or L/TA from the cost function specification.

[b] Results reported in the table are derived from estimated coefficients for a single equation panel data model 1993–1996. Estimates calculated for the mean values within each size category.

[c] The scale economies measure is $SE = (\partial \ln TC/\partial \ln Q_1) + (\partial \ln TC/\partial \ln Q_2) + (\partial \ln TC/\partial \ln Q_3)$ where TC is the actual cost of producing the average output bundle at the average input prices, financial capital and quality factors; Q_i is the volume of output i. $SE < 1$ indicates increasing returns to scale; $SE > 1$ indicates decreasing returns to scale; $SE = 1$ indicates constant returns to scale.

[d] The scale inefficiency measure is derived from the methodology suggested by Evanoff and Israilevich (1995).

[e] Overall technical progress can be measured as the elasticity of total cost TC with respect to time t, i.e., $T_C = \partial \ln TC/\partial T$.

* For the scale economy estimates, statistically different from one at the one percent level for two-tailed test for the scale results, for the technical progress estimates statistically different from zero at the one percent level.

** For values significantly different from one at the 10% level.

Table 5
Logistic regression parameter estimates[a]

Variable	Coefficient	Standard error	t-Value
Constant	0.1128	0.0715	1.578
D-City	−0.0159	0.0068	−2.338
TASSET	−0.0059	0.0025	−2.348
CRATIO	−0.4726	0.0263	−17.981
ROAA	−0.4429	0.0390	−11.363
NL/TASSET	−0.0498	0.0165	−3.015
OBS/TASSET	0.0143	0.0040	3.594
C&SF/TFUND	0.0438	0.0215	2.033
LA/TASSET	0.2207	0.0106	20.865
NPL/L	0.0909	0.0128	7.118

[a] Value of the likelihood function = 906.8683.

ratio and this should be inversely related to inefficiency on the grounds that banks with low inefficiency will have higher profits and hence will be able to (holding dividends constant) retain more earnings as capital. ROAA is a performance measure and this should be inversely related to inefficiency. NL/TASSET, OBS/TASSET, and C&SF/TFUND are proxies for business mix. The logistic parameter estimates are shown in Table 5.

In accordance with Mester's (1996) findings, inefficiencies are inversely correlated with the financial capital variable (CRATIO) and bank performance (ROAA). This is, of course, to be expected given that banks with low inefficiency will have more profits and will be able to (holding dividends constant) retain more earnings as capital. The level of non-performing loans is positively related to bank inefficiency, which again might suggest that efficient banks are better at evaluating credit risk (see Berger and DeYoung, 1997). Efficient banks also appear to have lower loan-to-assets ratios and lower liquidity ratios. Banks that do more off-balance sheet business also appear to be more X-inefficient.

4. Conclusion

Previous studies on the cost characteristics of Japanese banking have found strong evidence of scale economies across a wide range of bank sizes and even for the largest firms. This overall finding implies that substantial cost savings can be exploited through further expansion. These results, however, are limited because the approaches that have been taken to estimate cost economies do not take into account important asset quality and risk factors which influence bank inefficiency. This is especially relevant in the case of Japanese banking where many firms have experienced asset quality problems and low levels of capitalisation since the early 1990s. Our study extends the established literature in that it evaluates the impact of risk and asset quality on cost efficiency in Japanese commercial banking and shows that scale economies will tend to be overstated if these factors are not taken into account. Following the approach suggested in Mester (1996) we show that if risk and quality factors are not taken into account scale efficiency and optimal bank size tends to be overstated. That is, optimal bank size is considerably smaller when risk and quality factors are taken into account when modelling the cost characteristics of Japanese banks. We also find that the level of financial capital has the biggest influence on the scale efficiency estimates. This is perhaps a reflection of the decline in capital strength of the Japanese banks over the period of study. X-inefficiency estimates, range between 5% and 7% and appear less sensitive to risk and quality factors. The scale economy and efficiency results suggest that the largest banks, therefore, can be more effective in reducing cost by decreasing output rather than improving X-efficiency. We suggest that these are important findings because they contrast with previous Japanese studies suggesting an alternative policy prescription, namely, that banks should grow to benefit from scale efficiency. In addition, we also find that scale efficiency estimates are more sensitive to risk and quality factors than are X-inefficiencies. In particular it seems that financial capital has the biggest influence on determining optimal bank size.

Acknowledgements

The authors wish to acknowledge the helpful comments of two anonymous referees.

Appendix A

See Tables 6–8.

Table 6
Number of commercial banks and descriptive statistics according to assets sizes

Year	Total assets sizes (billion Yen)[a]							
	1–500	500–1000	1000–2000	2000–3000	3000–5000	5000–10,000	>10,000	All
1993	18	30	40	17	14	8	12	139
1994	18	28	42	17	14	8	12	139
1995	18	27	42	17	14	9	12	139
1996	18	26	39	20	13	10	10	136
Total	72	111	163	71	55	35	46	553
Mean	327.9	682.3	1524.9	2453.2	3693.5	6817.0	40,025.0	5072.0
Median	335.2	661.1	1529.2	2427.5	3425.2	6823.0	47,736.0	1581.0
St. Dev.	76.9	113.0	303.5	268.2	570.3	1215.0	17,196.0	11,742.0
Min	130.8	514.3	1013.4	2004.4	3060.8	5022.0	10,819.0	131.0
Max	472.6	999.8	1999.1	2952.6	4967.5	9896.0	75,577.0	75,577.0

[a] The figures have been deflated with a base year 1990.

Table 7
Maximum likelihood parameter estimation of the cost frontier

Variable	Parameters	RQCF			CF		
		Coefficient	Standard error	T-value	Coefficient	Standard error	T-value
Constant	α_0	−0.1720	0.0197	−8.715	−0.1572	0.0211	−7.447
$\ln Q_1$	α_1	0.6596	0.0390	16.903	0.6956	0.0293	23.775
$\ln Q_2$	α_2	0.1800	0.0262	6.874	0.2342	0.0235	9.977
$\ln Q_3$	α_3	0.0152	0.0058	2.607	0.0188	0.0084	2.244
$\ln P_1$	β_1	0.3430	0.0158	21.660	0.3141	0.0155	20.212
$\ln P_2$	β_2	0.6198	0.0132	46.880	0.6142	0.0118	52.192
$\ln E$	τ	0.0932	0.0373	2.499			
ln (NPL/L)	λ_1	−0.0130	0.0038	−3.424			
ln (L/TA)	λ_2	0.0016	0.0061	0.262			
T	t	−0.0535	0.0149	−3.602	−0.0613	0.0162	−3.795
$\ln Q_1 \ln Q_1$	δ_{11}	0.0297	0.0082	3.640	0.0324	0.0148	2.189
$\ln Q_1 \ln Q_2$	δ_{12}	−0.0010	0.0059	−0.175	−0.0241	0.0114	−2.114
$\ln Q_1 \ln Q_3$	δ_{13}	0.0283	0.0136	2.087	0.0045	0.0029	1.559
$\ln Q_1 \ln E$	$\theta_{1\tau}$	−0.0284	0.0180	−1.577			
$\ln Q_2 \ln Q_2$	δ_{22}	0.0299	0.0052	5.715	0.0200	0.0044	4.533
$\ln Q_2 \ln Q_3$	δ_{23}	−0.0015	0.0120	−0.125	−0.0013	0.0019	−0.682
$\ln Q_2 \ln E$	$\theta_{2\tau}$	0.1791	0.0430	4.162			
$\ln Q_3 \ln Q_3$	δ_{33}	0.0216	0.0101	2.145	0.0281	0.0106	2.661
$\ln Q_3 \ln E$	$\theta_{3\tau}$	−0.0338	0.0301	−1.123			
$\ln E \ln E$	$\theta_{\tau\tau}$	−0.0301	0.0278	−1.084			
$\ln P_1 \ln P_1$	γ_{11}	0.0835	0.0070	11.883	0.0960	0.0075	12.859
$\ln P_1 \ln P_2$	γ_{12}	−0.0340	0.0299	−1.138	−0.0606	0.0276	−2.197
$\ln P_2 \ln P_2$	γ_{22}	0.0656	0.0292	2.247	0.0856	0.0286	2.990
$\ln P_1 \ln Q_1$	ρ_{11}	−0.0503	0.0160	−3.153	−0.0864	0.0364	−2.375
$\ln P_1 \ln Q_2$	ρ_{12}	−0.0651	0.0264	−2.470	0.0153	0.0280	0.546
$\ln P_1 \ln Q_3$	ρ_{13}	0.0479	0.0171	2.797	0.0174	0.0175	0.994
$\ln P_1 \ln E$	$\rho_{1\tau}$	0.0425	0.0146	2.901			
$\ln P_2 \ln Q_1$	ρ_{21}	0.0232	0.0107	2.168	0.1087	0.0223	4.871
$\ln P_2 \ln Q_2$	ρ_{22}	0.0504	0.0204	2.474	−0.0075	0.0077	−0.968
$\ln P_2 \ln Q_3$	ρ_{23}	−0.0255	0.0099	−2.571	−0.0274	0.0097	−2.816
$\ln P_2 \ln E$	$\rho_{2\tau}$	−0.1683	0.0313	−5.374			
$T * T$	t^2	0.0138	0.0030	4.672	0.0152	0.0031	4.863
$\cos(z_1)$	a_1	0.0016	0.0006	2.864	−0.0008	0.0006	−1.284
$\sin(z_1)$	b_1	0.0012	0.0006	2.058	0.0002	0.0006	0.274
$\cos(z_2)$	a_2	−0.0102	0.0053	−1.924	−0.0083	0.0015	−5.406
$\sin(z_2)$	b_2	−0.0054	0.0015	−3.603	0.0067	0.0015	4.367
$\cos(z_3)$	a_3	−0.0012	0.0006	−2.045	−0.0090	0.0035	−2.553
$\sin(z_3)$	b_3	0.0044	0.0014	3.126	0.0030	0.0010	2.861
$\cos(z_1 + z_1)$	a_{11}	0.0079	0.0025	3.166	0.0017	0.0020	0.860
$\sin(z_1 + z_1)$	b_{11}	0.0036	0.0016	2.311	−0.0029	0.0056	−0.521
$\cos(z_1 + z_2)$	a_{12}	−0.0116	0.0058	−2.001	−0.0027	0.0058	−0.463
$\sin(z + z_2)$	b_{12}	0.0015	0.0016	0.909	0.0070	0.0030	2.356
$\cos(z_1 + z_3)$	a_{13}	0.0067	0.0057	1.173	−0.0075	0.0016	−4.712
$\sin(z_1 + z_3)$	b_{13}	−0.0090	0.0043	−2.111	0.0055	0.0014	4.012

Table 7 (Continued)

Variable	Parameters	RQCF			CF		
		Coefficient	Standard error	T-value	Coefficient	Standard error	T-value
$\cos(z_2+z_2)$	a_{22}	0.0072	0.0055	1.316	0.0089	0.0053	1.679
$\sin(z_2+z_2)$	b_{22}	0.0013	0.0013	0.973	−0.0027	0.0010	−2.714
$\cos(z_2+z_3)$	a_{23}	0.0030	0.0058	0.521	−0.0093	0.0036	−2.589
$\sin(z_2+z_3)$	b_{23}	0.0093	0.0051	1.822	0.0080	0.0036	2.239
$\cos(z_3+z_3)$	a_{33}	0.0020	0.0014	1.383	−0.0019	0.0048	−0.393
$\sin(z_3+z_3)$	b_{33}	0.0002	0.0004	0.498	−0.0038	0.0015	−2.605
	σ_u^2/σ_v^2	5.1414	1.0503	4.895	2.3365	0.2487	9.394
	σ_v^2	0.0815	0.0029	27.790	0.0771	0.0027	28.592
$\ln P_3$	β_3	0.0372			0.0717		
$\ln P_1\ \ln P_3$	γ_{13}	−0.0495			−0.0354		
$\ln P_2\ \ln P_3$	γ_{23}	−0.0316			−0.0250		
$\ln P_3\ \ln P_3$	γ_{33}	0.0811			0.0604		
$\ln P_3\ \ln Q_1$	ρ_{31}	0.0271			−0.0223		
$\ln P_3\ \ln Q_2$	ρ_{32}	0.0147			−0.0078		
$\ln P_3\ \ln Q_3$	ρ_{33}	−0.0224			0.0100		
$\ln P_3\ \ln E$	$\rho_{3\tau}$	0.1258					
Log likelihood function		912.8628			863.9332		
Variance components:							
	$\sigma^2(v)=$	0.0002			0.0009		
	$\sigma^2(u)=$	0.0064			0.0050		

Table 8
Maximum likelihood parameter estimation of the cost frontier using different variables

Variable	Parameters	No Equity	No NPL/L	No L/TA
Constant	α_0	−0.1761*	−0.1533*	−0.1703*
		(0.0218)	(0.0193)	(0.0195)
$\ln Q_1$	α_1	0.7016*	0.6381*	0.6579*
		(0.0299)	(0.0361)	(0.0386)
$\ln Q_2$	α_2	0.2283*	0.1826*	0.1811*
		(0.0239)	(0.0255)	(0.0257)
$\ln Q_3$	α_3	0.0173**	0.0171**	0.0155**
		(0.0088)	(0.0087)	(0.0075)
$\ln P_1$	β_1	0.3142*	0.3398*	0.3429*
		(0.0151)	(0.0160)	(0.0159)
$\ln P_2$	β_2	0.6147*	0.6164*	0.6190*
		(0.0120)	(0.0133)	(0.0129)
$\ln E$	τ	–	0.1100*	0.0941*
			(0.0353)	(0.0374)
ln (NPL/L)	λ_1	−0.0110*	–	−0.0129*
		(0.0044)		(0.0038)

Table 8 (Continued)

Variable	Parameters	No Equity	No NPL/L	No L/TA
ln (L/TA)	λ_2	0.0048	0.0009	–
		(0.0071)	(0.063)	
T	t	−0.0559*	−0.0599*	−0.0541*
		(0.0162)	(0.0146)	(0.0148)
$\ln Q_1\ \ln Q_1$	δ_{11}	0.0347**	0.0299*	0.0267*
		(0.0168)	(0.0109)	(0.0108)
$\ln Q_1\ {}_2$	δ_{12}	−0.0249**	−0.0010	−0.0032
		(0.0113)	(0.0059)	(0.0058)
$\ln Q_1\ \ln Q_3$	δ_{13}	0.0049	0.0294**	0.0280*
		(0.0028)	(0.0134)	(0.0114)
$\ln Q_1\ \ln E$	$\theta_{1\tau}$	–	−0.0386	−0.0295
			(0.0280)	(0.0280)
$\ln Q_2\ \ln Q_2$	δ_{22}	0.0203**	0.0269**	0.0286*
		(0.0104)	(0.0129)	(0.0122)
$\ln Q_2\ \ln Q_3$	δ_{23}	−0.0012	−0.0012	−0.0064
		(0.0018)	(0.0020)	(0.0042)
$\ln Q_2\ \ln E$	$\theta_{2\tau}$	–	0.1722*	0.1772*
			(0.0423)	(0.0422)
$\ln Q_3\ \ln Q_3$	δ_{33}	0.0281*	0.0287*	0.0264*
		(0.0105)	(0.0103)	(0.0098)
$\ln Q_3\ \ln E$	$\theta_{3\tau}$	–	−0.0185	−0.0330
			(0.0276)	(0.0301)
$\ln E\ \ln E$	$\theta_{\tau\tau}$	–	−0.0363	−0.0266
			(0.0275)	(0.0177)
$\ln P_1\ \ln P_1$	γ_{11}	0.0957*	0.0843*	0.0836*
		(0.0075)	(0.0070)	(0.0070)
$\ln P_1\ \ln P_2$	γ_{12}	−0.0516	−0.0252	−0.0281**
		(0.0274)	(0.0293)	(0.0143)
$\ln P_2\ \ln P_2$	γ_{22}	0.0780*	0.0778*	0.0646**
		(0.0290)	(0.0285)	(0.0291)
$\ln P_1\ \ln Q_1$	ρ_{11}	−0.0906*	−0.0470*	−0.0505
		(0.0362)	(0.0186)	(0.0259)
$\ln P_1\ \ln Q_2$	ρ_{12}	0.0198	−0.0661*	−0.0653*
		(0.0275)	(0.0269)	(0.0263)
$\ln P_1\ \ln Q_3$	ρ_{13}	0.0154	0.0473*	0.0471*
		(0.0174)	(0.0176)	(0.0170)
$\ln P_1\ \ln E$	$\rho_{1\tau}$	–	0.0399*	0.0427*
			(0.0146)	(0.0146)
$\ln P_2 \ln Q_1$	ρ_{21}	0.1085*	0.2200*	0.0232
		(0.0229)	(0.0299)	(0.0131)
$\ln P_2\ \ln Q_2$	ρ_{22}	−0.0073	0.0401**	0.0506*
		(0.0181)	(0.0202)	(0.0203)
$\ln P_2\ \ln Q_3$	ρ_{23}	−0.0268*	−0.0269*	−0.0253*
		(0.0094)	(0.0102)	(0.0099)
$\ln P_2\ \ln E$	$\rho_{2\tau}$	–	−0.1490*	−0.1692*
			(0.0303)	(0.0313)
$T * T$	t^2	0.0151*	0.0142*	0.0138*
		(0.0031)	(0.0029)	(0.0030)

Table 8 (Continued)

Variable	Parameters	No Equity	No NPL/L	No L/TA
cos (z_1)	a_1	−0.0008*	0.0014	0.0016
		(0.0003)	(0.0015)	(0.0015)
sin (z_1)	b_1	0.0002	0.0009	0.0010
		(0.0006)	(0.0054)	(0.0015)
cos (z_2)	a_2	−0.0087*	−0.0073*	−0.0105**
		(0.0025)	(0.0019)	(0.0052)
sin (z_2)	b_2	−0.0062*	−0.0062*	−0.0055*
		(0.0024)	(0.0015)	(0.0015)
cos (z_3)	a_3	−0.0003	−0.0022	−0.0011
		(0.0052)	(0.0015)	(0.0045)
sin (z_3)	b_3	0.0018	(0.0049)	0.0047*
		(0.0015)	0.0045	(0.0041)
$\cos(z_1+z_1)$	a_{11}	−0.0006	0.0075**	0.0081*
		(0.0051)	(0.0035)	(0.0035)
$\sin(z_1+z_1)$	b_{11}	0.0003	0.0041**	0.0038*
		(0.0056)	(0.0020)	(0.0011)
$\cos(z_1+z_2)$	a_{12}	−0.0033**	−0.0080**	−0.0121**
		(0.0016)	(0.0041)	(0.0055)
$\sin(z_1+z_2)$	b_{12}	0.0003	0.0010	0.0013
		(0.0064)	(0.0064)	(0.0064)
$\cos(z_1+z_3)$	a_{13}	0.0009	0.0064*	0.0065
		(0.0058)	(0.0026)	(0.0056)
$\sin(z_1+z_3)$	b_{13}	0.0004	−0.0016	−0.0091**
		(0.0051)	(0.0044)	(0.0043)
$\cos(z_2+z_2)$	a_{22}	0.0089*	0.0078	0.0073**
		(0.0035)	(0.0041)	(0.0034)
$\sin(z_2+z_2)$	b_{22}	−0.0020	0.0003	0.0012
		(0.0015)	(0.0043)	(0.0014)
$\cos(z_2+z_3)$	a_{23}	−0.0069	−0.0010	0.0031**
		(0.0036)	(0.0056)	(0.0016)
$\sin(z_2+z_3)$	b_{23}	0.0101**	0.0086**	0.0093*
		(0.0050)	(0.0043)	(0.0040)
$\cos(z_3+z_3)$	a_{33}	−0.0017	0.0005	0.0020
		(0.0048)	(0.0044)	(0.0014)
$\sin(z_3+z_3)$	b_{33}	−0.0032**	−0.0005	0.0002
		(0.0015)	(0.0040)	(0.0040)
	σ_u^2/σ_v^2	2.4183*	3.7697*	5.1332*
		(0.2618)	(0.5889)	(1.0452)
	σ_u^2	0.0770*	0.0789*	0.0815*
		(0.0027)	(0.0031)	(0.0029)
$\ln P_3$	β_3	0.0711	0.0438	0.0381
$\ln P_1 \ \ln P_3$	γ_{13}	−0.0441	−0.0591	−0.0555
$\ln P_2 \ \ln P_3$	γ_{23}	−0.0264	−0.0526	−0.0365
$\ln P_3 \ \ln P_3$	γ_{33}	0.0705	0.1117	0.0920
$\ln P_3 \ \ln Q_1$	ρ_{31}	−0.0179	0.2503	0.0273
$\ln P_3 \ \ln Q_2$	ρ_{32}	−0.0125	0.0260	0.0147
$\ln P_3 \ \ln Q_3$	ρ_{33}	0.0114	−0.0204	−0.0218
$\ln P_3 \ \ln E$	$\rho_{3\tau}$		0.1091	0.1265

Table 8 (Continued)

Variable	Parameters	No Equity	No NPL/L	No L/TA
Log likelihood function		869.2190	905.1077	912.8062
Variance components:				
	$\sigma^2(v) =$	0.0009	0.0005	0.0002
	$\sigma^2(u) =$	0.0051	0.0054	0.0064

References

Aigner, D., Lovell, C., Schmidt, P., 1977. Formulation and estimation of stochastic frontier production models. Journal of Econometrics 6, 21–37.

Allen, L., Rai, A., 1996. Operational efficiency in banking: An international comparison. Journal of Banking and Finance 20 (4), 655–672.

Altunbas, Y., Molyneux, P., 1994. Sensitivity of stochastic frontier estimation to distributional assumptions: The case of the German banks. Institute of European Finance Paper, preliminary version, unpublished in 1994.

Baltagi, B.H., 1995. Econometric Analysis of Panel Data. Wiley, Chichester.

Baltagi, B.H., Griffin, J.M., 1988. A general index of technical change. Journal of Political Economy 96 (1), 20–41.

Bank of Japan, 1995. Financial reports of Japanese financial institutions for fiscal year 1994. Quarterly Bulletin, November 3–4, 27–36.

Bank of Japan, 1996. Recent monetary and economic conditions and issues facing the Japanese financial institutions for fiscal year 1994. Quarterly Bulletin, August 3-4, 5–13.

Bauer, P., 1990. Recent developments in the econometric estimations of frontiers. Journal of Econometrics 46, 39–56.

Berger, A.N., DeYoung, R., 1997. Problem loans and cost efficiency in commercial banks. Journal of Banking and Finance 21, 849–870.

Berger, A.N., Humphrey, D.B., 1991. The dominance of inefficiencies over scale and product mix economies. Journal of Monetary Economics 28, 117–148.

Berger, A.N., Humphrey, D.B., 1997. Efficiency of financial institutions: International survey and directions for future research. European Journal of Operational Research 98, 175–212.

Berger, A.N., Leusner, J.H., Mingo, J.J., 1997. The efficiency of bank branches. Journal of Monetary Economics 40 (1), 141–162.

Cebenoyan, A.S., Cooperman, E.S., Register, C.A., Hudgins, S.C., 1993. The relative efficiency of stock versus mutual S&Ls: A stochastic cost frontier approach. Journal of Financial Services Research 7, 151–170.

Chow, G.C., 1960. Tests of equality between sets of coefficients in two linear regressions. Econometrica 28, 591–605.

Clark, J.A., 1996. Economic cost, scale efficiency, and competitive viability in banking. Journal of Money, Credit and Banking 28 (3), (August) 342–364.

Cornwell, C., Schmidt, P., Sickles, R.C., 1990. Production frontiers with cross-sectional and time-series variation in efficiency levels. Journal of Econometrics 46, 185–200.

DeYoung, R., Hasan, I., 1998. The performance of De-Novo commercial banks: A profit efficiency approach. Journal of Banking and Finance 22 (5), 565–587.

Evanoff, D.D., Israilevich, P.R., 1995. Scale elasticity versus scale efficiency in banking. Southern Journal of Economics 61, 1036–1047.

Fukuyama, H., 1993. Technical and scale efficiency of Japanese commercial banks: A non-parametric approach. Applied Economics 25, 1101–1112.

Goldfeld, S., Quandt, R., 1965. Some tests for homoscedasticity. Journal of the American Statistical Association 60, 539–547.

Greene, W.M., 1990. A gamma-distributed stochastic frontier model. Journal of Econometrics 46, 141–163.

Greene, W.M., 1993a. The econometric approach to efficiency analysis. In: Fried, H.O., Lovell, C.A., Schmidt, P. (Eds.), The Measurement of Productive Efficiency: Techniques and Applications. Oxford University Press, Oxford.

Greene, W.M., 1993b. Econometric Analysis. Macmillan, New York.

Hughes, J.P., Mester, L.J., 1993. A quality and risk-adjusted cost function for banks: Evidence on the 'too-big-to-fail' doctrine. Journal of Productivity Analysis 4, 293–315.

Hughes, J.P., Lang, W., Mester, L.J., Moon, C.G., 1995. Recovering banking technologies when managers are not risk-neutral. Conference on Bank Structure and Competition. Federal Reserve Bank of Chicago May 1995, 349–368.

Hunter, W.C., Timme, S.G., 1991. Technological change in large US commercial banks. Journal of Business 64, 339–362.

Jagtiani, J., Khanthavit, A., 1996. Scale and scope economies at large banks: Including off-balance sheet products and regulatory effects 1984–1991. Journal of Banking and Finance 20 (7), 1271–1287.

Jondrow, J., Lovell, C.A., Materov, I.S., Schmidt, P., 1982. On estimation of technical inefficiency in the stochastic frontier production function model. Journal of Econometrics 19 (July) 233–238.

Kaparakis, E.I., Miller, S.M., Noulas, A.G., 1994. Short-run cost inefficiencies of commercial banks. Journal of Money, Credit and Banking 26 (4) (November) 875–893.

Kasuya, M., 1986. Economies of scope: Theory and application to banking. BOJ Monetary and Economic Studies 4, 59–104.

Kumbhakar, S.C., 1993. Production risk technical efficiency and panel data. Economics Letters 41, 11–26.

Lang, G., Welzel, P., 1996. Efficiency and technical progress in banking: Empirical results for a panel of German cooperative banks. Journal of Banking and Finance 20, 1003–1023.

McAllister, P.H., McManus, D., 1993. Resolving the scale efficiency puzzle in banking. Journal of Banking and Finance 17, 389–405.

McKillop, D.G., Glass, J.C., Morikawa, Y., 1996. The composite cost function and efficiency in giant Japanese banks. Journal of Banking and Finance 20, 1651–1671.

Mester, L.J., 1993. Efficiency in the savings and loan industry. Journal of Banking and Finance 17, 267–286.

Mester, L.J., 1996. A study of bank efficiency taking into account risk-preferences. Journal of Banking and Finance 20, 1025–1045.

Mitchell, K., Onvural, N.M., 1996. Economies of scale and scope at large commercial banks: Evidence from the Fourier flexible functional form. Journal of Money, Credit and Banking 28 (2), 178–199.

Nelson, R.A., 1984. Regulation, capital vintage, and technical change in the electric utility industry. Review of Economics and Statistics 66 (February), 59–69.

Olson, R.E., Schmidt, P., Waldman, D.M., 1980. A Monte Carlo study of estimators of stochastic frontier production functions. Journal of Econometrics 13, 67–82.

Sealey, C., Lindley, J.T., 1977. Inputs, outputs and a theory of production and cost at depository financial institution. Journal of Finance 32, 1251–1266.

Spong, K., Sullivan, R.J., DeYoung, R., 1995. What makes a bank efficient? – A look at financial characteristics and bank management and ownership structure, FRB of Kansas City Review, December, 1–19.

Stevenson, R.E., 1980. Likelihood functions for generalised stochastic frontier estimation. Journal of Econometrics 13, 57–66.

Tachibanaki, T., Mitsui, K., Kitagawa, H., 1991. Economies of scope and shareholding of banks in Japan. Journal of the Japanese and International Economies 5, 261–281.

White, H., 1980. A heteroscedasticity-consistent covariance matrix estimator and a direct test for heteroscedasticity. Econometrica 48, 817–838.