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Joint estimation of technical efficiency and production risk for multi-output banks under a panel data cost frontier model

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Abstract This article generalizes production risk from a single output production function to a multiple output cost frontier, which is able to examine input-oriented technical efficiencies and production risk simultaneously in the context of a panel data. Furthermore, the joint confidence interval estimates for technical efficiencies are constructed by means of multiple comparisons with the best approach. Whether taking production risk into account or not offers quite dissimilar implications in terms of the average technical efficiency measure and the identification of multiple efficient banks achieving the optimal cost frontier. It is suggested that inferences drawn on the basis of the confidence intervals of technical efficiency provide much more fruitful and insightful information than the point estimation alone. Bank specific risk parameters are found to be highly and positively correlated with fixed-effect estimates, implying that the more risk-averse a bank is, the more technically efficient it will be.

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1 Introduction

Managers of firms typically make their decisions under conditions of risk and uncertainty. There are at least four types of risk conditions that a firm may face, viz., output price risk, input price risk, quality of input risk, and production function risk. Given the fact that uncertainty is pervasive, it is necessary to propose a theoretical model for explaining a firm's responses to risk in such a way that is amenable to empirical analysis.

Among the four sources of risk, output price risk appears to have been studied the most extensively. Numerous works have been devoted to the theme, such as Sandmo (1971), Batra and Ullah (1974), Hartman (1975), Ishii (1977), Hawawini (1978), Chambers (1983), and Wolak and Kolstad (1991), to name a few. However, most of the related studies theoretically formulate a versatile analytic framework to shed light on possible actions to competitive firms when responding to risk. Relatively few papers are involved in empirical implementation, except for Appelbaum (1991), who investigated the effects of output price uncertainty on firm behavior in the US textile industry, and Kumbhakar (2002a), who estimated Norwegian salmon farms' risk preferences.

Just and Pope (1978) developed a novel set of stochastic production functions, characterized by risk-reducing inputs. Using their production specifications, Wan et al. (1992), Kumbhakar (1993), Hurd (1994), Traxler et al. (1995), Battese et al. (1997), and Tveterås (1999) performed empirical studies of production risk mainly involving the agricultural sector. Robison and Barry (1987) pointed out that understanding the risk-reducing characteristics of inputs helps explain the risk responses of various types of decision makers. Conversely, a certainty model is devoid of such explanatory capacity.

Love and Buccola (1991, 1999), Saha et al. (1994), Chavaz and Holt (1990), and Kumbhakar (2002b) developed a model to permit the joint estimation of the risk preference structure, extent of risk aversion, and production technology. Starting from a (Just-Pope) production function with risk, they modeled producers' attitude toward risk in the context of a single output profit function. Kumbhakar (2002b) further considered the possibility of technical inefficiency. The current article examines similar issues to these papers under the framework of a dual cost frontier, instead of expected utility from profits. Our approach here may prove to be more advantageous since it allows for multiple outputs. Models based on the maximization of expected utility from profits typically involve single outputs. Such models are not easily applicable to firms producing multi-outputs, such as banks, insurance companies, and the like. Another advantage of our model is that it permits the all important construction of confidence intervals for technical efficiency (TE) estimates from an input-orientation.

The relationship between TE and production risk (or risk preference), although quite important, is generally unknown and has not been examined in the literature. It is crucial to note that both the primal production frontier and the dual single output cost frontier are unable to examine production risk and TE simultaneously. This can best be seen as an identification problem caused by the inclusion of production risk. We shall discuss this problem in the next section thoroughly. Alternatively, under the framework of a multiple output cost frontier the two topics are allowed to be analyzed together. Therefore, our model is capable of investigating whether a more risk-averse bank tends to be more technically efficient.

This article offers a new approach that can be employed to explicitly account for the unobservable risk attitudes and TE. In addition, under the framework of the so-derived cost frontier, the relative risk attitudes for each firm and the joint confidence intervals of the relative TE, as introduced by Horrace and Schmidt (1996, 2000) and Fraser and Horrace (2003),[1] are estimable, so long as panel data are available. As will be shown in Section 5, bank managers' risk attitudes tend to be highly correlated with a technical efficiency measure. There is a consensus in the literature that whenever price data exist, such as for financial institutions, cost minimization and profit maximization are likely to be more relevant behavioral objectives than the one simply pursuing a maximum attainable output from a given set of inputs.

With regard to the construction of confidence intervals for TE estimates, the method of multiple comparisons with the best procedure (MCB), proposed by, for example, Edwards and Hsu (1983), Hochberg and Tamhane (1987), and Hsu (1996), is exploited. This approach is particularly appropriate when a fixed-effect cost frontier is formulated due to the fact that it allows the construction of simultaneous confidence intervals for all differences between the unknown minimal fixed-effect and the remaining effects. Under a specific confidence level, MCB is able to detect possible multiple best-practice firms from the sample and to differentiate if those differences in fixed-effects achieve statistical significance.

The rest of this paper is organized as follows. Section 2 develops a theoretical model under the condition of production function risk, which leads to a certainty equivalent least cost frontier. An econometric model for a cost frontier together with its share equations is specified. In Section 3 the MCB technique is briefly introduced, followed by a concise data description. Empirical results are then presented

[1] It is to be noted that the papers cited are all based on production frontiers, instead of a cost frontiers, as we are using.

and analyzed thoroughly in the next section, while the last section concludes the paper.

2 Theoretical model

This section, first shows how the presence of production risk shrinks a firm's set of production possibilities and then results in a risk-adjusted dual cost frontier. The so-derived cost frontier is next associated with a flexible translog function form that embodies both production risk as well as TE. Some estimation difficulties are also addressed.

2.1 Production function risk

In order to describe properly the features of a joint production process and uncertain input–output process, a representative firm's set of stochastic production possibilities is formulated as:

$$T = \left\{(\tilde{Y}', X')|Y_n \leq f(Y', X')\varepsilon\right\}, \quad (2.1)$$

where $\tilde{Y} = (Y_1, \ldots, Y_n)'$ is an n-vector of outputs and its first $(n-1)$ elements are redefined as vector $Y = (Y_1, \ldots, Y_{n-1})'$, $X = (X_1, \ldots, X_m)'$ denotes an m-vector of inputs, $f(\cdot)$is the deterministic component of the joint production function, and the random component ε signifies the existence of production risk, which is assumed to be normally distributed with mean value unity and finite variance, σ_ε^2. Naturally, because of the presence of ε, the constraint in (2.1) does not hold with certainty. This implies that the stochastic production possibilities set T of (2.1) may not be binding under uncertainty.

Such a problem has been widely recognized by researchers, primarily in management science, utilizing a linear programming procedure. Charnes et al. (1958) proposed the concept of chance-constrained programming for the sake of dealing with uncertain conditions. Charnes and Cooper (1959, 1962) and Kataota (1963) also addressed this issue. According to the definition provided by Charnes and Cooper (1962), chance-constrained programming refers to the class of such cases, in which constraint violations are admissible up to pre-assigned probability levels. Following this idea, the constraint of (2.1) should be reformulated as:

$$\text{Prob}\left[f(Y', X')\varepsilon \geq Y_n\right] \geq 1-\lambda, \quad (2.2)$$

where "Prob" denotes probability and λ is a given probability level, assumed to be less than or equal to 0.5. Inequality (2.2) describes the situation in which the constraint may not always be satisfied. In fact, it is permissible to offend the constraint within a threshold probability λ for any feasible choice of X and Y.

Through standardization and some manipulations, inequality (2.2) becomes:

$$\Phi\left[\frac{Y_n - f(Y', X')}{\sigma_\varepsilon f(Y', X')}\right] \leq \lambda, \quad (2.3)$$

where $\Phi(\cdot)$ signifies the cumulative distribution function of a standard normal random variable. Inverting both sides of (2.3) and rearranging terms, the conventional production possibilities set T can be transformed into the certainty equivalent production possibilities set (T_{CE}):

$$T_{\text{CE}} = \left\{(\tilde{Y}', X')\,\middle|\,\frac{Y_n}{1+\Phi^{-1}(\lambda)\sigma_\varepsilon} \leq f(Y', X')\right\}. \quad (2.4)$$

The term $\Phi^{-1}(\lambda)$ is confined to be non-positive due to the assumption of $\lambda \leq 0.5$. As a result, the term $1+\Phi^{-1}(\lambda)\sigma_\varepsilon$ must be positive and less than unity, implying that the actual production of Y_n always falls short of the maximal possible output $f(\cdot)$, consistent with standard microeconomic theory. By contrast, a value of λ in excess of 0.5 will lead to a contradictory constraint of (2.4), because the production of Y_n is allowed to exceed the maximal output $f(\cdot)$.[2] This imposes a meaningful non-positive sign constraint on the value of an unknown risk parameter $R = \Phi^{-1}(\lambda)\sigma_\varepsilon$, because the estimation of R constitutes an important issue under uncertainty, which assists in explaining firms' decision behavior that is attributed to risk.

An estimation difficulty arises from the inseparability of $\Phi^{-1}(\lambda)$ from σ_ε, where the former reveals a manager's risk attitudes and the latter is the magnitude of production risk being confronted by the same firm. Consequently, one is forced to estimate them together and still translate R into the representation of the relative degree of risk aversion due to the fact that σ_ε is a constant accompanied with an uncertain production process, which is assumed to be uniform

[2] This can easily be seen by rewriting the constraint in equation (2.4) as: $Y_n \leq [1+\Phi^{-1}(\lambda)\sigma_\varepsilon]f(Y', X')$.

to the sample firms under consideration. This uncertainty may arise from the weather, business cycles, general financial crises, and so on.

The size of R is also dependent upon the threshold level of λ, which, however, must be firm specific. A more risk-averting producer tends to select a higher control level of $(1-\lambda)$, resulting in larger absolute values of $\Phi^{-1}(\lambda)$ and R in the sequel. The higher a firm's absolute value of R is, the more risk-averse it will be.

It is interesting to note that in the single output case the certainty equivalent production function of (2.4) reduces to:

$$\frac{Y}{1+R} \le f(X'). \tag{2.5}$$

Since the value of $(1+R)$ lies between zero and one, (2.5) turns out to be the model associated with the study of production efficiency, as proposed by Atkinson and Cornwell (1993, 1994a, 1994b). The denominator of (2.5) is used to capture output technical efficiency. In other words, the output technical efficiency measure is indistinguishable from risk parameter R.[3] However, in the context of multiple outputs, the current model of (2.4) deviates from the ones related to output technical efficiency, such as Kumbhakar (1996, 1997) and Huang and Wang (2004). The formulation shown in (2.4) appears to be new in the literature.

Figure 1 depicts the impact of production risk on manufacturing output Y_2; say, using a two-output production possibilities frontier (PPF) diagram. Starting from the certainty case, which can be viewed as a special case of (2.4) by letting $R=0$, when $\lambda=0.5$, the corresponding PPF is depicted by curve AB. When production risk in Y_2 alone is introduced into the model, the firm's certainty equivalent PPF is denoted by the dotted curve AC. It must lie below AB and keep the intercept at the horizontal axis unchanged. The vertical distance between the two curves, for instance, EF, measures the decrease in the production of Y_2 owing to its own production risks, while leaving Y_1 intact. More specifically, the ratio of DE/DF is exactly equal to the proportion $(1+R)$. Therefore, one can infer that a more risk-averting

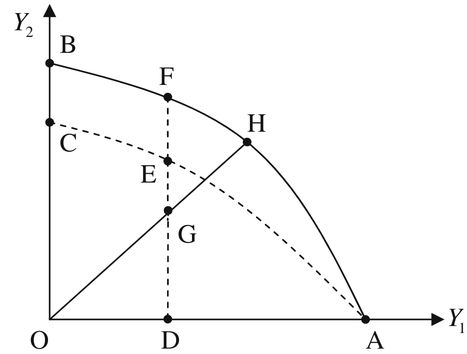

Fig. 1 Certainty equivalent production possibilities Frontier

firm, corresponding to a higher absolute value of R, will have larger responses in adjusting down its output quantities. Putting it another way, in order to maintain its output mix at point F, the producer is required to hire more factors of all kinds, which in turn leads to higher production costs.

Now suppose the actual output mix occurs at point G. The radial measure of TE is represented as usual by OG/OH, while DE/DF reflects the degree of the negative impact of production risk on the production of Y_2. Since, such risk appears to be a common feature of doing business, its exclusion from analytical models may lead to biased estimates for the production frontier and distorted statistical inferences. The resulting production frontier is very likely to be located between curves AB and AC, i.e., a mixture of the true production frontier AB with the certainty equivalent production frontier AC. Consequently, the implied radial measure of TE at G tends to overstate the true measure of OG/OH. This argument is indeed supported by the data at hand.

2.2 Cost function

Since Y_n, the product that is by assumption experiencing risk, must heuristically be reformulated as $Y_n/(1+R)$ in the production possibilities set T_{CE}, the same expression will be conveyed to a dual cost function derived from minimizing expenditures subject to the same set T_{CE}. Following Atkinson and Cornwell (1994a, b) and Kumbhakar (1996, 1997), a two-output cost frontier under production risk and with input technical inefficiency for the ith firm can be written as:

[3] The same is not true for the multiple output case, while there is no natural way of selecting a dependent variable from various outputs. A cost function is preferable as it consists of multiple outputs and input prices.

$$\begin{aligned}
C_i^*\left(\frac{W_i}{a_i}, Y_{1i}, \frac{Y_{2i}}{1+R_i}; \theta'\right) &= \min_{a_i X_i}\left[\frac{W_i}{a_i}(a_i X_i)\middle| F\left(Y_{1i}, \frac{Y_{2i}}{1+R_i}, a_i X_i'\right) = 0\right] \\
&= \frac{1}{a_i} C_i\left(W_i, Y_{1i}, \frac{Y_{2i}}{1+R_i}; \theta'\right), \qquad (2.6)
\end{aligned}$$

where $W_i = (W_{1i}, \ldots, W_{mi})$ is a $1 \times m$ input price row vector, $a_i (0 < a_i \leq 1)$ denotes Farrell's (1957) input technical efficiency measure that scales input usage and reflects the extent to which actual and optimal input mix differ, and θ signifies all unknown technology parameters of a cost function. These parameters will be estimated later in this exercise, in addition to a_i and R_i.

Setting $R_i = 0$, formula (2.6) simplifies to the one proposed by Atkinson and Cornwell (1994a, b) and Kumbhakar (1996, 1997) and is later applied by Huang and Wang (2003, 2004) using the Fourier flexible cost frontier to estimate TE of Taiwan's banking sector. To the best of our knowledge, (2.6) is new in that it combines TE with production risk in the context of a dual cost frontier. As a result, an estimation based on (2.6) may provide more insightful economic implications than other simplified models do. The cost frontier $C_i(\cdot)$ can be referred to as a risk-adjusted cost frontier, also known as a certainty equivalent cost frontier.

Let E_i be the actual expenditure incurred by producer i. It is readily shown that $E_i = C_i^*$, and hence:

$$\ln E_i = \ln C_i\left(W_i, Y_{1i}, \frac{Y_{2i}}{1+R_i}; \theta'\right) - \ln a_i, \quad (2.7)$$

where notation ln denotes the natural logarithm.

Term $-\ln a_i$ reveals that the existence of a possible technical inefficiency would raise firm is observed cost up to $1/a_i$ times as much as its risk-adjusted cost function. Hence, if firm i is capable of exploiting a minimal input mix to produce the same rate of output, then $a_i = 1$ and $C_i^*(\cdot)$ reduces to $C_i(\cdot)$. From an empirical standpoint, the term $-\ln a_i$ is frequently treated as a fixed effects term and is firm specific. Similarly, the presence of R_i in $C_i(\cdot)$ will also inflate the firm's realized production cost, but take a more complicated form. Such an impact on the production cost is like the effect of output technical inefficiency on a firm's cost. For details, please see the references mentioned in the above paragraph.

2.3 Econometric specification

For the sake of estimation, a particular functional form of $\ln C_i(\cdot)$ in (2.7) must be specified. We elect to use the flexible translog cost function. Differing from the conventional cost function, variable Y_{2i} must always be accompanied by $(1 + R_i)$, as can be seen from (2.7). Given panel data, our translog expenditure equation for firm i at time t is expressed as:

$$\begin{aligned}
\ln E_{it} = {} & \alpha_0 + \alpha_1 \ln Y_{1it} + \alpha_2 \ln Y_{2it}^* + \alpha_3 t \\
& + 0.5\alpha_{11}(\ln Y_{1it})^2 + 0.5\alpha_{22}(\ln Y_{2it})^2 \\
& + 0.5\alpha_{33}t^2 + \alpha_{12} \ln Y_{1it} \ln Y_{2it}^* \\
& + \alpha_{13} t \ln Y_{1it} + \alpha_{23} t \ln Y_{2it}^* \\
& + \sum_{j=1}^{m} \beta_j \ln W_{jit} \\
& + 0.5 \sum_{j=1}^{m}\sum_{k=1}^{m} \beta_{jk} \ln W_{jit} \ln W_{kit} \\
& + \sum_{j=1}^{m} \gamma_{1j} \ln Y_{1it} \ln W_{jit} \\
& + \sum_{j=1}^{m} \gamma_{2j} \ln Y_{2it}^* \ln W_{jit} \\
& + \sum_{j=1}^{m} \gamma_{3j} t \ln W_{jit} + u_i + v_{it}, \qquad (2.8) \\
& i = 1, \ldots, I, \qquad t = 1, \ldots, T,
\end{aligned}$$

where $Y_{2it}^* = Y_{2it}/(1 + R_{it}), u_i = -\ln a_i$ is regarded as a firm specific fixed effect, t and t^2 denote linear and quadratic trends, capturing possible technical change, αs, βs, and γs are unknown technology parameters and constitute elements of vector θ in (2.7), and v_{it} is the error term with mean zero and constant variance across firms and over time. It is seen that the firm specific fixed-effects term $-\ln a_i$ has been rewritten as u_i, which transforms production inefficiency into a (log) value that evaluates the discrepancy between actual and optimal expenditures.

Risk parameter R_{it} is in particular allowed to be both firm specific and time-variant capturing not only a variety of managers' risk preferences, but also reflecting their possible trends over time. It is parsimoniously specified as:

$$R_{it} = R_i + K_1 \text{tren} + K_2 \text{tren}^2, \quad (2.9)$$

where R_i, K_1, and K_2 are parameters to be estimated and tren and tren^2 are the same as t and t^2, respectively. Note that parameters K_1 and K_2 are legitimately specified as firm specific like R_i. This means that $2I$ extra parameters need to be added to (2.9), which lowers the degrees of freedom substantially. Hence, a dearth of insightful outcomes may be achieved. To warrant non-positive estimates of the firm specific risk parameters R_is, as imposed by the theoretical model, the dummy variable technique is adopted.

We first choose $R_j = \max_{i=1}^{I} R_i$ among firms, and then normalize it to zero. The chosen firm j corresponds to the one being the least risk aversive relative to the rest of the firms in the sample. The procedure of normalization plays a pivotal role in making the unobservable risk preferences estimable and it is justifiable that the remaining firm specific risk parameters uniformly fall short of zero. By doing so, the identification problem is concurrently solved as a by-product.

The estimation strategy proposed herein appears to be novel and useful due to its capability of extracting information on each firm's risk attitude as well as potential trending from a given sample. Perhaps another merit of the estimation procedure is that it does not rely on the behavioral assumption of risk aversion for each firm under examination. Therefore, this is a slight generalization of the theorem developed by Sandmo (1971), Hawawini (1978), and Chambers (1983). Only a firm's relative attitude toward risk to the normalized firm matters. The availability of a panel dataset is naturally required.

Parameter $\alpha_i = \alpha_0 + u_i$ will be treated as a fixed effect, changing across firms, but invariant over time, in order to exploit the MCB technique and construct the confidence intervals of TE, as suggested by Horrace and Schmidt (1996) and Fraser and Horrace (2003).[4] It should be pointed out that microeconomic theory limits a cost function, deduced through the process of cost minimization, to be linearly homogeneous in input prices and symmetrical both in input prices and output quantities. It follows that these restrictions must be imposed during estimation. Readers are also asked to refer to Varian (1992) for details. Other regularity conditions, e.g., monotonicity and concavity in factor prices, will be checked once the unknown parameters are estimated in order to check the congruence of the empirical cost function with its theoretical counterpart.

The share equations are easily obtained by taking partial derivatives of $\ln E_{it}$ with respect to $\ln W_{jit}$ ($j = 1, \ldots, m$). It can be proven that a simultaneous estimation of (2.8) and $(m - 1)$ share equations will not only add degrees of freedom, but also improve the precision of the parameter estimates due to the imposition of cross-equation restrictions introduced by economic theory and the use of more information, particularly cross equation correlations of random disturbances.[5] (see, for example, Berger 1993; Atkinson and Cornwell 1994b; Kumbhakar and Lovell 2000).

2.4 Discussion

This subsection is devoted to summarize the foregoing three subsections. To begin with, the model's simultaneous regression equations are composed of equation 2.8 and the $(m - 1)$ share equations obtained by taking partial derivatives of (2.8) with respect to any $(m - 1)$ of the m(log) input prices. Second, these three equations are jointly estimated by non-linear least squares, regarding both α_i and R_i as group specific constant terms in the regression model. These constant terms are empirically estimated as the coefficients of the dummy variables corresponding to the ith unit, $i = 1, \ldots, I$. In this sense, our econometric model can be referred to as a simultaneous non-linear least squares dummy variable model. In essence, it exemplifies the distribution-free approach, as proposed by Berger (1993). Finally, except for risk parameters R_is, all the technology parameters θ and fixed effects α_i can be estimated and identified directly. It is seen that some terms of (2.8) contain both the technology parameter and R_i, and thus the problem of identification is unavoidable. To our knowledge, the use of the

[4] It is to be noted that in the panel data setting we are, in fact, parsimoniously specifying TE as both firm specific and time variant, i.e., $\alpha_{it} = \alpha_i + \alpha_3 t + 0.5\alpha_{33} t^2$, as can been seen from (2.8), analogous to the formulation of R_{it} in (2.9).

[5] One of the m cost shares must be removed in order to avoid the singularity problem occurring at the variance-covariance matrix of the random disturbances.

dummy variable technique in the above manner appears to be an innovative way of solving the identification problem.

3 Interval estimation by the MCB technique

Equation (2.8) is reformulated with a panel data format:

$$\ln E_{it} = \alpha_i + X_{it}\beta + v_{it}, \tag{3.1}$$

where X_{it} is a K-vector of all explanatory variables present in (2.8) and β is the corresponding vector of parameters, v_{it} denotes a random error with zero mean and constant variance, and $\alpha_i = \alpha_0 + u_i, i = 1, \ldots, I$, are group specific constant terms in the regression model known as fixed effects. It is well known that a fixed effect treatment is free from distributional assumption on $\alpha_i(u_i)$ and does not rest on the mutual independence assumption among α_i, X_{it}, and v_{it}. The corresponding share equations to (3.1) can be inferred in a quite straightforward manner.

In order to employ the MCB technique, the fixed-effect parameter α_i must be in place of the constant term representing differences across units and can be estimated individually along with β. Let $\alpha_{[1]} \leq \alpha_{[2]} \leq \cdots \leq \alpha_{[I]}$ be the population ordering of α_i. Unit [1] denotes the most technically efficient firm, while unit $[I]$ corresponds to the least technically efficient firm. Define $u_i^* = \alpha_i - \alpha_{[1]} = u_i - u_{[1]}$, such that $0 \leq u_i^* \leq u_i$. Equation (3.1) can thus be expressed as:

$$\ln E_{it} = \alpha_{[1]} + X_{it}\beta + v_{it} + u_i^*. \tag{3.2}$$

The relative technical inefficiency measures u_i^* can be monotonically transformed into the cost efficiency (CE) measure by $\text{CE}_i = \exp(-u_i^*)$. Obviously, CE_i is bounded between zero and one by construction. A value of CE_i equaling unity means that the ith unit is the best-practice firm over the sample, which attains the minimum feasible cost frontier. By contrast, a unit having the smallest value of CE_i corresponds to the least efficient firm, whose production cost lies the farthest apart from the benchmark partners.

The inefficiency measure u_i deviates from u_i^* considerably in that the former is conventionally estimated through a maximum likelihood procedure on the basis of the stochastic frontier model dating back to Aigner et al. (1977) and Meeusen and van den Broeck (1977), whereas the latter measure, used in this paper as the inefficiency measure, must be estimated by non-linear least squares and conforms to the distribution-free approach of Berger (1993). Schmidt and Sickles (1984) and Park and Simar (1994) proved that estimators $\hat{u}_i^*$s are consistent, as both I and T approach to infinity. In a finite sample with small T, however, $\hat{\alpha}_{[1]}$ tends to be biased downward. This gives rise to under-estimations of relative efficiency. Such a bias is mainly ascribable to the operator "min" in the calculation of $\hat{\alpha}_{[1]} = \min_{i=1}^{I} \hat{\alpha}$, where $\hat{\alpha} = (\hat{\alpha}_1, \ldots, \hat{\alpha}_I)'$, and it can be removed under the conditions $I \to \infty$, $T \to \infty$, and $T^{-1/2} \ln N \to 0$. Readers are suggested to refer to Schmidt and Sickles (1984), Horrace and Schmidt (2000), and Fraser and Horrace (2003) for the case of a production frontier.

When obtaining fixed-effects estimates $\hat{\alpha}_i$ and $\hat{u}_i^*$ in turn, one is ready to use the MCB technique to construct simultaneous confidence intervals for $\hat{u}_i^*, i = 1, \ldots, I$. Fraser and Horrace (2003) stated that fixed-effects estimation is a semi-parametric estimation, not only having an unknown asymptotic distribution, but also having asymptotically valid confidence intervals that are hard to construct. They suggest applying the MCB technique to find the joint confidence intervals for $\hat{u}_i^* = \hat{\alpha}_i - \hat{\alpha}_{[1]}$, which are able to, at least in part, correct the bias of $\hat{u}_i^*$ arising from the "min" operation in addition to accounting for simultaneous probability statements implied by the rankings of $\hat{\alpha}_{[1]} \leq \hat{\alpha}_{[2]} \leq \cdots \leq \hat{\alpha}_{[I]}$.

There are a few other noticeable features pertaining to the MCB technique. First of all, this powerful technique allows for the construction of joint confidence intervals for the parameters of interest, u_i^*s, irrespective of whether the best-practice units are known, a priori, or not. This is in sharp contrast with the point estimates of α_i and $\hat{u}_i^*$, in which the benchmark partner is implicitly assumed to be known, a priori. Second, the MCB intervals do not preclude the likelihood of multiple best practice peers, while the point estimations for α_i and $\hat{u}_i^*$ solely permit a single firm to reach the minimum cost frontier. Lastly, the MCB intervals are not centered on the point estimates $\hat{u}_i^*$, recognizing the bias responsible for the "min" operation. Employing the midpoint of the MCB intervals as the point estimates of $\hat{u}_i^*$ is alternatively suggested by, for example, Edwards and Hsu (1983), in such a way as to lower the bias.

The complete MCB technique has been illustrated thoroughly by Horrace and Schmidt (1996, 2000) and Fraser and Horrace (2003) for econometric applications up to the stochastic production frontier model. The current paper goes a step further to a fixed-effect cost frontier specification. Let $\hat{\Omega}$ be the covariance matrix of the vector estimates $\hat{\alpha} = (\hat{\alpha}_1, \ldots, \hat{\alpha}_I)'$, where each element is denoted by $\hat{\omega}_{ij}$ $(i, j = 1, \ldots, I)$. Under a pre-specified significance level λ, the allowance term h_{ji} is defined as:

$$h_{ji} = d_j^*(\hat{\omega}_{ii} + \hat{\omega}_{jj} - 2\hat{\omega}_{ij})^{1/2}, \tag{3.3}$$

where $i, j = 1, \ldots, I$, but $i \neq j$, and d_j^* is the solution to:

$$\text{Prob}(\max_{1\leq i\leq I-1} |Z_i| \leq d_j^*) = 1 - \lambda, \tag{3.4}$$

in which Z_i signifies an $I - 1$ dimensional random vector distributed as an $(I - 1)$-variate t distribution with degrees of freedom $I(T - 1) - K$ and a suitable covariance matrix (for details, see Horrace and Schmidt 2000).

The lower and upper bounds of simultaneous $(1 - \lambda)100\%$ multiple comparisons with a control (MCC) confidence interval for the difference between the ith unit and the pre-selected unit j (usually the best practice firm) will take the form:

$$LB_i^j = \hat{\alpha}_i - \hat{\alpha}_j - h_{ji}, \tag{3.5}$$

$$UB_i^j = \hat{\alpha}_i - \hat{\alpha}_j + h_{ji}. \tag{3.6}$$

Define the following notations:

$$\begin{aligned} S &= \left\{ i \,\middle|\, UB_j^i \geq 0 \quad \forall\, j \neq i \right\} \\ &= \left\{ i \,\middle|\, \hat{\alpha}_i \leq \hat{\alpha}_j + h_{ij} \quad \forall j \neq i \right\}, \end{aligned} \tag{3.7}$$

$$\begin{aligned} LB_i &= \max\left[0, \min_{j\in S} LB_i^j\right] \\ &= \max\left[0, \min_{j\in S} \hat{\alpha}_i - (\hat{\alpha}_j + h_{ji})\right], \end{aligned} \tag{3.8}$$

$$\begin{aligned} UB_i &= \max\left[0, \max_{j\neq i} UB_i^j\right] \\ &= \max\left[0, \max_{j\neq i} \hat{\alpha}_i - (\hat{\alpha}_j - h_{ji})\right]. \end{aligned} \tag{3.9}$$

The $(1 - \lambda)100\%$ MCB confidence interval on u_i^* can then be written as:

$$\begin{aligned} \text{Prob}\,\{&[1] \in S \text{ and } LB_i \leq u_i^* \leq UB_i, \\ &i = 1, \ldots, I\} \quad \geq 1 - \lambda. \end{aligned} \tag{3.10}$$

Edwards and Hsu (1983) provide the proof. Equation (3.10) states that with a probability of at least $(1 - \lambda)$, the joint intervals between LB_i and UB_i will contain the true relative cost inefficiency of firm $i(i = 1, \ldots, I)$, when the true identity of the best-practice firm is unknown with certainty. There exist important dissimilarities between the production frontiers, (e.g., Horrace and Schmidt 1996, 2000; Fraser and Horrace 2003), and the cost frontier in (3.7) through (3.9) deserves specific mention. When a production frontier is adapted to obtain intervals for u_i^*, all the terms of h_{ij} and h_{ji}s present in these equations need to be multiplied by -1. In addition, the inequality signs of (3.7) have to be reversed, as well as the arguments of the min and max operators in the brackets on the right-hand side of the remaining two equations are multiplied by -1.

Set S can never be empty, which contains the indices of all detected best-practice firms in the sample with a probability of at least $(1-\lambda)$. The MCB procedure splits the whole sample into three components. One of them includes firms having $LB_i = 0$ and in the set S, which are identified to be the benchmark partners. Firms not in S, but having $0 = \text{LB}_i < \text{UB}_i$, belong to the second component, while the last component accommodates those firms not in S and having $0 < LB_i < UB_i$. If S is a singleton, then it must be the least cost firm with the smallest estimate of α_i. Only under this special case are the MCB intervals for the remaining firms aligned with the MCC intervals with that firm as the control. The joint confidence intervals (3.10) of u_i^*s are readily translated into those of $\text{CE}_i = \exp(-u_i^*)$. The converted probability statement takes the following form:

$$\begin{aligned} \text{Prob}\Big\{&[1] \in S \text{ and } \exp(-UB_i) \leq \exp(-u_i^*) \\ &\leq \exp(-LB_i), \quad i = 1, \ldots, I\Big\} \geq 1 - \lambda. \end{aligned} \tag{3.11}$$

4 Data description

The source of the data used by this paper comes mainly from publications of the Central Bank and the Ministry of Finance, Taiwan, the Republic of China. The sample period spans 1981–2001. This dataset includes 22 of Taiwan's domestic banks, of which 11 are sizable public enterprises when compared in terms of total assets with the other 11 private banks, at the outset of the sample period. Starting from the second half of the sample period, the government took steps to liberalize the banking sector and to encourage the privatization of public banks for the sake of enhancing productivity and efficiency of the industry. As a result, three public banks remain at the end of the sample period. Since one of the now private banks started business in 1982, the unbalanced panel data consist of 461 observations.

In line with the intermediation approach, we are able to identify two outputs and three inputs from the collected data. The output items contain investments (Y_1), which are composed of government and corporate securities, and various loans (Y_2) with distinct terms of maturity. All kinds of deposits and borrowed money (X_1), the number of full-time equivalent employees (X_2), and physical capital net of depreciation (X_3) are classified as inputs. In 2001 the aggregated book values of total assets, investments, and loans over the 22 sample banks constituted about 61.97, 64.55, and 65.78% of the respective industry values. It is noteworthy that these ratios are even much higher for previous years. In fact, they have become diluted over time due to more and more new entrants into the industry prompted by the adaptation of the deregulation policy. Viewed from this angle, the current sample appears to be a good representative of Taiwan's banking industry. Sample statistics of all variables are summarized in Table 1.

Based on Table 1, Y_2 is obviously the primary output produced by the sample banks, and it is nearly five times as much as Y_1. In reality, a bank's excess reserves are often used to make a variety of loans to its customers prior to buying securities. This is likely to be the case, because the former usually earns higher marginal revenue than the latter, but inevitably at the expense of incurring higher risks. It is therefore assumed that a bank's production of Y_2 is subject to the production risk caused possibly by loan defaults and/or arrears.

Except for the variables suggested by microeconomic theory, (2.8) includes several extra terms in the cost frontier as well, for the sake of gaining further insight on bank managers' behavior. A linear trend (t), a quadratic trend (t^2), and all the interaction terms between t and other variables are added to the simultaneous equations model, consisting of the translog cost frontier (2.8) and its corresponding share equations, in order to capture potential shifts of the cost frontier caused by a technical change over time. Following Hughes et al. (1996), Mester (1996), Berger and Mester (1997), and Huang (2000), the inclusion of variables pertaining to the quality of a bank's assets may help shed some light on a bank's performance, as well as risk preferences.

The amount of non-performing loans (NPL) is used to account for loan quality. A bank granting more risky loans may reveal either that its managers are less risk-averse, or that it spends fewer resources in the process of credit evaluation and hence incurs fewer costs. Moreover, financial capital (FK), also referred to as equity capital, plays a key role in the production process of a financial institution due to the fact that it renders a buffer against portfolio losses, on the one hand, and replaces deposits and borrowed money to finance loans, on the other. Risk-averse managers will attempt to retain a higher ratio of FK to deposits than risk-neutral ones. This may adversely give rise to the realized level of FK differing from the cost-minimizing one. Given the foregoing, it may be appropriate to take account of FK into the econometric model, so as to control for differences in attitudes towards risk.

Table 1 Sample statistics

Variable name	Mean	Standard deviation
Real actual cost (E)*	20787.33	22072.59
Real investments (Y_1)*	48438.11	65694.47
Real loans (Y_2)*	233174.67	265123.68
Price of deposits and borrowed Money (W_1)	0.0597	0.0222
Real wage of labor (W_2)*	0.8033	0.3226
Price of capital (W_3)	0.5333	0.5417

* millions of real New Taiwan Dollars
Base year 1996
Number of observations 461

5 Empirical analysis

The first subsection, presents parameter estimates of the cost frontier, followed by the construction of the MCB confidence intervals for cost efficiency. As stated previously, multiple best-practice banks are likely to be present.

5.1 Parameter estimates

To underscore the differences between models with and without regards to production risk, we estimate two sets of translog cost frontiers, where Model 1 considers risk, while Model 2 does not. Table 2 summarizes all the coefficient estimates for the two models and the fixed-effects estimates are shown in Appendix. It is seen that most of the coefficients are statistically significant for the two models. Indeed, all the fixed-effects and risk parameters are statistically significant even at the 1% level of significance. The proposed models fit the data quite well due to their high coefficients of determination (not shown) for the share and cost equations. The regularity conditions imposed by microeconomic theory on a cost function are checked for every observation using those parameter estimates. Most of the sample observations are found to be consistent with the theory.[6] One is led to conclude that these estimates may be sufficient enough to represent an average bank's production technology and cost structure.

The estimated risk parameters are distributed roughly between −0.80 and −0.33 and are skewed toward the left end. A vast majority of the risk parameters are found to be greater than one half in absolute value. There are as few as five firm specific risk parameters (including the normalized one) below one half in absolute value, indicating that these banks tend to have less risk aversion in comparison with the remaining banks. It is important to note that putting the absolute discrimination on banks' risk attitudes into categories of risk aversion, risk neutrality, and risk loving is less of an issue under the framework of the production risk extending to the cost frontier. However, the relative measure of risk preferences against the normalized unit, corresponding to the least risk-averse decision maker, is consequential. More specifically, a bank with a large value of $|\hat{R}_i|$ indicates that its managers tend to dislike risk much more than a normalized bank. The magnitude of $|\hat{R}_i|$ can then be viewed as an indicator of the relative risk aversion for bank i to the normalized bank, very similar to the concept of the degree of risk aversion defined in the area of uncertainty. Given the available information, it is difficult and moreover unnecessary to tell which category the ith bank belongs to.

Parameters K_1 and K_2 are significantly estimated to be −0.0149 and 0.00041, respectively, at the 1% level. Based on those estimates, it can be seen that the linear and quadratic trends cause R_{it} to initially go down at a decreasing rate, until a turning point at about tren = 18, after, which R_{it} begins to rise at an increasing rate. This indicates that the sample banks' managers first tend to be more risk-averse and conservative over time, whereas later in the sample period their preferences on risk change and become less risk-averse, due possibly to the major financial deregulation and liberalization that occurred in 1989 with the enactment of the New Banking Law. The Law, perhaps the most important financial one enacted in Taiwan, removed barriers to entry and liberalized the establishment of new privately-owned commercial banks in the spirit of intensifying the degree of competition in the banking sector. To survive in a more market-oriented atmosphere, individual banks (new and old) have to be more responsive and willing to take more aggressive strategies, prompting the overall risk attitudes to deviate from risk aversion and toward risk neutrality or even risk preferring.

An interesting question can be immediately raised. Is efficiency correlated with risk attitudes? A simple correlation coefficient between bank specific risk parameters and fixed-effects estimates is calculated to be as high as around 0.85, indicating that they are closely related to each other. A bank with a higher estimated fixed effect, which means that the bank deviates farther from the best-practice partners, tends to be willing to take more risks in pursuit of greater production of output Y_2. The potential risks

[6] More specifically, all the estimated cost shares of X_1 and X_3 are positive and there are only two observations having negative labor shares. As for the conditional factor demand functions, the demand for X_1 is found to be negative with respective to its own price for all sample points, while 122 sample points and six sample points are found to be positive to their own prices for X_2 and X_3, respectively, which are inconsistent with the theory. More than 339 out of 461 observations satisfy the negativity condition of a cost function.

Table 2 Parameter estimates

Variable name	Model 1 Estimate	Model 1 Standard error	Model 2 Estimate	Model 2 Standard error	Variable name	Model 1 Estimate	Model 1 Standard error
$\ln Y_1$	0.4910***	0.0877	0.2843***	0.0811	risk 1	−0.7698***	0.0284
$\ln Y_2$	−0.0264	0.1804	0.5395***	0.1463	risk 2	−0.7385***	0.0309
$\ln W_1$	0.3404***	0.0336	0.5023***	0.0269	risk 3	−0.6015***	0.0465
$\ln W_2$	0.5332***	0.0210	0.3764***	0.0167	risk 4	−0.6607***	0.0379
$\ln NPL$	0.1891***	0.0545	0.0678	0.0488	risk 5	−0.5713***	0.0497
$\ln FK$	−0.1626	0.1327	−0.2032*	0.1228	risk 6	−0.5192***	0.0571
t	0.0355	0.0225	0.0952***	0.0210	risk 7	−0.3859***	0.0681
t^2	0.0016***	0.0006	0.0008*	0.0005	risk 8	−0.4664***	0.0591
$\ln Y_1 \times \ln Y_1$	0.0808***	0.0117	0.0760***	0.0152	risk 9	−0.4108***	0.0650
$\ln Y_2 \times \ln Y_2$	0.1269***	0.0274	0.1008**	0.0394	risk 10	−0.3320***	0.0825
$\ln NPL \times \ln NPL$	0.0133***	0.0047	0.0138**	0.0056	risk 11	−0.8022***	0.0252
$\ln FK \times \ln FK$	0.0782***	0.0268	0.0781**	0.0355	risk 12	−0.6889***	0.0364
$\ln Y_1 \times \ln Y_2$	−0.0609***	0.0134	−0.0638***	0.0190	risk 13	−0.7882***	0.0264
$\ln Y_1 \times \ln W_1$	0.0176***	0.0037	0.0165***	0.0045	risk 14	0	0
$\ln Y_1 \times \ln W_2$	0.0048**	0.0021	0.0011	0.0029	risk 15	−0.6490***	0.0397
$\ln Y_1 \times \ln NPL$	0.0004	0.0063	0.0094	0.0087	risk 16	−0.6919***	0.0370
$\ln Y_1 \times \ln FK$	−0.0553***	0.0132	−0.0361**	0.0169	risk 17	−0.6323***	0.0443
$\ln Y_2 \times \ln W_1$	0.0619***	0.0047	0.0548***	0.0059	risk 18	−0.6780***	0.0395
$\ln Y_2 \times \ln W_2$	−0.0506***	0.0030	−0.0358***	0.0038	risk 19	−0.6826***	0.0398
$\ln Y_2 \times \ln NPL$	−0.0239***	0.0084	−0.0245**	0.0108	risk 20	−0.7719***	0.0303
$\ln Y_2 \times \ln FK$	0.0060	0.0210	−0.0065	0.0292	risk 21	−0.7435***	0.0341
$\ln W_1 \times \ln W_2$	−0.0810***	0.0031	−0.0784***	0.0039	risk 22	−0.7425***	0.0312
$\ln W_1 \times \ln W_3$	−0.0423***	0.0034	−0.0403***	0.0037			
$\ln W_1 \times \ln NPL$	−0.0044**	0.0021	−0.0120***	0.0024			
$\ln W_1 \times \ln FK$	−0.0273***	0.0056	−0.0247***	0.0056			
$\ln W_2 \times \ln W_3$	−0.0233***	0.0018	−0.0291***	0.0022			
$\ln W_2 \times \ln NPL$	0.0006	0.0012	0.0062***	0.0015			
$\ln W_2 \times \ln FK$	0.0013	0.0033	−0.0044	0.0036			
$t \times \ln Y_1$	0.0094***	0.0020	0.0060***	0.0021			
$t \times \ln Y_2$	−0.0048	0.0030	−0.0066*	0.0035			
$t \times \ln W_1$	−0.0028***	0.0008	0.0011	0.0007			
$t \times \ln W_2$	−0.0024***	0.0005	−0.0059***	0.0005			
$t \ln NPL$	0.0016	0.0011	−0.0017	0.0012			
$t \times \ln FK$	−0.0109***	0.0022	−0.0051*	0.0028			
tren	−0.0149***	0.0025					
tren^2	0.0004***	0.0001					
Log likelihood	2501.23		2229.01				

* significant at the 10% level
** significant at the 5% level
*** significant at the 1% level

come naturally from loan defaults/arrears, as stated previously. This finding has important policy implications on improving cost efficiency in the banking industry. It suggests that a stable economic environment is likely to foster highly efficient financial institutions.

While a lack of technical efficiency is important information for bank managers, its impact on costs is perhaps of greater concern. The individual estimates of the $\hat{u}_i^*$s and cost efficiency measures of $\text{CE}_i = \exp(-\hat{u}_i^*)$ are shown in Tables 3 and 4 for Models 1 and 2, respectively. Both models' average cost efficiencies are computed as 0.48 and 0.60, respectively. This implies that potential respective cost savings are roughly 52 and 40% when achieving technical efficiency, and that on average a fully technically efficient bank requires nearly 48% (60%) of resources currently used to produce an equal amount of outputs. Differences between the two models are substantial in terms of possible cost reductions, illustrating the importance of incorporating production risk explicitly into the analytical model. As addressed at the end of Subsection 2.1, failure to consider production risk confounds the true production frontier with the certainty equivalent production frontier and consequently leads to higher estimates of TE. The empirical results confirm this argument.

5.2 The MCB confidence intervals

The relative technical inefficiencies, $\hat{u}_i^*$s, are transformed into the cost efficiency measures using the estimates of the α_is. Although all the fixed-effect parameters display statistical significance, as shown in Table 2, they nevertheless are incapable of providing useful information on the precision of u_i^*. This weakness can be readily rectified by the MCB technique. To show how different confidence levels exert an influence on the widths of confidence intervals, the authors choose to construct two sets of confidence intervals on the basis of 95 and 75% confidence levels. The 95% (75%) simulated critical values of d_j^* in (3.4) range from 2.799 (2.074) to 2.969 (2.318) for Model 1 and from 2.631 (1.884) to 2.920 (2.262) for Model 2. The relative technical inefficiency measures and the corresponding joint confidence intervals, translate into the cost efficiency measures at the 95 and 75% confidence levels, are summarized in Tables 3 and 4, respectively.

The distribution of the point estimates $\hat{u}_i^*$s is well dispersed, with values falling largely within the interval zero to 1.76 for Model 1, while falling within zero to 0.96 for the other model. This appears to indicate that the variability of these relative efficiency levels is substantial. With respect to these estimates, one may unduly infer that the specific sample banks exhibit considerable technical inefficiency and that the efficiency measures are inaccurately estimated. However, the picture that is depicted from investigating the MCB confidence intervals is entirely in contrast to the one from point estimates with regard to a deficiency of TE (see below).

Model 1 shows that four banks lie on the efficient cost frontier with a probability of at least 95 (and 75%), i.e., $S_1 = \{1, 13, 20, 21\}$, while Model 2 identifies merely two such banks under the same probability level, i.e., $S_2 = \{1, 21\}$, even though the latter model comes up with a higher average CE measure, 0.60, as opposed to the former, 0.48. This means that, for Model 1, the differences among the four most efficient banks' estimated fixed effects are statistically insignificant, while for Model 2 a pair of such banks

Table 3 The MCB confidence intervals of Model 1 with production risk

Bank number	$\hat{u}_i^*$	$CE_i = \exp(-\hat{u}_i^*)$	Rank of cost efficiency	75% Lower bound	75% Upper bound	95% Lower bound	95% Upper bound
1	0	1	1	0.8946	1	0.8229	1
2	0.4938	0.6103	7	0.5257	0.8810	0.5024	0.9481
3	1.3541	0.2582	16	0.2113	0.4067	0.1965	0.4508
4	0.9392	0.3909	13	0.3311	0.5732	0.3147	0.6201
5	1.2629	0.2828	15	0.2356	0.4247	0.2229	0.4632
6	1.5302	0.2165	18	0.1801	0.3213	0.1703	0.3490
7	1.7380	0.1759	21	0.1454	0.2624	0.1372	0.2855
8	1.6189	0.1981	19	0.1649	0.2948	0.1559	0.3206
9	1.6957	0.1835	20	0.1522	0.2726	0.1438	0.2962
10	1.4338	0.2384	17	0.1894	0.3587	0.1766	0.3915
11	0.2461	0.7818	5	0.6717	1	0.6413	1
12	0.7309	0.4815	8	0.3971	0.6673	0.3745	0.7119
13	0.1695	0.8441	4	0.7060	1	0.6687	1
14	1.7568	0.1726	22	0.1417	0.2503	0.1335	0.2698
15	0.9083	0.4032	12	0.3325	0.5668	0.3136	0.6045
16	0.8141	0.4430	11	0.3614	0.6113	0.3397	0.6479
17	0.9455	0.3885	14	0.3160	0.5431	0.2967	0.5782
18	0.7435	0.4754	10	0.3833	0.6582	0.3590	0.6876
19	0.7399	0.4772	9	0.3830	0.6629	0.3582	0.6932
20	0.1495	0.8611	3	0.6732	1	0.6246	1
21	0.1281	0.8798	2	0.6822	1	0.6314	1
22	0.2912	0.7474	6	0.6154	1	0.5800	1

$S_1 = \{1, 13, 20, 21\}$

Table 4 The MCB confidence intervals of Model 2 without production risk

Bank number	$\hat{u}_i^*$	$\mathrm{CE}_i = \exp(-\hat{u}_i^*)$	Rank of cost efficiency	75% Lower bound	75% Upper bound	95% Lower bound	95% Upper bound
1	0.0708	0.9316	2	0.8196	1	0.7790	1
2	0.4195	0.6574	6	0.5787	0.7525	0.5501	0.7855
3	0.8341	0.4343	18	0.3662	0.5154	0.3423	0.5509
4	0.5919	0.5533	14	0.4873	0.6313	0.4634	0.6606
5	0.7193	0.4871	17	0.4170	0.5690	0.3920	0.6052
6	0.9592	0.3832	22	0.3241	0.4539	0.3032	0.4843
7	0.9477	0.3876	21	0.3338	0.4502	0.3145	0.4778
8	0.9294	0.3948	19	0.3403	0.4580	0.3208	0.4858
9	0.9438	0.3891	20	0.3353	0.4516	0.3161	0.4791
10	0.6126	0.5419	15	0.4817	0.6203	0.4596	0.6390
11	0.4378	0.6455	7	0.5746	0.7396	0.5487	0.7593
12	0.4689	0.6257	9	0.5632	0.7303	0.5402	0.7488
13	0.2781	0.7527	5	0.6904	0.8862	0.6655	0.9093
14	0.7064	0.4934	16	0.4276	0.5711	0.4039	0.6028
15	0.5263	0.5908	12	0.5314	0.6835	0.5095	0.6990
16	0.5613	0.5705	13	0.5141	0.6649	0.4933	0.6814
17	0.5238	0.5923	11	0.5338	0.6900	0.5123	0.7071
18	0.4426	0.6424	8	0.5895	0.7594	0.5697	0.7815
19	0.4709	0.6244	10	0.5729	0.7428	0.5537	0.7659
20	0.2066	0.8133	3	0.7603	1	0.7297	1
21	0	1	1	0.9220	1	0.8812	1
22	0.2319	0.7930	4	0.7220	0.9335	0.6956	0.9595

$S_2 = \{1, 21\}$

may be detected. The above results are robust to changes in the confidence levels, namely the 75 and the 95% levels. Clearly, S_2 is a subset of S_1, indicating that a failure to be concerned with production risk implies an identification of fewer benchmark partners and an overstatement of TE, according to this sample.

It is quite interesting to note that, even being one of the most efficient banks in Model 1, bank 13 has cost efficiency equal to 84.4% of the maximal efficiency in the sample. Its cost efficiency may be as low as 66.9% relative to the most efficient bank, based on the MCB confidence intervals. Point estimates are apparently unable to detect this type of statistical detail, but instead they suggest a priori that an exact single best practice bank exists in the sample. No ties are allowed in the sample for the best. Moreover, the widest confidence intervals are about 0.44 and 0.33 for both models at the 95% level, implying that to some extent the relative cost efficiency CE_is are precisely estimated.

Banks with binding MCB upper bounds, but not in S, are classified in the second best group.[7] Model 1 identifies two such banks, i.e., banks 11 and 22, while Model 2 finds one, i.e., bank 20. Those banks are likely efficient at the 95% level. It is important to note that all banks belonging to the first two best groups reach an MCB upper bound of unity, in which the point estimates CE_is are less than about 0.75 in Model 1. However, the largest value of CE_i in the remaining group is equal to around 0.61. Given that CE_is are precisely estimated, the gap of 0.14 is large enough to distinguish the first two groups from the least efficient group. The remaining banks belong to the class deficient of TE. The upper bounds of the 95% confidence intervals for these are uniformly lower than unity. There are, respectively, 16 and 19 technically inefficient banks found for the two models at the 95% (75%) level.

6 Concluding remarks

In this paper, we have first proposed a theoretical model involving production risk and then a tractable dual cost frontier, which is fairly suitable for dealing with situations whereby firms produce multiple outputs and employ knowledge that concerns quasi-fixity of some inputs. This model has been derived

[7] Readers are advised to refer to Horrace and Schmidt (2000) and Fraser and Horrace (2003) for details in this regard.

in a straightforward fashion under the framework of a certainty-equivalent production frontier. The primary concern of this paper is to see that the uncertainty of the input-output process is explicitly modeled and imbedded in a cost frontier—one that itself accounts for production efficiency. The cost frontier deduced in this manner is appealing since it has been modified in response to production risk and the decision maker's attitude toward risk. This is perhaps a fills an important gap in the literature to date. Only relative attitudes toward risk among firms make economic sense in the context of the certainty-equivalent cost frontier, in lieu of absolute risk attitudes, not only for the purpose of facilitating estimation, but also for helping to shed light on the distribution of risk preferences over the sample. It is from this that essential policy implications may be drawn.

Another potential contribution of this work is the construction and interpretation of MCB confidence intervals for the (likely biased) point estimates of TE for the sample of banks. The results on multiple best practice banks indicate that inferences based on the point estimates of TE tend to be misleading. The specific data uncovered at the 95 (75%) level that six (three) out of the 22 banks analyzed may be efficient as far as Model 1 (2) is concerned.

By comparing the empirical results of Models 1 and 2, we naturally conclude that the model, taking production risk into account, appears to preferable so long as the risk parameters are significantly estimated, as exemplified by this exercise. Therefore, Model 1 is a valid structure to be adopted to analyze a firm's behavior of cost-minimization particularly in a world of uncertainty. Evidence is found that Taiwan's banking industry can be characterized as highly risk-averse, which causes the output level of Y_2 to go down substantially, by reference to (2.4). However, the sample banks take up more risk after the banking reform, giving rise to instructive implications, i.e., the salutary effects of a more orderly and responsive financial system, more transparent banking practices, and a more market-oriented and competitive environment. All may assist in reducing production risk confronted by banks, nurture a more efficient and reliable financial system, and ultimately benefit the whole economy. The major financial deregulation and liberalization that occurred in 1989 appears to have prompted Taiwan's financial development and advancement. Finally, Model 1s average cost efficiency measure is computed to be 0.48, well within the interval of 0.31–0.97, as found by Berger and Humphrey (1997) after reviewing the results of 130 financial institution efficiency studies.

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Appendix

Table A.1 The fixed-effect estimates and standard errors

Bank number	Model 1		Model 2	
	Estimate	Standard error	Estimate	Standard error
1	2.6887***	0.7163	1.9327***	0.4903
2	3.1826***	0.7213	2.2814***	0.4968
3	4.0428***	0.7337	2.6960***	0.4745
4	3.6279***	0.7276	2.4538***	0.4948
5	3.9516***	0.7286	2.5812***	0.4812
6	4.2190***	0.7265	2.8211***	0.4867
7	4.4268***	0.7303	2.8096***	0.4853
8	4.3077***	0.7305	2.7913***	0.4862
9	4.3844***	0.7304	2.8057***	0.4862
10	4.1225***	0.7283	2.4745***	0.4951
11	2.9348***	0.7270	2.2997***	0.4971
12	3.4197***	0.7238	2.3308***	0.5017
13	2.8582***	0.7230	2.1400***	0.4970

Table A.1 continued

Bank number	Model 1		Model 2	
	Estimate	Standard error	Estimate	Standard error
14	4.4455***	0.7241	2.5683***	0.4919
15	3.5970***	0.7234	2.3882***	0.4991
16	3.5029***	0.7181	2.4232***	0.4993
17	3.6342***	0.7190	2.3857***	0.4984
18	3.4322***	0.7102	2.3045***	0.4964
19	3.4286***	0.7071	2.3328***	0.4975
20	2.8382***	0.6853	2.0685***	0.4815
21	2.8169***	0.6825	1.8619***	0.4761
22	2.9800***	0.7110	2.0938***	0.4950

*** significant at the 1% level

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