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126

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RETURNS TO SCALE, PRODUCTIVITY AND EFFICIENCY IN US BANKING (1989-2000): THE NEURAL DISTANCE FUNCTION REVISITED

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ABSTRACT

Productivity and efficiency analyses have been indispensable tools for evaluating firms' performance in the banking sector. In this context, the use of Artificial Neural Networks (ANNs) has been recently proposed in order to obtain a *globally* flexible functional form which is capable of approximating any existing output distance function while enabling the *a priori* imposition of the theoretical properties dictated by production theory, globally. Previous work has proposed and estimated the so-called Neural Distance Function (NDF) which has numerous advantages when compared to widely adopted specifications. In this paper, we carefully refine some of the most critical characteristics of the NDF. First, we relax the simplistic assumption that each equation has the same number of nodes because it is not expected to approximate reality with any reasonable accuracy and different numbers of nodes are allowed for each equation of the system. Second, we use an activation function which is known to achieve faster convergence compared to the conventional NDF model. Third, we use a relevant approach for technical efficiency estimation based on the widely adopted literature. Fitting the model to a large panel data we illustrate our proposed approach and estimate the Returns to Scale, the Total Factor Productivity and the Technical Efficiency in US commercial banking (1989-2000). Our approach provides very satisfactory results compared to the conventional model, a fact which implies that the refined NDF model successfully expands and improves the conventional NDF approach.

Keywords: Output distance function; Neural networks; Technical efficiency; US banks

*JEL classification codes:*C50, C45, C30

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1. Introduction

There is no doubt that estimating a functional form for output distance functions that satisfies globally the curvature conditions dictated by neoclassical production theory has been "one of the most vexing problems applied economists have encountered in estimating flexible functional forms" (Diewert and Wales, 1987) and remains "one of the most difficult challenges faced by empirical economists" (Terrell, 1996). After all, "Ultimately, the biggest challenge for researchers remains the issue of the appropriate … specification to represent the underlying process technology" (Vaneman and Triantis, 2007).

Recently, a novel approach for measuring technical efficiency was proposed in Vouldis *et al.* (2010) using the advantages of the nonlinear nature of Artificial Neural Networks (ANNs) to deal with the endogeneity of outputs issue raised in Kumbhakar and Lovell (2000). In Michaelides *et al.* (2010) (MVT thereafter), this approach for dealing with the endogeneity of outputs was extended by enabling the *a priori* imposition of the properties dictated by neoclassical production theory globally, providing thus a *globally* flexible functional form.

Analytically, the authors proposed and estimated the so-called Neural Distance Function (NDF) which has the following advantages when compared to the widely adopted specifications: (a) it gives an approximation to any arbitrary production process; (b) it is flexible with respect to time; (c) it allows for arbitrary returns to scale; (d) it is simple to estimate; (e) it avoids the need for nonlinear estimation; (f) it uses fewer estimated parameters than other globally flexible functional forms; (g) it provides a very good fit to real-world data; (h) it has a functional form which is consistent with neoclassical production theory data; (i) it is based on a system of equations which deals with the endogeneity of outputs issue in estimation; and (j) it satisfies the properties dictated by production theory globally and not only over the set of inputs and outputs where inferences are drawn. It should be stressed that the NDF enables the *a priori* imposition of the properties dictated by neoclassical economic theory, *globally.*

In this paper, we carefully refine some of the critical characteristics of the NDF proposed by MVT. Analytically: First, the authors, for reasons of convenience, used "the same number of nodes for each equation". However, this assumption is not expected to approximate reality with any reasonable accuracy. In this paper, this arbitrary assumption is relaxed, in the sense that different numbers of nodes are allowed for each equation of the system. Second, the ANN has to be implemented by choosing its activation function. The authors, in their application, used probably, the most popular activation function, i.e. "the so-called sigmoidal". By contrast, in this paper, we use an activation function which is known to achieve faster convergence. Third, we use a relevant approach for technical efficiency estimation based on the widely adopted approaches proposed, among others, in Kumbhakar and Lovell (2000).

An application investigating the model's performance illustrates our technique. Fitted to the same data set which consists of all US commercial banks over the period 1989-2000, the refined approach explains a slightly higher proportion of the variance and satisfies all the theoretical properties dictated by production theory. Moreover, in order to assess whether the refined NDF model provides satisfactory results, we refer to the conventional NDF and the refined NDF model is found to expand and improve significantly upon the conventional NDF model.

2. The neural distance function (NDF): a brief overview

2.1 The model

An output distance function provides a measure of how close a particular level of output is to the maximum attainable level of output that could be obtained from the same level of inputs. In other words, it represents how close a particular output vector is to the production frontier given a particular input vector.

The output distance function takes a value of unity if Y is located on the production frontier (i.e. the maximum attainable output) for the specific input vector x. We adopt a setup consistent with revenue maximization so that production technology can be described by a distance function of the form:

$$\Delta(x, Y) = 1 - \varepsilon \tag{1}$$

where the Y s are endogenous, the x s are predetermined and ε is a non-negative stochastic term representing inefficiency (Kumbhakar and Lovell, 2000). Because of the presence of inefficiency, we have:

$$\Delta(x,Y) \leq 1 \tag{2}$$

The proposed output distance function allows for multi-output approaches without having to aggregate outputs. Analytically, any given output Y_J is expressed as a function of the others: $\ln Y_J = f(\ln x, \ln Y_1,...,\ln Y_{J-1})$. In order to account for endogeneity, the reduced form is considered: $\ln Y_{-J} = g(\ln x)$, where $\ln Y_{-J} = [\ln Y_1,...,\ln Y_{J-1}]'$, and g is a vector function $g: R^N \to R^{J-1}$. The reduced form expresses all other outputs as functions of the inputs alone. Thus, a system of equations is formed:

$$\ln Y_J = f(\ln x, \ln Y_1,...,\ln Y_{J-1}) + e_J \tag{3}$$

$$\ln Y_{-J} = g(\ln x) + e_{-J} \tag{4}$$

where $e_{-J} = [e_1,...,e_{J-1}]'$, and $e = [e'_{-J}, e_J]'$ represents a *J*-dimensional random vector. The crucial part is, however, to specify the g and f functions. The neural reduced form function, for each output, is given by:

$$\ln Y_j(x) = a_{0j} + \sum_{k=1}^{m_j} a_{kj} \phi_j(\ln x \cdot \beta_{kj}) + \ln x \cdot \theta_j + \delta_j t\ , \quad j = 1,...,J-1 \tag{5}$$

where $Y_j(x)$ is the reduced form function of *j*-th output, m_j is the number of intermediate nodes, *t* is a time index and $\delta_j, a_{kJ} \in R$, $\beta_{kJ} \in R^N, \theta_j \in R^N$ are parameters. In general, for vectors a and b , $a \cdot b$ denotes the inner product. Thus, given equation (5) the output distance function can be written as:

$$\ln D = a_{0J} + \sum_{k=1}^{m_J} a_{kJ} \phi_J(\ln x \cdot \beta_{kJ}) + \ln Y \cdot \gamma + \ln x \cdot \xi + \delta_J t \tag{6}$$

where $\delta_J, a_{kJ} \in R, \beta_{kJ} \in R^N, \gamma \in R^{J-1}$ are parameters, m_J is the number of intermediate nodes for output *J* and *t* is a time index. Equation (6) represents the specification for the distance function, and equations (5) are reduced forms.

An alternative form imposing homogeneity of degree one in inputs is:

$$-\ln Y_J(x) = a_{0J} + \sum_{k=1}^{m_J} a_{kJ}\phi(\ln x \cdot \beta_{kJ}) + \ln\left(\frac{Y_{-J}}{Y_J}\right)\cdot \gamma_{-J} + \ln x \cdot \xi + \delta_J t + u \qquad (7)$$

where $u = -\ln D$ is a non-negative term such that $0<D\leq 1$, $-\infty < \ln D \leq 0$ that captures the effects of inefficiency (Kumbhakar and Lovell, 2000). If we add a symmetric error term *e* to capture the effects of white noise, the neural output distance function f takes the form:

$$-\ln Y_J(x) = a_{0J} + \sum_{k=1}^{m_J} a_{kJ}\phi(\ln x \cdot \beta_{kJ}) + \ln\left(\frac{Y_{-J}}{Y_J}\right)\cdot \gamma_{-J} + \ln x \cdot \xi + \delta_J t + u + e \qquad (8)$$

2.2 The theoretical properties

MVT showed that in order for *monotonicity, curvature and homogeneity conditions to be satisfied for any economically admissible value of inputs and outputs, the values of the parameters need to be as follows*: $\gamma_j \geq 0$, $\sum_{j=1}^{J}\gamma_j = 1$, $\xi_i \leq 0$, $a_{kJ} \leq 0$, $\beta_{kiJ} \geq 0$, ($j = 1,\ldots,J$, $i = 1,\ldots N$, $k = 1,\ldots m_J$), $x\geq 1$.

2.3. Returns to scale and total factor productivity

MVT showed that the RTS index is equal to:

$$\text{RTS}=-\frac{1}{\gamma_J}\left\{\sum_{i=1}^{N}\left[\sum_{k=1}^{m_J} a_{kJ}\beta_{kiJ}\phi_J'(\ln x \cdot \beta_{kJ}) + \sum_{j=1}^{J-1}\gamma_j\left(\sum_{i=1}^{N}\sum_{k=1}^{m_j} a_{kj}\beta_{kij}\phi_i'(\ln x \cdot \beta_{kj}) + \sum_{i=1}^{N}\theta_{ji}\right) + \xi_i\right]\right\}$$

(9)

Also, the TFP index is equal to:

$$TFP = -\frac{1}{\gamma_J}\left[\sum_{j=1}^{J-1}\gamma_j\delta_j + \delta_J\right] \qquad (10)$$

3. Technical efficiency

Farrell (1957) provided us with a definition of technical efficiency and until the late 1970s its empirical application was relatively limited. However, Aigner et *al*. (1977) introduced the stochastic frontier production function, and Meeusen and van den Broeck (1977) presented the Cobb-Douglas production function with a (multiplicative) disturbance term. Since then, Farrell's idea became a useful tool for estimating technical (in)efficiency.

In the conventional approach, the typical assumption about equation (8) is that *e* are *iid* $(0, \sigma^2)$ and uncorrelated with the regressors. Of course, distributional assumptions on the two error components should be made. In this context, a conventional assumption, typically employed in empirical work, is that $u \sim N^{+}(0,\sigma^2)$. In the typical approach of measuring efficiency by means of an output distance function for any given year, the technical efficiency (TE_i) of firm *i* is equal to

$$D_i = TE_i = \exp(-\hat{u}_{i^*}) \tag{11}$$

The estimation leads to consistent estimators for all the parameters, under the assumption that *e* is normally and *u* is half-normally distributed (Kumbhakar and Lovell, 2000).

Empirical estimation of equation generates the residuals *e*. The second and third central moments of the residuals, $m_2(e)$ and $m_3(e)$ respectively, are calculated, as follows:

$$m_2(e) = [1/(N-k)]\ \Sigma\ e_i^2 \tag{12}$$

$$m_3(e) = [1/(N-k)]\ \Sigma\ e_i^3 \tag{13}$$

where: *N* is the number of observations and *k* is the number of regressors, the constant term included. Then, we estimate σ^2_u and σ^2_v using the formulae:

$$\sigma^2_u = [(\pi/2)[(\pi/(\pi-4)\ m_2(e)]^{2/3} \tag{14}$$

$$\sigma^2_v = m_2(e) - [(\pi\text{-}2)/\pi)]\, \sigma^2_u \tag{15}$$

According to Kumbhakar and Lovell (2000), the point measure of technical efficiency is:

$$TE_i = E(\exp\{-u_i\}/\varepsilon_i) = [[1\text{-}F[\sigma_{\cdot}\text{-}(M_i^*/\sigma_{\cdot})]/[1\text{-}F_{\cdot}(\text{-}M_i^*/\sigma_{\cdot})]\exp[\text{-}M_i^* + (\sigma_{\cdot}^2/2)] \tag{16}$$

where $F_{\cdot}$ denotes the distribution function of the standard normal variable. Also:

$$M_i^* = (-\sigma^2_u\varepsilon_i)(\sigma^2_u + \sigma^2_v)^{-1} \tag{17}$$

$$\sigma_{\cdot}^2 = \sigma^2_u\, \sigma^2_v\, (\sigma^2_u + \sigma^2_v)^{-1} \tag{18}$$

Finally, given the measures of TE and TFP change, a measure of technical change may be computed routinely (Färe et *al.* 1994).

3.1. Econometric estimation

We know that typical transfer functions must be continuous, bounded, differentiable and monotonically increasing (e.g. Hornik et *al.*, 1989, 1990). The activation function may be defined as:

$$\phi(Z) = \frac{e^x - e^{-x}}{e^x + e^{-x}}, z \in R \tag{19}$$

Another popular activation function which is employed by MVT is the so-called *sigmoidal* which differs in a linear transformation. However, Eq. (19) is chosen in this paper because it achieves faster convergence (Berndt, 1991).

Our approach is based on a four-step algorithm which employs the SUR equations technique for estimating the coefficients of a system of linear equations and an iterative optimization algorithm for the nonlinear parameters of the NDF as in MVT. However, note that in the present paper, *different* numbers of nodes are allowed for each equation of the system. For reasons of convenience we use a maximum of three (3) nodes for each equation.

The number of nodes *m* will be selected using the generalized R^2, $\tilde{R}^2$ goodness-of-fit criterion which is a modification of R^2 for systems of equations. According to this criterion one should select the number of nodes for each equation that maximizes $\tilde{R}^2$.

3.2 Result analysis

For reasons of comparison, we use the same dataset as in MVT. The data set comes from the commercial bank and bank holding company database managed by the Federal Reserve Bank of Chicago (1989-2000). It is based on the Report of Condition and Income (Call Report) for all U.S. commercial banks that report to the Federal Reserve banks and the FDIC. There are five output variables: (1) instalment loans (to individuals for personal/household expenses), (2) real estate loans, (3) business loans, (4) federal funds sold and securities purchased under agreements to resell, and (5) other assets (assets that cannot be properly included in any other asset items in the balance sheet). There are also five input variables, namely: (1) labour, (2) capital, (3) purchased funds, (4) interest-bearing deposits in total transaction accounts and (5) interest-bearing deposits in total non-transaction accounts.

The estimation procedure, described in great detail in MVT, is used to estimate the propose NDF model. A choice has to be made regarding the number of nodes of the ANN. In this paper, we drop the simplistic assumption that every equation has the same number of node. Thus, we use a different number of nodes for each equation. For reasons of convenience we use a maximum of three (3) nodes for each equation. The $\tilde{R}^2$ criterion has a maximum value for $m_i = 1,\ 1,\ 2,\ 1,\ 1$ nodes for each of the five (i=5) estimated equations, respectively (see Fig. 1). For reasons of simplicity, we have plotted 3 lines where each line represents the value of $\tilde{R}^2$ for the different possible number of nodes (m=1, 2, 3) of the J-th (i.e. fifth) equation. The horizontal axis depicts *all the combinations* of the remaining nodes corresponding to the previous four (4) equations. In addition, Fig. 2 presents the $\tilde{R}^2$ values obtained when the iterative estimation algorithm is applied to the best node configuration for 2000 iterations and is found to provide very satisfactory results. In Table 1, the estimated coefficients for the NDF are shown along with their t-values in parentheses. We can note that they all take values that are consistent with production theory and the great majority of the estimated coefficients are highly significant.

Next, the RTS are calculated (Fig. 3) and are found to follow a Gaussian-like distribution with the following characteristics: Mean=0.875, Skewness=0.101, Kurtosis=3.436. Finally, TE is calculated by means of the methodology described above and is depicted in Fig. 4. It follows a Gaussian-like distribution (Mean= 0.589, Skewness=0.015, Kurtosis= 3.294).

4. Comparison and conclusion

Recently, the advantages of the nonlinear nature of ANNs have been exploited in order to obtain a globally flexible output distance function which is capable of approximating any existing distance function while enabling the *a priori* imposition of the properties dictated by neoclassical production theory, globally. In this paper, we carefully refined some of the most critical characteristics of the conventional NDF. An application investigating the proposed model's performance illustrated our approach.

In order to assess whether the refined approach provides satisfactory results, we briefly compare it with the conventional NDF specification. More precisely, simple visual inspection of the RTS, TFP and TE results calculated routinely with the aid of the conventional NDF specification are found to be very close to the ones calculated by means of the proposed NDF. The proposed refined NDF is found to provide very similar results in terms of RTS, TFP and TE, and very good results in model fitting which is a clear indication of the fact that it successfully expands the conventional NDF.

More precisely, in this paper, we carefully refined some of the critical characteristics of the NDF. First, we relaxed the assumption that "the same number of nodes for each equation" had to be used, given that this extremely simplistic and restrictive assumption was not expected to approximate reality with any reasonable accuracy. In this context, this arbitrary assumption was relaxed in the sense that different numbers of nodes were allowed for each equation of the system.

Second, the ANN had to be implemented by choosing its activation function. In this paper, we used an activation function which is known to achieve faster convergence than the "popular activation function" used in the MVT paper, i.e. "the so-called sigmoidal”. Third, we used a relevant approach for technical efficiency according to Kumbhakar and Lovell (2000).

Finally, we should bear in mind that the proposed refined NDF approach still has the desired properties of the conventional NDF model, namely it satisfies the properties dictated by neoclassical production theory globally; it gives an approximation to any arbitrary production process; it is flexible with respect to time; it allows for arbitrary returns to scale; it is simple to estimate; it avoids the need for nonlinear estimation; it uses fewer parameters than other globally flexible functional form; it provides a very good fit to real world data; it deals with the endogeneity issue in estimation, and, most important, it has a functional form which is consistent with neoclassical production theory. We believe that the proposed NDF approach which is superior in three respects to the conventional NDF approach could inspire further research in the field.

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FIGURE CAPTIONS

Figure 1: R^2 as a function of the number of nodes

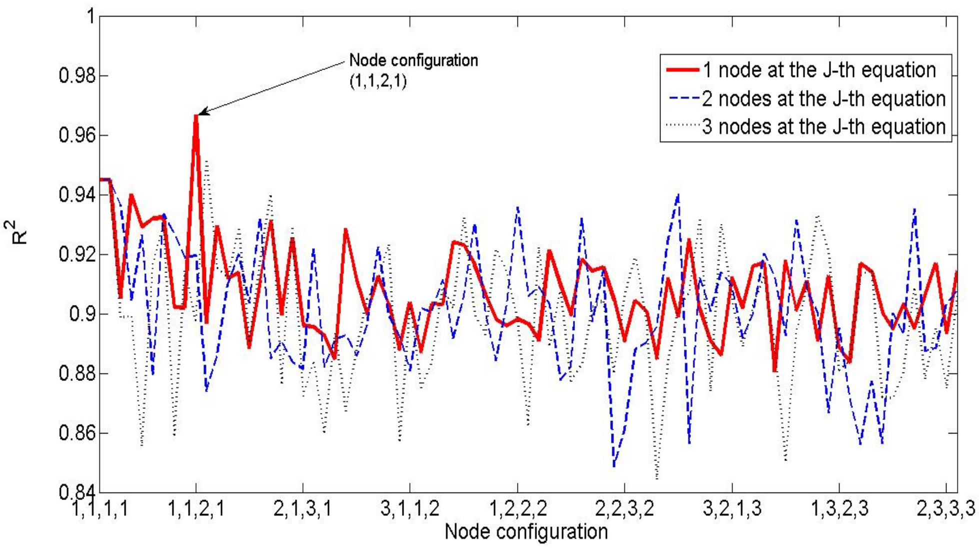

Figure 2: R^2 as a function of the iteration number using the best node configuration (1,1,2,1)

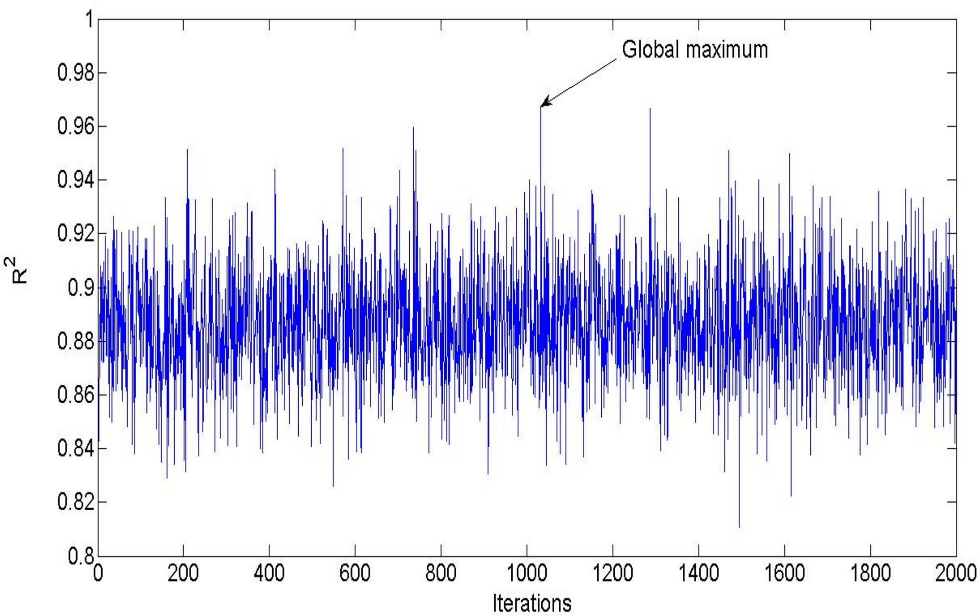

Figure 3: Returns to scale

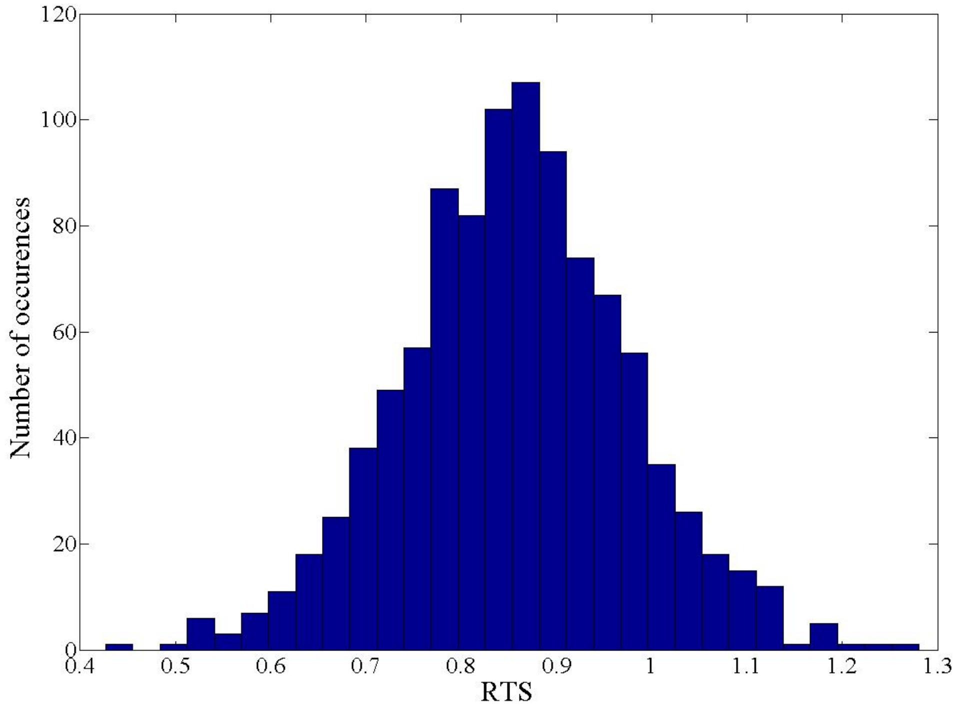

Figure 4: Technical efficiency

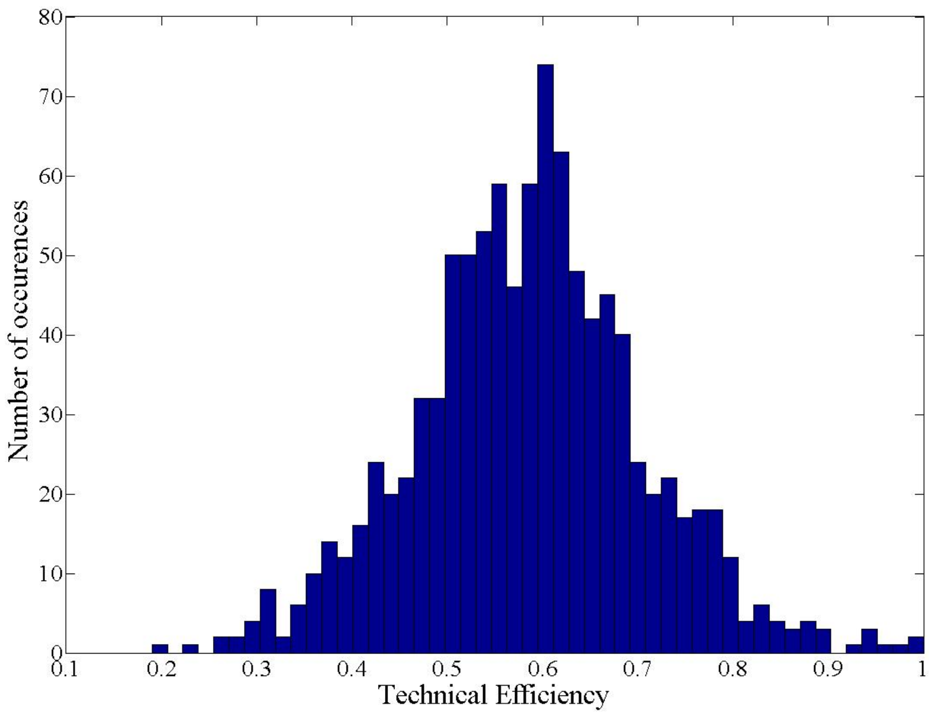

TABLE CAPTIONS

Table 1: NDF estimate (t-statistic in parenthesis)

	Equation 1	Equation 2	Equation 3	Equation 4	Equation 5
α_{0j}	-5.2700 (-2.5806)	-308.5769 (-3.8605)	29.0721 (3.5523)	-17.8371 (-0.6754)	107.9164 (20.5504)
α_{1j}	15.2114 (1.9200)	611.6839 (3.8498)	-47.4426 (-3.0725)	39.8154 (0.7836)	84.7833 (9.7530)
α_{2j}			17.3787 (4.6673)		
θ_1	0.7541 (9.9443)	2.0900 (3.6331)	0.7297 (7.4347)	0.0654 (0,1895)	
θ_2	0.0674 (4.6327)	1.0780 (3.2661)	0.2476 (2.4704)	0.0298 (0.4327)	
θ_3	0.1416 (1.3694)	0.2499 (2.6522)	0.4623 (3.7308)	0.0547 (0.2707)	
θ_4	0.0751 (3.5507)	1.6980 (3.9244)	0.3447 (3.4439)	0.0626 (0.3656)	
θ_5	0.1787 (5.9576)	1.8812 (2.7077)	0.3203 (6.3425)	0.0713 (0.1773)	
δ_j	-0.0034 (-1.5483)	-0.0263 (-5.6816)	-9.1032e-004 (-0.1770)	0.0368 (2.803)	0.0557 (4.8433)
$b_{1,1}$	0.1313	0.3072	0.5678	0.6407	0.7693
$b_{1,2}$	0.6099	0.1698	0.5697	0.0720	0.0634
$b_{1,3}$	0.6562	0.0488	0.7788	0.3658	0.9715
$b_{1,4}$	0.8410	0.2258	0.5902	0.2873	0.5952
$b_{1,5}$	0.4998	0.3670	0.1107	0.7414	0.4861
$b_{2,1}$			0.1445		
$b_{2,2}$			0.5392		
$b_{2,3}$			0.7234		
$b_{2,4}$			0.7944		
$b_{2,5}$			0.6761		

Table 1: continued

ξ_1					-1.8462
ξ_2					-4.4378
ξ_3					-2.0384
ξ_4					-5.5632
ξ_5					-0.6749
γ_1					0.2281
γ_2					0.0336
γ_3					0.3422
γ_4					0.0463
TFP					0.1585
$\tilde{R}^2$					0.9670

Note: Equations (1) – (4) above refer to Eq (5) for $j = 1, \ldots, 4$. Also, Equation (5) above refers to Eq (6) for J=5.

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