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ESTIMATION OF TECHNICAL AND ALLOCATIVE INEFFICIENCY USING FOURIER FLEXIBLE COST FRONTIERS FOR TAIWAN'S BANKING INDUSTRY*

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We construct a Fourier flexible functional form which can globally approximate the unknown true function, taking into account both technical inefficiency and allocative inefficiency components to avoid possible specification error. Empirical results suggest that technical inefficiency alone raises a bank's cost about 12 per cent on average, that allocative inefficiency alone raises an average bank's cost 15.8 per cent, and that the cost rises due to allocative inefficiency decrease over time. Translog evidence on economic efficiency suggests a much higher cost savings when achieving both technical and allocative efficiency than does the Fourier flexible function.

1 Introduction

Financial institutions in Taiwan before 1991 were tightly regulated by the government. However, ever since 1991 the structure of the island's financial service industry has been experiencing a rapid change due to financial deregulation. New commercial banks have been allowed to enter and existing banks can now open up branches. Foreign commercial banks and insurance companies have been allowed to set up operations on the island, as well. This deregulation has intensified the competition in banking and appears to have successively enhanced the efficiency of financial institutions. This is evidenced by the fact that in the wake of the Asian financial crisis, which began in mid-1997 in Thailand, and later extended to Malaysia, Indonesia, the Philippines, South Korea, Japan and Hong Kong, Taiwan has weathered the storm remarkably well. Both the stock and exchange markets have been relatively stable, while the rate of economic growth has been maintained at above 4.5 per cent.

For this reason, the current paper examines economic efficiency in Taiwan's banking industry with panel data from 22 domestic banks, spanning the period 1981–97.[1] A subset of the data has been used by Huang (1999,

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[1]In 1997 the book values of net total assets, investments and loans owned by the 22 banks constituted 77.82, 62.58 and 76.81 per cent respectively of the corresponding values possessed by the industry as a whole.

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2000) and Huang and Wang (2001, 2002). Efficiency studies of the banking sector have attracted much attention in applied work for the past two decades. However, many earlier studies were aimed at scale and scope efficiencies and mainly utilized data from the US banking industry, where lack of efficiencies was found to account for less than 5 per cent of costs, as pointed out by Berger *et al.* (1993b). Some studies on similar issues using data outside the USA have emerged, e.g. Murray and White (1983), Kim (1986), Kolari and Zardkoohi (1990), Berg and Kim (1994, 1998), Lang and Welzel (1996) and Resti (1997), to name a few. Measured economic inefficiency, often referred to as X-inefficiency, consists of technical and allocative inefficiencies and consumes 20 per cent or more of costs in banking, as suggested by research to date. In other words, differences in managerial ability to reduce costs or increase revenues are likely to be more important than the cost-saving effects resulting from the choice of scale and scope of production.

The translog cost function has been widely applied to studies of the economies of scale and product mix, merger, and X-efficiency, especially for the past decade. However, the commonly used translog function form can only locally approximate the underlying unknown cost function, because it is derived from a second-order Taylor expansion of an arbitrary function around a point. McAllister and McManus (1993) showed that the translog cost function specification gives a poor approximation when applied to banks of all sizes, because it forces large and small banks to lie on a symmetric U-shaped average cost curve. Therefore, it may perform poorly for observations far from the sample means (Berger and DeYoung, 1997). Even worse, White (1980) proved that the ordinary least squares estimates of the translog cost function are biased.

Gallant (1981, 1982) developed the Fourier flexible functional form (henceforth, the FF function), which can be used to approximate any unknown cost function.[2] The FF function is composed of two parts. The first is the usual translog function, while the second is the non-parametric Fourier series, which includes trigonometric transformations of the variables.[3] This function can globally approximate the unknown true function over the entire range of data, because the sine and cosine terms are mutually orthogonal over the interval $[0, 2\pi]$, and so each additional term will lead to a better approximation of the data's true path. For this reason, it has been shown to dominate the translog approximation. Elbadawi *et al.* (1983) and Chalfant

[2]Another approach that has been attempted to address the issue of a better-fitting functional form is the Box–Cox transformation, which has been applied by Pulley and Braunstein (1992), Pulley and Humphrey (1993), Noulas *et al.* (1993) and Humphrey and Pulley (1997). The authors are indebted to one of the referees for pointing this out.

[3]It is noteworthy that coefficients of the second-order terms in the translog component are derived from the Fourier series (to be discussed in Section 2.1). Therefore, the two parts of the FF function are not independent from each other, which may have been overlooked by Berger and DeYoung (1997), Berger *et al.* (1997), Berger and Mester (1997), DeYoung *et al.* (1998) and Altunbas *et al.* (2000).

and Gallant (1985) found that the estimates of elasticity of substitution using the parameters of an FF function have negligible bias when the sample size is large.

Despite its superior properties, it was not until recently that the FF function began drawing much attention; for example, McAllister and McManus (1993), Mitchell and Onvural (1996), Ivaldi *et al*. (1996), Berger and DeYoung (1997), Berger *et al*. (1997), Berger and Mester (1997), DeYoung *et al*. (1998) and Altunbas *et al*. (2000) have exploited it to examine the efficiency as well as scale and scope economies of banks. A potential difficulty inherent to an FF function is that its construction involves a complicated and tedious process, and some restrictions implied by economic theory must be imposed. Recently, Wheelock and Wilson (2001) pointed out that the FF function form presents a few open statistical problems.

Although Berger and DeYoung (1997), Berger *et al*. (1997), Berger and Mester (1997) and DeYoung *et al*. (1998) considered technical inefficiency (TI), they failed to model allocative inefficiency (AI) explicitly. This may actually lead to misspecification. Consequently, their parameter estimates are likely to be biased substantially.[4] In addition, these works included the scaled variables of output quantities and input prices only in the Fourier series. For the translog part of the function, they used original (unscaled) variables, inconsistent with Gallant's (1981, 1982) idea in constructing an FF function, which implicitly assumes that the translog and the Fourier series parts are independent. It has been shown by Gallant (1982) that the coefficients of the second-order terms in the translog portion are associated with the chosen Fourier series. Thus, their FF functions may not be able to achieve a close approximation in Sobolev norm. This invalid assumption may also lead to biased and inconsistent parameter estimates.

This paper is devoted to uncovering new evidence on the X-efficiency of Taiwan's commercial banks, where an FF shadow cost function is utilized to escape the recognized problems in applying the translog specification. More importantly, this FF function accounts for both TI and AI in order to avoid specification errors. The parameter estimates from the more complete and appropriate function are then used to compute the potential percentage cost reductions, representing the degree of inefficiency due to TI or AI or both.

It is a useful exercise to decompose the overall economic inefficiency into AI and TI and then to compute the costs incurred by them. Higher potential cost savings from achieving allocative efficiency indicate that a greater reduction in cost would be possible by optimizing the input mix. The allocative distortions may be attributed to government regulation of the industry under consideration and/or a slow adjustment to past changes in

[4]Atkinson and Cornwell (1994a, 1994b) suggested that TI and AI are highly correlated in a study of the American airline industry, and the bias from assuming TI or AI alone is significant.

input prices. Higher cost savings due to a greater technical efficiency imply that managers should direct their attention to enhancing the productivity of all inputs such that firms can always be operating on their efficient production frontiers.

Section 2 of the paper outlines the construction of an FF cost function and introduces TI and AI parameters into the cost function, which permits the identification and consistent estimation of firm-specific AI and TI with panel data. Section 3 describes the data set, while in Section 4 we discuss the empirical findings. Section 5 concludes the paper.

2 The Methodology

This section briefly introduces the construction of an FF cost function in Section 2.1, and readers are suggested to refer to Gallant (1981, 1982) for details. Section 2.2 derives the TI and AI parameters in the FF cost function and depicts the estimation procedures.

2.1 FF Cost Function

The FF function represents a semi-nonparametric approach, combining a standard translog form with the non-parametric Fourier form; hence, it is more flexible than the translog form alone and nests the translog form as a special case. The FF form has additional terms that are linear combinations of sine and cosine functions (called a Fourier series), which can represent exactly any well-behaved multivariate function, such as the cost function, due to the fact that sine and cosine functions are mutually orthogonal and function space spanning. The procedure for constructing an FF function is outlined here and readers are suggested to refer to Gallant (1981, 1982), Elbadawi *et al.* (1983), Chalfant and Gallant (1985), Eastwood and Gallant (1991) and Gallant and Souza (1991) for detailed discussions.

Let $\ln C^*(p, y)$ be the true logarithmic cost function of a cost-minimizing firm, where $p = (p_1, \ldots, p_N)'$ denotes an $N \times 1$ vector of input prices and $y = (y_1, \ldots, y_M)'$ is an $M \times 1$ vector of output quantities. Let p and y be rescaled by

$$l_i = \ln p_i + \ln a_i > 0 \qquad i = 1, 2, \ldots, N \tag{1}$$

$$q_j = \mu_j(\ln y_j + \ln a_j) > 0 \qquad j = 1, 2, \ldots, M \tag{2}$$

where the l_i and q_j are scaled input prices and output quantities, respectively. Location parameters $\ln a_i$ and $\ln a_j$ are commonly specified as $\ln a_i = -\min(1 n p_i) + 10^{-5}$, $i = 1, \ldots, N$, and $\ln a_j = -\min(\ln y_i) + 10^{-5}$, $j = 1, \ldots, M$. This guarantees that the minimum values of the scaled log-input prices and log-output quantities will be slightly greater than zero. Notation μ_j ($j = 1, \ldots, M$) is the scaling factor of output j to be determined shortly.

Let $l = (l_1, \ldots, l_N)'$ and $q = (q_1, \ldots, q_M)'$ be $N \times 1$ and $M \times 1$ vectors of scaled input prices and output quantities, respectively. A logarithmic version of the FF function, $g_K(x|\theta)$, can approximate the true (log) cost function $g(x') = g(l',q') = \ln C^*$ as closely as desired in Sobolev norm. Function $g_K(x|\theta)$ may be expressed as[5]

$$g_K(x|\theta) = u_0 + b'x + \frac{1}{2}x'\psi x + \sum_{\alpha=1}^{A}\left\{\beta_\alpha + 2\sum_{j=1}^{J}\left[u_{j\alpha}\cos(j\lambda k'_\alpha x) - v_{j\alpha}\sin(j\lambda k'_\alpha x)\right]\right\} \tag{3}$$

with $\psi = -\Sigma_{\alpha=1}^{A}\beta_\alpha\lambda^2 k_\alpha k'_\alpha$, and the elementary multi-index k_α, which is an $N + M$ vector with integer components, has length $|k_\alpha| = \Sigma_{i=1}^{N+M}|k_{i\alpha}| \le K$ (a constant). The criteria for selecting k_α and the chosen vectors of k_α by this exercise are shown in Appendix A.

The common scaling factor λ is computed as

$$\lambda = \frac{2\pi - \varepsilon}{\max(l_i\colon i = 1, 2, \ldots, N)}$$

for some ε between 0 and 2π. Gallant (1982) suggested $2\pi - \varepsilon = 6$. The purpose of λ is to make the largest of the scaled log-input prices slightly less than 2π. While λ is required to be common to all the input prices, output quantities can be measured by using a distinct scale of measurement without any impact on the analysis. The μ_j, $j = 1, \ldots, M$, are the scaling factors for outputs and are used to make each of the largest scaled log-output variables the same. They are defined as[6]

$$\mu_j = \frac{\max(l_1, l_2, \ldots, l_N)}{\ln y_j^{\max} + \ln a_j} \qquad j = 1, 2, \ldots, M$$

where $y_j^{\max}$ is the maximum value of output j in the sample. Vectors k_α and b can be partitioned into $k_\alpha = (r'_\alpha, \mathrm{r}'_\beta)'$ and $b = (c', d')'$, where r_α and c are both $N \times 1$ vectors, and r_β and d are $M \times 1$ vectors. Therefore,

$$\begin{aligned} S &= \frac{\partial}{\partial l}g_K(x|\theta) \\ &= c - \lambda\sum_{\alpha=1}^{A}\left\{\beta_\alpha\lambda k'_\alpha x + 2\sum_{j=1}^{J} j\left[u_{j\alpha}\sin(j\lambda k'_\alpha x) + v_{j\alpha}\cos(j\lambda k'_\alpha x)\right]\right\}r_\alpha \end{aligned} \tag{4}$$

The optimal input share equation (4) together with equation (3) form a system of simultaneous equations with $1 + N + M + A\ (1 + 2J)$ unknown parameters, which should be estimated simultaneously after appending

[5]Function $g_K(x|\theta)$ can also be given as a complex-valued exponential representation. Please see Gallant (1982).

[6]Mitchell and Onvural (1996) defined their u_j using 6 as the numerator, which differs from Gallant (1982).

random disturbances to each equation. A simultaneous estimation will not only improve the efficiency of the estimators, but also make the joint estimation of technical and allocative efficiencies possible.

Microeconomic theory imposes several restrictions on the parameters of a cost function.[7] Some of them, e.g. homogeneity and symmetry, have to be imposed directly on the cost function during estimation. Others, such as concavity and the characteristics of a firm's production function, can be tested.

2.2 *X-efficiency*

A firm's production plan may exhibit TI and/or AI. The most extensively used definition of TI has been proposed by Farrell (1957). This definition leads to two distinct measures, namely output TI and input TI, which are equal if and only if a firm's technology exhibits constant returns to scale. An output technically inefficient firm is characterized by its failure to produce maximal output given a set of inputs. An input technically inefficient firm is described as having an over-utilization of inputs given output and the input mix. A firm is said to be allocatively inefficient if it fails to equate the marginal rate of technical substitution between any two of its inputs to the ratio of corresponding input prices.

As the widely used standard econometric stochastic frontier approach, sometimes referred to as the error component approach, often imposes restrictive assumptions on the distributions of the random disturbances, such as normality and independence, in order to estimate TI and AI we adopt the parametric approach, first proposed by Lau and Yotopoulos (1971) and later generalized by Toda (1976), Atkinson and Halvorsen (1980, 1984), Lovell and Sickles (1983), Atkinson and Cornwell (1993, 1994a, 1994b) and Kumbhakar (1996a, 1996b, 1997). This approach refers to output TI as a factor that scales output up from the production frontier and to input TI as a factor that scales down input usage. The utilization of the parametric approach allows us to model AI explicitly, and further to derive the exact relationship between AI and cost (see, for example, Kumbhakar, 1996b, 1997; Kumbhakar and Lovell, 2000). By contrast, only an approximate relationship can be specified by the error component approach, as has been suggested by Bauer (1985, 1990), Ferrier and Lovell (1990) and Kumbhakar (1991).

In the context of a parametric approach, all firms' decisions are assumed to be based on shadow input prices, which differ from the observed input prices due to regulation or sluggish adjustment to past changes in input prices. The shadow scaled input prices are defined as $l_i^* = l_i + \ln h_i$, $i = 1, \ldots, N$, where the h_i are positive but unknown parameters to be estimated

[7]According to microeconomic theory, a cost function must be (i) non-decreasing in input prices, (ii) homogeneous of degree one in input prices, (iii) concave in input prices and (iv) continuous in input prices.

and are used to measure the extent to which the shadow and actual input prices differ.[8] Clearly, when $h_i = 1$, for all inputs, there will be no AI.

Kumbhakar (1997) suggested that the appropriate measure of TI is input savings, which gives the maximum rate at which the use of all the factors can be decreased leaving the output quantities intact, because outputs are treated as exogenous in a cost-minimizing framework. Thus, the (log) observed cost function and the corresponding cost shares are expressed as (see Atkinson and Cornwell (1994a) for a detailed derivation)

$$\ln C = -\ln B + g_K(x^* | \theta) + \ln \sum_i S_i^* h_i^{-1} \tag{5}$$

$$S_i = \ln\left(S_i^* h_i^{-1}\right) - \ln \sum_i S_i^* h_i^{-1} \qquad i = 1, \ldots, N \tag{6}$$

where $\ln C$ is the actual (observed) logarithmic cost for a representative firm, $x^{*\prime} = (l^{*\prime}, q')$, $g_K(x^*|\theta)$ is the FF shadow cost function approximated by the FF form, $S_i^* = \partial g_k(x^*|\theta)/\partial l_i^*$ is the shadow cost share of the ith input and S_i its observed counterpart, and B ($0 < B \leq 1$) is a scaling parameter representing the extent to which the actual input mix diverges from its optimal counterpart.

Translated into cost, term B in equation (5) captures the addition to efficient cost $g_K(x^*|\theta)$ due to TI. The higher the value of input-saving TI B is, the more technically efficient the firm is. When $B = 1$, the firm is said to be fully technically efficient. The terms of $-\ln B + g_K(x^*|\theta)$ can also be referred to as the FF efficiency-adjusted shadow cost function. It is noteworthy that TI B only appears in equation (5). In other words, the presence of TI has no effect on a firm's cost shares; this does not imply that the presence of TI is incapable of affecting a firm's demand for inputs, but rather that the presence of B raises all of a firm's input demands equi-proportionately, leaving these input shares unchanged.

Equations (5) and (6) form a system of simultaneous equations, composed of a cost function and $N - 1$ cost shares, which can be estimated after classical random disturbances are added to each of these equations.[9] Some additional structures need to be put on the behaviour of TI and AI over time and across firms so as to make the model estimable and reasonable. Specifically, TI B is assumed to vary both across firms (n) and over time (t), and is parsimoniously formulated as

$$-\ln B_{nt} = -\ln K_{0n} + K_1 t + K_2 t^2 \qquad n = 1, \ldots, F, \quad t = 1, \ldots, T$$

[8]Following Atkinson and Halvorsen (1980) and Atkinson and Cornwell (1994a), we assume that $p_i^* = h_i p_i$, $i = 1, \ldots, N$. Therefore, $l_i^* = \ln(h_i p_i a_i) > 0$, $i = 1, \ldots, N$. The same specification has been exploited in the estimation of the shadow profit function by, for example, Berger *et al.* (1993a), Kumbhakar (1996a) and Huang (1999, 2000).

[9]Since the N cost shares must sum to unity, one of these share equations must be deleted in the estimation to avoid the problem of singularity in the variance–covariance matrix of the random disturbances.

where K_{0n} is firm-specific parameters, and K_1 and K_2 are both invariant over time and across firms.[10]

The formulation above reduces to a standard fixed-effect model when $K_1 = K_2 = 0$. In fact, terms $K_1 t$ and $K_2 t^2$ capture the pure effect of technical change, keeping constant the input mix and output quantities. In practice, it is possible that no firm is fully technically efficient. Thus, for the purpose of estimation, we have to normalize K_{0n} to unity for the most efficient firm (say firm e) in the sample, so that the relative input technical efficiency of firm n ($\neq e$) is defined as $K_{0n}/K_{0e} = K_{0n}$. Namely, TI enters the cost equation through a firm-specific intercept, $-\ln K_{0n}$, $n = 1, \ldots, F$ and $n \neq e$, together with the linear and quadratic time trends.

As far as AI is concerned, the AI terms (h_i) are restricted similarly to the specification of TI as follows:

$$h_{int} = H_{0in} + H_{1i}t + H_{2i}t^2 \qquad i = 1, \ldots, N, \quad n = 1, \ldots, F, \quad t = 1, \ldots, T$$

where only the intercept H_{0in} is allowed to change across firms, while the other two coefficients are invariant across firms and over time, capturing the linear and quadratic time effects. Since equations (5) and (6) are homogeneous of degree zero in the h_i, one of the N inputs (say the Nth) has to be elected as the *numéraire* and the corresponding H_{0Nn} is normalized to unity in addition to $H_{1N} = H_{2N} = 0$ for each firm in the sample under consideration. The remaining $N - 1$ relative H_{0in} and $2(N - 1)$ coefficients of time effects in turn can be estimated for each firm. If $H_{0in} < 1$ ($H_{0in} > 1$), then firm n mistakenly employs more (less) of input i relative to the *numéraire*. The presence of allocative distortion would thus raise the firm's actual cost above its cost frontier. The foregoing specifications for $-\ln B_{nt}$ and h_{int} are the same as those of Huang (2000) using similar data.

A non-linear iterative seemingly unrelated regression technique is utilized to estimate these equations simultaneously, using panel data on Taiwan's banking industry as described in Section 3. No further distributional assumptions on the error vector are needed. This technique is equivalent to the maximum likelihood when convergence is achieved.

3 Data Description

Following the financial intermediation approach, we identify three output categories including investments y_1, which consist of government and corporate securities, short-term loans y_2 and long-term loans y_3. Deposits and borrowed money X_1, labour X_2 and physical capital X_3 are defined as inputs. We collect panel data from 1981 to 1997 on 22 of Taiwan's domestic banks,

[10]Both K_1 and K_2 can certainly be specified as firm-specific parameters, as suggested by Cornwell *et al.* (1990). However, during estimation, it was very difficult to reach convergence.

TABLE 1
SAMPLE STATISTICS

Variables	*Mean*	*Standard deviation*	*Minimum*	*Maximum*
COST[a]	15068.38	16740.28	138.33	78873.50
y_1[a]	34542.18	48647.70	4.68	504106.28
y_2[a]	59165.81	66790.06	208.60	273550.94
y_3[a]	104853.40	143540.67	271.08	746363.69
p_1	0.0624	0.0234	0.0238	0.2108
p_2	0.6124	0.2386	0.1756	1.3691
p_3	0.5107	0.5736	0.0522	7.6172
S_1	0.7163	0.0793	0.4396	0.9012
S_2	0.1427	0.0545	0.0370	0.3931
S_3	0.1410	0.0473	0.0350	0.3850
ln COST[b]	8.8548	1.4716	4.9296	11.2756
$\ln y_1$[b]	9.4066	1.7960	1.5430	13.1305
$\ln y_2$[b]	10.1023	1.6196	5.3404	12.5192
$\ln y_3$[b]	10.5622	1.6764	5.6024	13.5230
$\ln p_1$[b]	−2.8323	0.3331	−3.7401	−1.5570
$\ln p_2$[b]	−0.5699	0.4085	−1.7394	0.3142
$\ln p_3$[b]	−0.8653	0.5443	−2.9531	2.0304
l_1	0.9077	0.3331	0.00001	2.1831
l_2	1.1695	0.4085	0.00001	2.0536
l_3	2.0878	0.5443	0.00001	4.9835
q_1	3.3819	0.7724	3.49509D-06	4.9835
q_2	3.3056	1.1243	6.43187D-06	4.9835
q_3	3.1206	1.0548	6.20799D-06	4.9835

Notes: l_1, l_2 and l_3 are scaled log-input prices, while q_1, q_2 and q_3 are scaled log-output quantities. Number of observations 373.
[a]Measured in millions of New Taiwan dollars.
[b]Notation ln denotes the natural logarithm.

of which 11 are substantially large public banks when compared in terms of total assets with the remaining 11 private banks. The main source of data comes from publications of the Central Bank and the Ministry of Finance, Taiwan. However, the number of workers and labour costs of each bank are not available prior to 1991, and hence they are collected by a survey conducted in 1992. After 1992, the public has access to the two variables. One of the sample banks entered the industry in 1982. Thus, there are 373 observations in the sample. Sample statistics for each of the original and transformed variables are summarized in Table 1.

4 EMPIRICAL RESULTS

To produce bias-minimizing and asymptotically normal estimators, we take the number of parameters approximately equal to the number of effective sample observations raised to the two-thirds power, as suggested by Chalfant and Gallant (1985) and Eastwood and Gallant (1991), and later adopted by Mitchell and Onvural (1996). For the purpose of comparison, parameters of both the FF and translog efficiency-adjusted shadow cost functions are estimated using TSP 4.5 software; they are reported in Table 2. All the coefficient estimates of the Fourier series are shown in Appendix B since these terms are used to allow the FF function to approximate the true function more closely and have no economic implications to the question at hand. Because size effects on TI and AI are an interesting issue and in order to make convergence easier, the full sample is further divided into five groups according to their total assets. Each group is then treated as if it were a single firm, leaving only four firm-specific intercepts (one is normalized to unity) plus ten shadow parameters, together with the original parameters in the cost function, to be estimated.

As argued by Gallant (1982), the imposition of monotonicity (a cost function is non-decreasing in all input prices and output quantities) or concavity (a cost function is concave in input prices), or both, will not affect the ability of the FF cost function to approximate the true function. These two conditions are only checked for the translog function and are found to be satisfied by most observations, and thus hold on average.[11] One is led to conclude that the coefficient estimates in Table 2 can properly describe the representative bank's technology. However, the joint test of the hypothesis that all the Fourier series have zero coefficients is decisively rejected using the Wald test even at the 1 per cent level of significance, indicating that the FF cost function is more relevant than the translog counterpart in describing firms' cost-minimizing behaviours. Given the above test results, inferences on scale and scope economies and X-efficiency using the FF function will be more reliable and may lead to sharply different policy implications from those using the translog specification. Because the test for homotheticity of a production function is decisively rejected even at the 1 per cent significance level by both the FF and translog functions, it is not necessary to test for the homogeneity condition.

The coefficient estimates of the linear and quadratic trends for the AI parameters (H_{ji}, $j = 1, 2$) are ignored by the FF specification, because they are insignificantly estimated, while they are considered only for the AI parameter corresponding to the labour input in the translog specification for the same reason. Similar to Altunbas *et al.* (2000), both specifications find the presence of technical progress in the banking sector, though the rate of technical advancement declines over time due to positive estimates of the quadratic trend. On the other hand, the allocative distortion of the labour input in the translog function deteriorating over time is due to positive estimates of both linear and quadratic trends. It is expected that the cost incurred by

[11]It is a common difficulty faced by most empirical studies, e.g. Gropper (1995), Glass *et al.* (1995) and Röller (1990), that the regularity conditions can only be passed by most, but not all, of the sample. This is potentially due to large adverse random disturbances. In other words, these conditions are only required to hold on average.

TABLE 2
ESTIMATES OF THE FOURIER COST FUNCTION AND THE TRANSLOG COST FUNCTION

Fourier cost function			*Translog cost function*		
Parameter	*Estimate*	*Standard errors*	*Parameter*	*Estimate*	*Standard errors*
Intercept	−12.9953**	4.2863	Intercept	1.2619***	0.2905
l_1	0.5466***	0.0490	$\ln p_1$	0.3897***	0.0328
l_2	0.4410***	0.0490	$\ln p_2$	0.5833***	0.0365
q_1	5.8258***	1.4844	$\ln y_1$	−0.1097	0.0883
q_2	3.3763***	1.0506	$\ln y_2$	−0.0479	0.0801
q_3	−3.2747**	1.3690	$\ln y_3$	0.8934***	0.0817
q_1^2	5.2036**	1.6079	$\ln y_1^2$	0.0175	0.0202
q_2^2	4.3638***	1.4662	$\ln y_2^2$	0.2183***	0.0194
q_3^2	5.3173***	1.5691	$\ln y_3^2$	0.1382***	0.0219
$l_1 * l_2$	−0.1793***	0.0212	$\ln p_1 * \ln p_2$	−0.1108***	0.0123
$l_1 * l_3$	−0.0089*	0.0047	$\ln p_1 * \ln p_3$	0.0007	0.0006
$l_1 * q_1$	0.0016	0.0088	$\ln p_1 * \ln y_1$	0.0011	0.0029
$l_1 * q_2$	0.0216***	0.0045	$\ln p_1 * \ln y_2$	0.0065**	0.0027
$l_1 * q_3$	0.0547***	0.0052	$\ln p_1 * \ln y_3$	0.0310***	0.0042
$l_2 * l_3$	0.0031*	0.0018	$\ln p_2 * \ln p_3$	−0.0052*	0.0032
$l_2 * q_1$	0.0016	0.0088	$\ln p_2 * \ln y_1$	−0.0005	0.0031
$l_2 * q_2$	0.0216***	0.0045	$\ln p_2 * \ln y_2$	−0.0070**	0.0029
$l_2 * q_3$	0.0547***	0.0052	$\ln p_2 * \ln y_3$	−0.0321***	0.0043
$q_1 * q_2$	−1.4466*	0.7628	$\ln y_1 * \ln y_2$	0.0101	0.0170
$q_1 * q_3$	−3.0502**	0.9503	$\ln y_1 * \ln y_3$	−0.0068	0.0182
$q_2 * q_3$	−2.3526***	0.8116	$\ln y_2 * \ln y_3$	−0.1743***	0.0143
Time	−0.0146***	0.0034	LabT	0.5475*	0.2842
Time2	0.0005***	0.0002	LabT2	0.0651***	0.0229
			Time	−0.0668***	0.0092
			Time2	0.0019***	0.0004
Log-likelihood 1858.98			Log-likelihood 1739.57		

Notes: Notations Time and Time2 are linear and quadratic trends, respectively, and LabT and LabT2 represent the same trends for AI of labour input.
***Significant at the 1 per cent level.
**Significant at the 5 per cent level.
*Significant at the 10 per cent level.

a misallocation of labour input increases through time. Such expectation is indeed confirmed by referring to Table 4 (later).

The estimated firm-specific TI measures of B and the AI measures of h are reported in Table 3. Evidence from the FF function shows no clear pattern of technical efficiency as bank size grows, consistent with the finding of Ferrier and Lovell (1990). Conversely, translog evidence shows that technical efficiency improves with bank size except for the last (the largest) group, and its variation is larger than the FF function estimates. In addition, TI terms in the FF function are larger than those in the translog function (except for group III), indicating that the latter tends to overestimate banks' TI.

Since allocative efficiency parameter estimates of labour are all greater than unity and those of physical capital are all less than unity for all five

TABLE 3
ESTIMATES OF EFFICIENCY PARAMETERS

Groups	*Total assets*[a]	*Technical efficiency*	*Allocative efficiency* Labour (X_2)	Capital (X_3)	*Number of firms (sample size)*
Fourier cost function					
I	12,000–50,000	0.8433***	5.0591***	0.2347*	4 (68)
		(0.0454)	(0.7217)	(0.1339)	
II	50,001–90,000	0.7946***	3.8725***	0.2121*	5 (84)
		(0.0293)	(0.5238)	(0.1203)	
III	90,001–220,000	0.8782***	5.6472***	0.2656*	4 (68)
		(0.0247)	(0.7465)	(0.1502)	
IV	220,001–460,000	1	6.6792***	0.2945*	4 (68)
			(0.9816)	(0.1671)	
V	460,001–800,000	0.8908***	3.2412***	0.2756*	5 (85)
		(0.0246)	(0.5808)	(0.1558)	
Input-specific (with TI)			5.2994***	0.3483**	22 (373)
			(0.6429)	(0.1781)	
Input-specific (without TI)			5.6278***	0.1478	22 (373)
			(0.6752)	(0.1754)	
Translog cost function					
I	12,000–50,000	0.6863***	5.6476***	0.3144	4 (68)
		(0.0395)	(1.5371)	(0.2004)	
II	50,001–90,000	0.7574***	9.2296***	0.3663	5 (84)
		(0.0317)	(2.2485)	(0.2320)	
III	90,001–220,000	0.8943***	16.625***	0.4148	4 (68)
		(0.0290)	(3.2864)	(0.2643)	
IV	220,001–460,000	1	15.281***	0.4082	4 (68)
			(3.9918)	(0.2553)	
V	460,001–800,000	0.8661***	16.121***	0.5111	5 (85)
		(0.0307)	(4.0075)	(0.3197)	
Input-specific (with TI)			7.2153***	0.4848**	22 (373)
			(1.4299)	(0.2301)	
Input-specific (without TI)			6.9501***	0.1593	22 (373)
			(1.3998)	(0.2301)	

Notes: Numbers in parentheses are standard errors.
[a]Measured in millions of New Taiwan dollars.
***Significant at the 1 per cent level.
**Significant at the 5 per cent level.
*Significant at the 10 per cent level.

groups, both functions reveal that our sample banks are inclined to have an under-utilization of labour and an over-utilization of capital, relative to deposits and borrowed money (the *numéraire*). To eliminate allocative distortion and to lower total costs, banking firms should increase their employment of labour and decrease employment of physical capital. Viewed in a different way, banks should decrease the use of inputs X_1 as well as X_3 so as to improve their allocative efficiency. The reduction of X_1 implies that banks should increase their own capital and/or decrease loans, which in turn would increase the capital adequacy ratio and lessen the possibility of bank insolvency. As a side note, in 1989 the Banking Law of Taiwan was modified to require banks to maintain a capital adequacy ratio of at least 8 per cent.

Assuming that allocative efficiency parameters are equal among banks for each input, these industry-level input-specific allocative efficiency parameters can be estimated with and without imposing technical efficiency and are also shown in Table 3. Although the two allocative efficiency parameter estimates for the labour input from the FF and from the translog cost functions are different, they are nevertheless quite close to each other. By contrast, the same two estimates for the capital input obtained from the respective cost functions are not only substantially distinct from each other, but also one of them is turning insignificant. This result suggests that TI and AI are correlated in the banking sector, and hence any model neglecting such association may suffer biased estimates due to specification error—Atkinson and Halvorsen (1980, 1984), Atkinson and Cornwell (1994b), Mitchell and Onvural (1996) and Altunbas *et al*. (2000) completely ignored TI and AI, and Berger (1993), Mester (1993), Lang and Welzel (1996), Berger *et al*. (1997), Berger and DeYoung (1997), Bauer *et al*. (1998) and Cummins and Zi (1998) did not separate TI from AI.

Table 4
Cost of Inefficiency (%)

Groups	Total assets[a]	Technical inefficiency (%)	Allocative inefficiency (%) X_2	X_3	$X_2 + X_3$	Economic inefficiency (%)	Number of firms (sample size)
Fourier cost function							
I	12,000–50,000	15.67	18.87	3.05	21.32	33.65	4 (68)
II	50,001–90,000	20.54	14.96	3.99	18.37	35.14	5 (84)
III	90,001–220,000	12.19	14.01	2.78	16.43	26.61	4 (68)
IV	220,001–460,000	0	12.78	1.86	14.43	14.43	4 (68)
V	460,001–800,000	10.92	6.77	2.91	9.50	19.38	5 (85)
Full sample		12.19	13.24	2.97	15.81	25.95	22 (373)
1981–91		12.18	14.28	2.50	16.42	26.50	22 (241)
1992–97		12.21	11.33	3.81	14.71	24.94	22 (132)
Translog cost function							
I	12,000–50,000	31.37	32.74	2.44	34.38	54.97	4 (68)
II	50,001–90,000	24.26	36.28	1.86	37.47	52.64	5 (84)
III	90,001–220,000	10.57	39.23	1.38	40.05	46.39	4 (68)
IV	220,001–460,000	0	41.19	1.55	42.11	42.11	4 (68)
V	460,001–800,000	13.39	41.93	0.78	42.38	50.10	5 (85)
Full sample		16.10	38.36	1.57	39.34	49.43	22 (373)
1981–91		16.15	35.77	1.61	36.82	47.40	22 (241)
1992–97		16.18	43.08	1.51	43.95	53.12	22 (132)

Note: [a]Measured in millions of New Taiwan dollars.

If a bank is either technically inefficient or allocatively inefficient, or both, then its cost must be higher than an efficient cost facing the same input prices and producing equal amounts of output quantities. Table 4 shows the percentage increases in costs due to TI alone, to AI alone, and to both inefficiencies. Following Atkinson and Cornwell (1994a), numbers in the table are calculated as one minus the ratio of restricted fitted costs and by imposing either $B = 1$ or $h = 1$, or both, to unrestricted fitted costs without these impositions. Not surprisingly, the two cost functions bring forth considerably different inefficiency measures. Translog evidence on cost efficiency suggests that the overall potential cost savings are nearly twice as large as those of the FF function, which is consistent with Berger and DeYoung (1997) and can be attributed to the fact that the FF function does not impose as much structure as does the translog function, so that it is able to fit the data more closely.

Based on the FF cost function, the presence of economic inefficiency raises a bank's cost by about 25.95 per cent on average. This figure is nearly three times as large as found by Berge and DeYoung (1997) and Berger *et al.* (1997), and about twice as large as that of Berger and Mester (1997), in which each utilized the FF function but failed to model AI and to estimate cost share equations simultaneously. As can be seen, economic inefficiency comes primarily from factor misallocation rather than TI, implying that an inappropriate input mix gives rise to a larger cost increase than does over-utilization of inputs. The finding that TI plays a relatively small role here is inconsistent with, for instance, Berger and Humphrey (1991), Kumbhakar (1991), Berger *et al.* (1993a) and Huang (1999, 2000), all of whom did not apply the FF function. However, this finding is in accordance with Atkinson and Cornwell (1994a), who used a parametric shadow translog cost function to examine the TI and AI of US airlines with panel data.

The cost of misallocated labour alone uniformly decreases as bank size grows and constitutes more than 80 per cent of total AI, indicating that the greatest reduction in cost could be achieved by optimizing the input mix, especially labour usage. Such serious allocative distortions may reflect the government's heavy regulation of the banking sector through the first 11 years of the sample period. One may expect that financial deregulation in Taiwan, starting in 1991, is likely to have improved banks' economic efficiency. Evidence shown in Table 4 appears to support, though weakly, this expectation. Although deregulation had an insignificant effect on TI, it indeed decreased the potential cost percentage due to AI from 16.42 to 14.71 per cent, with the main source of the reduction coming from labour input, while the AI of capital input worsened a little.

The picture that emerges from the estimated FF shadow cost function is as follows: (1) the lack of production efficiency raises a bank's average cost around 12.19 per cent, relatively small but nevertheless pervasive; (2) banks operate at observed costs approximately 25.95 per cent greater than efficient frontier costs, due primarily to deficient labour utilization; (3) financial liberalization helped to enhance our sample banks' allocative efficiency, especially for labour input. The gradual improvement in efficiency may be one of the reasons that these banks were capable of withstanding the severe impacts from the aforementioned Asian financial crisis.

Berger and Humphrey (1997) have surveyed the results of 130 financial institution efficiency studies and found an annual average efficiency ranging from 0.31 to 0.97 of actual costs, with a mean of 0.79. The figure of 0.79 means that potential cost savings of the industry as a whole are 21 per cent on average, keeping the level of output intact. Our FF evidence falls into this range in the literature. Although a similar translog estimate is much larger, it is still within the same range.

5 Summary and Conclusions

We constructed a theoretically more flexible cost function, the FF cost function, which has been proved to be able to globally approximate an unknown true cost function over the entire range of data, along with the corresponding cost shares. Within the parametric shadow cost framework and a panel data setting, input- and firm-specific AI with possible time trends, as well as firm-specific TI, can be identified and estimated. In this context the current paper differs significantly from previous work using a translog function, which can only locally approximate the true cost function, and from a few recent papers mentioned earlier that apply the FF function but fail to distinguish TI from AI. The failure of separating TI from AI may lead to specification error, and in turn to biased parameter estimates, as well as a bias in the various inefficiency measures based on these estimates.

Evidence is found that a greater reduction in cost could come from optimizing the input mix rather than from improving banks' production technology and managerial performance. The improvement in allocative distortions over time depicted in Table 4 may be attributed to financial liberalization in Taiwan. It is most likely that newly entered private banks have intensified the degree of competition in the industry and have attracted some customers away from the original banks. Consequently, the levels of output for these original banks were compelled to shrink, while their input usage did not adjust swiftly enough at the same time. Such a sluggish adjustment in factors of production to output changes not only causes allocative distortions, but also tends to force banks off their efficient frontiers, which results in input TI. As far as government policy is concerned, the conventional wisdom which argues that liberalization will enhance efficiency and productivity is likely to be correct.

Appendix A: Elementary Multi-indexes $\{k_\alpha\}_{\alpha=1}^{37}$

Vectors of k_α shown below are elected according to the following criteria: (i) k_α cannot be a zero vector and its first non-zero element must be positive; (ii) its elements cannot have a common integer divisor; (iii) these qualified k_α have to be further arranged into a sequence such that $k_1, \ldots, k_A$ are the elementary vectors and that their lengths are non-decreasing in α.

α	1	2	3	4	5	6	7	8	9	10	11	12
l_1	0	0	0	0	0	0	0	0	0	1	1	0
l_2	0	0	0	0	0	0	0	0	0	−1	0	1
l_3	0	0	0	0	0	0	0	0	0	0	−1	−1
q_1	1	0	0	1	1	0	1	1	0	0	0	0
q_2	0	1	0	1	0	1	−1	0	1	0	0	0
q_3	0	0	1	0	1	1	0	−1	−1	0	0	0
$\lvert k_\alpha\rvert^*$	1	1	1	2	2	2	2	2	2	2	2	2

α	13	14	15	16	17	18	19	20	21	22	23	24
l_1	1	1	1	1	1	1	0	0	0	0	0	0
l_2	−1	−1	−1	0	0	0	0	0	0	0	0	0
l_3	0	0	0	−1	−1	−1	0	0	0	0	0	0
q_1	−1	0	0	−1	0	0	1	1	1	1	4	0
q_2	0	−1	0	0	−1	0	1	1	−1	−1	0	4
q_3	0	0	−1	0	0	−1	1	−1	1	−1	0	0
$\lvert k_\alpha\rvert^*$	3	3	3	3	3	3	3	3	3	3	4	4

α	25	26	27	28	29	30	31	32	33	34	35	36	37
l_1	0	0	0	0	0	0	0	0	0	0	0	0	0
l_2	0	0	0	0	0	0	0	0	0	0	0	0	0
l_3	0	0	0	0	0	0	0	0	0	0	0	0	0
q_1	0	2	1	1	2	2	1	1	1	1	1	3	1
q_2	0	1	2	1	−1	1	−2	2	−1	1	3	1	0
q_3	4	1	1	2	1	−1	1	−1	2	−2	0	0	3
$\lvert k_\alpha\rvert^*$	4	4	4	4	4	4	4	4	4	4	4	4	4

APPENDIX B: ESTIMATES OF FOURIER SERIES

Parameter	*Estimate*	*Standard errors*	*Parameter*	*Estimate*	*Standard errors*
β_1	9.6981***	3.1079	V16	–0.0008	0.0008
β_2	8.1407***	2.8938	U17	0.0008*	0.0004
β_3	10.6645***	3.1938	V17	0.0004	0.0009
β_4	–1.4465*	0.7628	U18	–0.0012	0.0015
β_5	–3.0502***	0.9503	V18	0.0011*	0.0005
β_6	–2.3523***	0.8116	U19	0.0318	0.0321
β_{10}	–0.2572***	0.0229	V19	0.0699*	0.0398
β_{11}	–0.0089*	0.0047	U20	–0.0067	0.0918
β_{12}	0.0031*	0.0018	V20	–0.0661	0.0713
β_{13}	0.0016	0.0088	U21	–0.2671***	0.0926
β_{14}	0.0216***	0.0045	V21	0.1606**	0.0663
β_{15}	0.0547***	0.0051	U22	–0.4761***	0.1002
U1	0.5934***	0.2118	V22	0.0858	0.0884
V1	–0.0445	0.0869	U23	–0.0331*	0.0179
U2	0.7057***	0.1978	V23	–0.0049	0.0156
V2	0.0627	0.1483	U24	0.0264*	0.0147
U3	0.5935**	0.2335	V24	0.0434***	0.0162
V3	–0.0680	0.1213	U25	–0.0151	0.0139
U4	0.1129	0.0878	V25	–0.0093	0.0157
V4	–0.0646	0.0802	U26	0.0238	0.0524
U5	0.2508***	0.0957	V26	0.0264	0.0438
V5	–0.2218**	0.0872	U27	0.0312	0.0323
U6	–0.2148***	0.0803	V27	–0.0014	0.0332
V6	0.1995***	0.0661	U28	–0.0322	0.0295
U7	–1.3899***	0.4994	V28	–0.0155	0.0310
V7	0.1691	0.2249	U29	–0.0958**	0.0398
U8	–1.4739**	0.5902	V29	0.1278***	0.0395
V8	1.5000***	0.3283	U30	0.0561	0.0523
U9	–2.3266***	0.7791	V30	–0.0085	0.0442
V9	0.6592***	0.2475	U31	0.3175***	0.0988
U10	0.0145	0.0110	V31	–0.0144	0.0523
V10	0.0570***	0.0126	U32	0.0002	0.0301
U11	0.0040	0.0026	V32	0.0149	0.0219
V11	–0.0007	0.0025	U33	0.0252	0.0241
U12	0.0034	0.0021	V33	0.0189*	0.0230
V12	–0.0004	0.0021	U34	0.1356	0.1027
U13	0.0038	0.0052	V34	–0.3127***	0.0835
V13	0.0043	0.0057	U35	–0.0561**	0.0258
U14	–0.0101**	0.0041	V35	–0.0642*	0.0329
V14	–0.0178***	0.0036	U36	0.0569	0.0361
U15	0.0128***	0.0040	V36	0.0112	0.0305
V15	0.0105***	0.0041	U37	0.0268	0.0242
U16	0.0013*	0.0014	V37	0.0074	0.0244

Notes: ***Significant at the 1 per cent level.
**Significant at the 5 per cent level.
*Significant at the 10 per cent level.

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