Applying Input Distance Function to Measure Pre-Recession Efficiencies of Surviving and Critically Insolvent Banks of the Late 2000s Financial Crisis

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Introduction

In recent decades, rural financial markets have undergone a period of rapid transition to adapt to structural changes in the agricultural economy and the financial services industry. The U.S. agriculture, on one hand, has undergone massive consolidation and integration since the 20th century, which has been driven by business decisions to take advantage of larger economies of scale (Lamb, 1999). Meanwhile, commercial banks have been increasingly involved in farm lending as agricultural debt comprised about 33% of their total loan portfolios in the last decade (Stam et al., 2003; Walraven et al., 1993). In the farm sector’s national balance sheets released annually by USDA’s Economic Research Service, commercial banks continue to be the dominant provider of agricultural loans. Their share of farm loan disbursements in the national aggregate farm loan portfolios has steadily increased from 35.09% in 1990 to 44.47% in 2006.

Efficiency analysis is an efficient measurement for different performing units. It can be used to gauge the degree of deviation of observed performance from a reference potential performance. This analysis was introduced to the financial industry since 1990s. As in any competitive industry, banks have always been pressured to implement innovative business strategies that enhance operating efficiency in order to sustain their competitiveness in the industry. These business strategies are vital to the health of the rural economy, considering the banks’ role in influencing regional flows of funds (Samolyk, 1989).

Over the past several years, many studies have been conducted to measure the efficiency of financial institutions, particularly of commercial banks, and detected some degree of inefficiency existing in the banking industry. Specifically, Berger and Mester (1997) claimed that the unexpected costs due to inefficiency account for at least 20% of total banking industry costs
and erodes the industry’s potential profits by about 50%. Additionally, the banking industry has experienced a massive number of losses from the recent financial crises, with a total number of 466 bank failures between 2007 and 2012. The operation inefficiency, as well as the meltdown of subprime mortgages, has affected the financial condition of banks that even by the end of 2012, there were still more than 130 banks placed under the “High Risk of Failing Watch List” of Federal Deposit Insurance Corporation (FDIC). In this regard, a study on banking efficiency will not only be beneficial to the banks to identify strategies to survive in a competitive market but will also be useful for the general public, whose confidence in the economy will be influenced by the financial health of financial institutions, and policy makers, who are responsible for formulating more appropriate new bank legislations.

However, the efficiency analysis have not been well exhausted for banking industry during this recent recession, especially among agricultural banks. In agricultural finance literature, only a few studies have explored the application of efficiency models to agricultural lending (Ellinger and Neff, 1993; Featherstone and Moss, 1994; Neff, Dixon and Zhu, 1994). Compared to regular commercial banks, agricultural banks usually have more concerns on liquidity. One third of all agricultural debts are held by rural banks with assets of less than $50 million. Thus, agricultural banks are unable to diversify their clientele to include other non-agricultural business clientele due to funding constraints. The specialized nature of their lending operations and the large variability of the agricultural products’ prices result in greater risks and uncertainty. In this regard, results of efficiency analyses based on commercial banks have less relevance to agricultural banks as no parallel conclusions can be drawn directly given these banks’ different styles of lending operations.
Stochastic Frontier Analysis (SFA) was introduced as an approach in developing an efficiency analytical framework by Aigner, et al in 1977. According to Coelli (2000, 2003), there are several outstanding merits when to apply input distance function: (1) it can be used to deal with the production with multi-outputs and multi-inputs; (2) it does not require price information; (3) it will provide robust estimation in case that there are systematic deviations from cost minimizing behavior; (4) it will not encounter the problem of the simultaneous equations bias when firms are cost minimizers or shadow cost minimizers. In addition, it has another important advantage as showed by (Atkinson and Primont, 2002): (5) there is tight relationship between cost function and input distance function according to the duality theory, which indicates the input distance function has meaningful economic explanation.

Thus, it is important to conduct an efficiency analysis for agricultural banks to determine how they thrive in an increasingly competitive financial environment. This paper applies the stochastic Translog input distance function and the stochastic frontier analysis (SFA) to evaluate the operational efficiency for the banking industry. In addition, considering that bank’s characteristics may affect its operational efficiency in different ways, the efficiency analysis is conducted on categorized banks classified based on industry specialization (agricultural banks vs commercial banks). Furthermore, the inefficiency level is also measured on categorized banks classified based on banks’ solvency condition (failed banks vs non-failed banks) during this late 2000s recession in order to find out some early warning signals in bank’s operation.

**Methodology**

The Shephard (1953) input distance function is defined as follows:

\[
D'(x, y) = \sup_{\rho} \rho > 0 : (x/\rho) \in L(y)
\]
where the superscript $I$ implies that it is the input distance function; the input set $L(y) = \{x \in \mathbb{R}_+^n : x \text{ can produce } y \in \mathbb{R}_+^m \}$ represents the set of all input vectors, $x$, which can produce the output vector, $y$; and $\rho$ measures the possible proportion of the inputs which can be reduced to produce the quantity of the outputs not less than $y$. So in other word, input distance function is the maximum retraction proportion of inputs to achieve the outputs on the production frontier.

Farrell and Primont (1995) and Cornes (1992) showed and approved the following properties of the input distance function:

(1) $D^I(x,y)$ is dual of the cost function.

(2) $x$ belongs to the input set of $y$ (e.g. $x \in L(y)$) if and only if $D^I(x,y) \geq 1$.

(3) When a firm operates on the production frontier, isoquant $L(y)$, $D^I(x,y)$ is equal to 1. In this case, the firm achieves the technical efficiency.

(4) $D^I(x,y)$ is non-decreasing in inputs, $x$, and non-increasing in outputs, $y$.

(5) $D^I(x,y)$ is homogeneous of degree 1 in $x$.

(6) $D^I(x,y)$ is concave in $x$ and quasi-concave in $y$.

The stochastic frontier analysis (SFA) approach is introduced to estimate the flexible Translog distance function. Distance functions can be used to estimate the characteristics of multiple output production technologies in the absence of price information and whenever the
cost minimization or revenue maximization assumptions are inappropriate. Sometimes, banking industry, unlike other competitive markets, would not set the minimum costs (or maximum profits) as their unique objective, especially for agricultural banks and some other policy banks. In addition, it is obvious that almost all banks would operate in the operational environment with multi-outputs and multi-inputs. Moreover, banks have more power to control over the inputs instead of outputs. So the stochastic input distance function would be proper for banks’ efficiency analysis. The Translog function overcomes the shortcomings of the usual Cobb-Douglas function form which assumes that all firms have the same production elasticities, which sum up to 1. The Translog function is more flexible with less restriction on production and substitution elasticities. The flexibility reduces the biased estimate’s possibility due to the improper function form’s assumption.

The stochastic input distance function for each observation $i$ is estimated by:

$$
\ln D_i^t = \beta_0 + \sum_{k=1}^{M} \beta_{y_k} \ln y_{k,it} + \frac{1}{2} \sum_{k=1}^{M} \sum_{t=1}^{M} \beta_{y_k y_{t}} \ln y_{k,it} \ln y_{t,it} + \sum_{j=1}^{N} \beta_{x_j} \ln x_{j,it} + \frac{1}{2} \sum_{j=1}^{N} \sum_{h=1}^{N} \beta_{x_j x_{h}} \ln x_{j,it} \ln x_{h,it} \\
+ \sum_{j=1}^{N} \beta_{x_j z_{d,f}} \ln x_{j,it} \ln y_{k,it} + \sum_{d=1}^{P} \beta_{z_{d,t}} \ln z_{d,it} + \frac{1}{2} \sum_{d=1}^{P} \sum_{f=1}^{P} \beta_{z_{d,t} z_{f,t}} \ln z_{d,it} \ln z_{f,it} + \sum_{k=1}^{M} \beta_{y_{k,t} y_{d,f}} \ln y_{k,it} \ln z_{d,it} \\
+ \sum_{j=1}^{N} \beta_{x_j z_{d,f}} \ln x_{j,it} \ln z_{d,it} + \sum_{k=1}^{M} \alpha_k (t \ln y_{k,it}) + \sum_{j=1}^{N} \delta_j (t \ln x_{j,it}) + \sum_{d=1}^{P} \theta_d (t \ln z_{d,it}) + \lambda_1 t + \frac{1}{2} \lambda_2 t^2 + d_{a,i} \text{dum}_{a,it}
$$

(2)

where $dum_{a,it}$ is the dummy variable for agricultural banks; $k, l = 1, \ldots M$ and $M = 5$ (number of outputs); $j, h = 1, \ldots N$ and $N = 4$ (number of inputs); $d, f = 1, \ldots P$ and $P = 2$ (number of indexes to measure financial risks and loan’s quality).
A necessary property of the inputs distance function is homogeneity of degree one in input quantities, which implies that the parameters in equation (2) should satisfy the following constraints:

\[
\sum_{j=1}^{N} \beta_{x_j} = 1 \quad (R1)
\]

\[
\sum_{j=1}^{N} \beta_{x_{jh}} = 0, \quad \forall h = 1,\ldots,N \quad (R2)
\]

\[
\sum_{j=1}^{N} \beta_{xy_{jk}} = 0, \quad \forall k = 1,\ldots,M \quad (R3)
\]

\[
\sum_{j=1}^{N} \beta_{xz_{jd}} = 0, \quad \forall d = 1,\ldots,P \quad (R4)
\]

\[
\sum_{j=1}^{N} \delta_j = 0 \quad (R5)
\]

In addition, the property of homogeneity can be expressed mathematically as:

\[
3 \quad D_{it}^I (\lambda x, y) = \lambda D_{it}^I (x, y), \quad \forall \lambda > 0
\]

Assuming \( \lambda = 1/x_{N,it} \), equation (3) can be expressed in logarithmic form as:

\[
4 \quad \ln D_{it}^I (x/x_{N,it}, y) = \ln D_{it}^I (x, y) - \ln x_{N,it}
\]

---

\(^1\) \( \lambda \) can be selected as arbitrary input to serve as the denominator considering that input distance function is homogeneity of degree one in inputs (here the \( N^{th} \) input is selected as the denominator).
According to the definition of the input distance function, the logarithm of the distance function in (4) measures the deviation of an observation \((x, y)\) from the efficient production frontier \(L(y), \varepsilon_{it}\).

\[(5) \ln D_t^l(x, y) = \varepsilon_{it}\]

Following the literature of the SFA, this deviation from the production frontier can be explained by two components (Irz and Thirtle, 2004). The most extraordinary characteristic of the SFA is that it decomposes \(\varepsilon_{it}\) as \(\varepsilon_{it} = v_{it} - u_{it}\). Then equation (5) can be expressed as:

\[(6) \ln D_t^l(x, y) = u_{it} - v_{it}\]

where \(u_{it}\) measures the technical inefficiency and follows the positive half normal distribution as \(u_{it} \sim N^+(\mu, \sigma_u^2)\); while \(v_{it}\) measures the pure random error and follows the normal distribution as \(v_{it} \sim N(0, \sigma_v^2)\).

Substituting equation (6) into equation (4), equation (4) can be rewritten as:

\[(7) -\ln x_{N,it} = \ln D_t^l(x/x_{N,it}, y) + v_{it} - u_{it}\]

Besides the homogeneity restrictions, the symmetric restrictions also need to be imposed when to estimate the Translog input distance function. The symmetric restrictions require the parameters in equation (2) should satisfy the following constraints:

\[\beta_{\gamma_{kl}} = \beta_{\gamma_{lk}}, \text{ where } k, l = 1, \ldots, M \quad \text{(R6)}\]

\[\beta_{x_{jh}} = \beta_{x_{hj}}, \text{ where } j, h = 1, \ldots, N \quad \text{(R7)}\]
\[ \beta_{c_{d,f}} = \beta_{c_{d,f}^*}, \] where \( d, f = 1, \ldots, P \)

(R8)

Imposing restrictions (R1) through (R8) and equation (2) upon equation (7) yields the estimating form of the input distance function as follows:

\[
-\ln x_{nit} = \beta_0 + \sum_{k=1}^{M} \beta_{y_{it}} \ln y_{k,it} + \sum_{j=1}^{N-1} \beta_{x_{it}} \ln x_{j,it}^* + \sum_{d=1}^{P} \beta_{z_{it}} \ln z_{d,it} \\
\quad + \frac{1}{2} \left[ \sum_{k=1}^{M} \beta_{y_{it}} (\ln y_{k,it})^2 + \sum_{j=1}^{N-1} \beta_{x_{it}} (\ln x_{j,it})^2 + \sum_{d=1}^{P} \beta_{z_{it}} (\ln z_{d,it})^2 \right] \\
\quad + \sum_{k=1}^{M} \sum_{l=1, l \neq k}^{M} \beta_{y_{it}} \ln y_{k,it} \ln y_{l,it} + \sum_{j=1}^{N-1} \sum_{k=1, k \neq j}^{N-1} \beta_{x_{it}} \ln x_{j,it} \ln x_{k,it}^* + \sum_{d=1}^{P} \sum_{f=1, f \neq d}^{P} \beta_{z_{it}} \ln z_{d,it} \ln z_{f,it} \\
\quad + \sum_{j=1}^{N-1} \sum_{k=1}^{M} \beta_{y_{it}} \ln y_{k,it} \ln x_{j,it}^* + \sum_{d=1}^{P} \beta_{z_{it}} \ln z_{d,it} \ln x_{j,it}^* \\
\quad + \sum_{k=1}^{M} \alpha_k (\ln y_{k,it}) + \sum_{j=1}^{N-1} \delta_j (\ln x_{j,it}^*) + \sum_{d=1}^{P} \theta_d (\ln z_{d,it}) + \lambda_t t + \frac{1}{2} \lambda_2 t^2 \\
\quad + \nu_t - u_t^d u_{it} \]

where \( x_{j,it}^* = x_{j,it} / x_{N,it} \) is the normalized input \( j \).

Since our model is estimated for panel data, the hypothesis of time-invariant \((\eta = 0)\) need to be tested. For general model form, the inefficiency effects can be modeled as

\[ u_t^i \overset{iid}{\sim} N^\dagger(\mu, \sigma^2_{\mu}). \]

If \( \eta = 0 \), the time-invariant hypothesis will fail to be rejected and model will be the time-invariant model. If the hypothesis is rejected, it means that the model is time-variant, and then time-variant constraint \((\eta \neq 0)\) must be imposed when to estimate equation (8). Additionally, the sign of the \( \eta \) can tell the efficiency change across the time series.
Positive sign means the efficiency achievement, while the negative sign indicates the efficiency decaying.

After estimating all coefficients in equation (8), the coefficients for the \(N^{th}\) input can be calculated by the homothetic restrictions (R1) to (R5).

To have a better view of the decomposition of the efficiency, firstly the scenario of one output with two inputs is used to illustrate how the Technical efficiency (TE) and allocative efficiency (AE) is measured in Figure 1. Assume a firm use input \(x_1\) and \(x_2\) at point A to produce the output \(y\), technical inefficiency would occur since the same amount of the output would be produced with fewer inputs by movement from point A to point C. So the TE can be calculated as \(TE = OC/OA\) which represents the percentage of the input saved. Aligning the definition of the input distance function, it is not hard to find the link between \(D^I(x,y)\) and \(TE\).

\[
(9) \quad TE = 1/D^I(x,y)
\]

Given the input prices \(p_1\) and \(p_2\), the AE would be illustrated in Figure 1. The move from C to D on the isoquantity curve shows that the firm’s output keep the same while operate on the lower isocost curve \(fI\). It implies that the firm could save costs without output decrease. Following the same concept to calculate TE, AE can be calculated as \(AE = OB/OC\).

To make this study more realistic, the estimated input distance function will be used to further differentiate the technical efficiency and allocative efficiency. The technical inefficiency levels can be calculated by

\[
(10) \quad TE_{it} = 1/D_{it} = 1/E[\exp(u_{it}) \mid v_{it} - u_{it}]
\]
where \( 0 \leq \text{TE}_u \leq 1 \). The closer is \( \text{TE}_u \) to unity, the more technically efficiently the bank performs. Considering the panel data, \( u_a \) can be expressed as equation

\[
(11) \quad u_a = \exp\{-\eta(t - T_i)\}.u_i
\]

\( \eta = 0 \) implies that the distance function won’t fluctuate by time series. The model in case is time-invariant. Otherwise, the model is time-variant. There are two scenarios for time-variant model, when \( \eta > 0 \), the degree of inefficiency decreases over time; when \( \eta < 0 \), the degree of inefficiency increases over time. Since \( t = T_i \) in the last period, the last period for firm \( i \) contains the base level of inefficiency for the firm. \( \eta > 0 \) means that the level of inefficiency decays toward the base level. Oppositely \( \eta < 0 \) means that the level of inefficiency increases to the base level.

Allocative efficiency can be assessed by estimating shadow prices. Initially, the studies were based on the estimation of the system equations composed by cost function and cost share equations (Atkinson and Halvorsen, 1986; Eakin and Kniesner, 1988). However, the validation of this system equations’ estimation requires the assumption of the cost minimization. Recently, some researchers provided an alternative method to get shadow prices out of inputs using Shephard’s distance function (Fare and Grosskopf, 1990; Banos-Pino et al., 2002; Atkinson and Primont, 2002; Rodriguez-Alvarez et al., 2004). Under this new analysis scheme, the assumption of the cost minimization is not necessary to get the consistent estimates. They allow the difference between the market prices and shadow prices with respect to the minimum costs. As illustrated for simplified situation by Figure 1, shadow price ratio \( p_1^s / p_2^s \) is the slope of the isocost curve \( f3 \) which indicates the minimum cost at given level of inputs to produce the same
quantity of the outputs. In another word, a firm would be allocative efficient if it could operate at point C which is on the isocost curve $f3$ to satisfy the condition required by the allocative efficiency. This condition requires that the marginal rate of technical substitution (MRTS) between any two of its inputs is equal to the ratio of corresponding input prices ($p_i^s / p_j^s$). So the deviation of the market price ratio ($p_i / p_j$) from the shadow price ratio ($p_i^s / p_j^s$) reflects the allocative inefficiency. The ratio can be expressed as $k_{12} = \frac{p_i^s / p_j^s}{p_i / p_j}$. Specifically, if the ratio equals to 1, the allocative efficiency achieved. Otherwise, the allocative inefficiency is detected. The larger does $|k_{12}|$ deviate from 1, the larger allocative inefficiency is.

More generally, the allocative inefficiency for each observation $i$ at time $t$ can be measured by relative input price correction indices:

$$k_{jh, it} = k_{jt, it} / k_{ht, it} = \frac{p_{j, it}^s / p_{j, it}^s}{p_{h, it}^s / p_{h, it}^s} = \frac{p_{j, it}^s}{p_{j, it}^s} \cdot \frac{p_{h, it}^s}{p_{j, it}}$$

where $k_{jt, it} = p_{j, it}^s / p_{j, it}$ is the ratio of the shadow price, $p_{j, it}^s$, to market price, $p_{j, it}$, for input $j$ of the observation $i$ at time $t$. If $k_{jt, it} = 1$, there is no allocative inefficiency; If $k_{jt, it} > 1$, the input $j$ is being underutilized relative to the input $h$; If $k_{jt, it} < 1$, the input $j$ is being overutilized relative to the input $h$.

Atkinson and Primont (2002) derived the shadow cost function from a shadow distance system. In shadow distance system, the cost function can be expressed as:

$$C(y, p) = \min_x \{ px : D(y, x) \geq 1 \}$$
Implementing the duality theory and imposing input distance function’s linear homogeneity property, they showed how to derive the dual Shephard’s lemma as:

$$
\frac{\partial D^I_u(x, y)}{\partial x_{j,it}} = \frac{P^*_j, it}{C(y, p^*)}
$$

From equation (14), the ratio of the shadow prices can be calculated by:

$$
\frac{p_{j, it}}{p_{h, it}} = \frac{\partial D^I_u(x, y)/\partial x_{j, it}}{\partial D^I_u(x, y)/\partial x_{h, it}}
$$

Applying the derivative envelope theory to the numerator and denominator of the equation (15) separately, equation (15) can be expressed as:

$$
\frac{p_{j, it}}{p_{h, it}} = \frac{\partial D^I_u(x, y)/\partial x_{j, it}}{\partial D^I_u(x, y)/\partial x_{h, it}} = \frac{[\partial (D^I_u(x, y) \cdot x_{j, it})]/\partial \ln D^I_u(x, y)/\partial \ln x_{j, it}]}{[\partial (D^I_u(x, y) \cdot x_{h, it})]/\partial \ln D^I_u(x, y)/\partial \ln x_{h, it}}
$$

$$
= \frac{x_{h, it}}{x_{j, it}} \cdot \frac{\partial \ln D^I_u(x, y)/\partial \ln x_{j, it}}{\partial \ln D^I_u(x, y)/\partial \ln x_{h, it}}
$$

Finally, substituting the equation (16) into equation (12), the relative allocative inefficiency shown by the relative input price correction indices can then be expressed as:

$$
k_{j, it} = \frac{p_{h, it}}{p_{j, it}} \cdot \frac{x_{h, it}}{x_{j, it}} \cdot \frac{\partial \ln D^I_u(x, y)/\partial \ln x_{j, it}}{\partial \ln D^I_u(x, y)/\partial \ln x_{h, it}}
$$

$$
= \frac{p_{h, it}}{p_{j, it}} \cdot \frac{x_{h, it}}{x_{j, it}} \sum_{j=1}^{N} \frac{\beta_{x_j} \ln x_{j, it} + \sum_{k=1}^{M} \beta_{y_{jk}} \ln y_{k, it} + \sum_{d=1}^{P} \beta_{z_{jd}} \ln z_{d, it} + \delta f}{\beta_{x_j} \ln x_{j, it} + \sum_{k=1}^{M} \beta_{y_{jk}} \ln y_{k, it} + \sum_{d=1}^{P} \beta_{z_{jd}} \ln z_{d, it} + \delta f}
$$
Data

This study will utilize a panel data set collected from the call report database published online by the Federal Reserve Board of Chicago during period 2000 to 2005.\(^2\) The available quarterly data were annualized for purposes of this study. Instead of using branch-level, consolidated-level financial information were used in this study as financial variables, which were calculated from consolidated banking financial statements that summarized the annual financial performances of all branches. Certain selection criteria were applied to the database such as only banks that continuously reported their financial conditions during the six-year period were retained, and banks with any missing observations for any variable or in any year were discarded. These filtering requirements resulted in a total of 2298 observations, or a panel dataset of 383 banks over 6 years.

In this study, banks are classified as either agricultural or non-agricultural banks based on their agricultural loan ratios using the criterion of Federal Deposit Insurance Corporation (FDIC) applied to commercial banks.\(^3\) Banks that exceed the FDIC cutoff agricultural loan ratio of 25% are categorized as “agricultural banks.” Using such criterion, the percentages of the agricultural banks in this study’s dataset range from 16.2% to 17.75%.

Five bank output data were collected including the total dollar amounts of agricultural loans \((y_1)\), non-agricultural loans \((y_2)\), consumer loans \((y_3)\), fee-based financial services \((y_4)\),

\(^2\) The period of study covered qualifies as part of the bubble period when rising land prices have driven the market to engage in significant land investment transactions and consequently pose as an impediment to implementing cost minimization strategies. Ogawa (2008) points out that since concavity condition on cost functions is based on the implicit assumption that firms are indeed minimizing costs. Thus, analyzing firm’s cost decisions during bubble periods with an imposed concavity condition will lead to model misspecification.

\(^3\) The FDIC criterion for defining agricultural banks provides a compromise between the Federal Reserve System approach (periodically changing agricultural loan ratios ranging from 10% to 15% based on actual financial conditions of all commercial banks) and the methods used by the American Banking Association (based on either the absolute dollar volume of agricultural loans or an agricultural loan ratio of 50%).
and other assets that cannot be classified under the other asset accounts in the balance sheet ($y_3$).

The input price data categories considered are labor expense per employee (salaries and employee benefits divided by number of full-time equivalent employees, $p_1$), physical capital (occupancy and fixed asset expenditures divided by net premises and fixed assets, $p_2$), purchased financial capital inputs (expense of federal funds purchased and securities sold and interest on time deposits of $100,000 or more divided by total dollar value of these funds, $p_3$), and deposits (interest paid on deposits divided by total dollar value of these deposits, $p_4$).

Measures of loan quality index ($z_1$) and financial risk index ($z_2$) are also included in this analysis to introduce a risk dimension to the efficiency models. The index $z_1$ is calculated from the ratio of non-performing loans to total loans (NPL) to capture the quality of the banks’ loan portfolios\(^4\) (Stirob and Metli, 2003). The index $z_2$ is based on the banks’ capital to asset ratio\(^5\), which is used in this study as proxy for financial risk. The role of equity has been understated in efficiency and risk analyses that focus more on NPL and other liability-related measures (Hughes et al., 2000). Actually, as a supplemental funding source to liabilities, equity capital can provide cushion to protect banks from loan losses and financial distress. Banks with lower capital to asset ratios (CAR) would be inclined to increasingly rely on debt financing, which, in turn, increases the probability or risk of insolvency.

\(^4\) $z_1 = 10000 \times \frac{\text{nonaccrual loans} + \text{loans 90 days or more past due}}{\text{total loans}}$. The reason to use $z_1$ but instead of NPL is because $\ln z_1$ is a monotonic transformation of NPL which will only change the magnitude of the NPL but still keep all other properties of NPL. In addition, after the transformation, $\ln z_1$ would be all positive numbers with less extreme values.

\(^5\) $z_2 = 1000 \times \frac{\text{Equity Capital}}{\text{Total Assets}}$. The reason to develop $z_2$ is the same as $z_1$. 
Empirical Results

Table 1 is the ANOVA table to compare TE between Agricultural Banks and Non Agricultural Banks. The table shows that both Agricultural Banks and Non Agricultural Banks are not technically efficient. The efficiency level of Agricultural Banks is 62%. While the efficiency level of Non Agricultural Banks is only 58%. The TE of Agricultural Banks is significantly 4% more efficient than Non Agricultural banks (p-value<0.0001). Graph 2 illustrates the TE trend between 2000 and 2005. This graph showed the evidence that Agricultural Banks are more efficient than Non Agricultural Banks. Additionally, we notice that the time series efficiency trend is quite stable in each classified group.

As introduced previously, $k_{jth}$ calculated by equation (17) can be used to measure the relative allocative inefficiency level. Table 2 and Table 3 summarized the average $k_{jth}$ over years by Bank Characteristics and Bank solvency condition respectively.

Figure 3 showed that the inefficiency level may be different over years but the relative allocative inefficiency exists widely in both agricultural banks and non agricultural banks between any two inputs. The graph of $k_{12}$ showed the efficiency difference between agricultural and non agricultural. It also showed the fluctuation between labor input and physical capital input ratio over years. This phenomenon implies adjustments to optimize the use of labor and physical capital were constantly made by both groups of banks. In general, this allocative inefficiency reflects over-utilized labors against the physical capitals since $k_{12} < 1$ is true for all years except for agricultural banks in 2001. Additionally, agricultural banks have shown a

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6 Since the input distance in this study is the time-invariant model, one way ANOVA analysis without time series factor is applied for both bank characteristics and bank size TE comparison.
stronger tendency to balance these input allocations than non agricultural banks. This may implies that the agricultural banks have more flexibility to adjust physical capitals compared to the non agricultural banks. The graph also showed that agricultural banks fluctuate around $k_{12} = 1$ in most years. It may indicate that the efforts made by agricultural banks to adjust labors and physical capitals are more effective than non agricultural banks. The graph for $k_{13}$ trend showed the significant improvement of the allocative efficiency between labor and financial capital inputs over years by relatively increasing the input of labor and reducing the financial capital. Additionally, it is notable that this adjustment came through two stages. The first stage is the fast adjusted process to efficient ratio before 2003. It was observed that the sharper slope of $k_{13}$ tendency to one. After adjustment at the first stage, the banking industry achieved the goals to operate around the optimal inputs ratio between labor and financial capital. At this stage, agricultural banks are relatively more efficient than non agricultural banks. The second stage occurred after 2003. At second stage, more efforts are made to keep banks operating around the efficient resource allocation level. At this stage, non agricultural banks are slightly more efficient than agricultural banks. But the difference of the allocative efficiency between these two inputs narrowed down after 2003. $k_{14} < 1$ in all years implies that the labor is overutilized compared to the deposit for a long time in banking industry. The graph for $k_{14}$ trend showed that this improper proportion between two inputs is getting worse over years. Meanwhile, agricultural banks consistently allocate these two input resources in a slightly more efficient way over the years. Similar to $k_{14}$, $k_{23}$ is less than one over years regardless of bank characteristics. This implies overutilized physical capital vis-a-vis financial capital in this study’s bank samples. The graph of $k_{23}$ also showed that the 2003 is the point of contraflexure. Before this point, non
agricultural banks perform much better than agricultural banks. But after 2003, this difference is getting closer and reversed to reflect the higher performance of agricultural banks versus non agricultural banks. The graph for $k_{24}$ showed that both agricultural and non agricultural banks perform far below the efficient way in utilizing physical capital and deposits. Overall, they only reached less than 20% of the allocative efficiency. The physical capital is overutilized compared to the deposit. The fact that $k_{34}$ is less than one indicates that the financial capital is overutilized compared to the deposit. But variation of this ratio is relatively small. It means that the adjustment between financial capital and deposit was seldom made. Notably, agricultural banks allocated these two inputs in a more efficient way over years.

The results for $k_{jh}$ by bank’s solvency condition during 2000 to 2005 are shown in figure 4. The six years time interval were chosen prior to the beginning of recession in the end of 2007 since this study is designed to find out any early warning signals in operating efficiency before the financial crisis hit the banking industry. $k_{12}$ is the relative input price index between labor expense and physical capital. Compared to the surviving banks, there is a clear fluctuation between labor and physical capital over years for critically insolvent banks. Labor has been underutilized vis-a-vis physical capitals since $k_{12} > 1$ for all the periods except 2002 and 2005. Notably, critically insolvent banks were performing more efficiently since 2003 by relatively reducing the financial capital and increasing the use of labor. However, $k_{12}$ became less than 1 in 2005 for those banks, which could indicate that they were operating under a high cost with labor overutilization. On the contrary, labor inputs have been overutilized for surviving banks since 2000. However, after 2002, surviving banks were operating more efficiently through adjustments in their labor and physical capital inputs. Their efficiency index also has the tendency to get closer to the ideal $k_{12} = 1$. Graph $k_{13}$ showed that both the critically insolvent banks and
surviving banks have underutilized labor over financial capital inputs. Similar to the graph between agricultural banks and non-agricultural banks, the allocative efficiency between labor and financial capital inputs has been improved through two stages. First stage is from 2000 to 2003, with steeper slope of $k_{12}$ for either critically insolvent banks or surviving banks, the banking industry achieved the goals to operate around the optimal inputs ratio between these two inputs. In additions, surviving banks were performing more efficiently than critically insolvent banks at this stage. The second stage occurred after 2003. At this stage, surviving banks made more efforts to keep their operations around the efficient resource allocation level. On the other hand, critically insolvent banks once again operated inefficiently by overutilizing labor inputs.

Graph $k_{14}$ showed the improper proportion between labor and deposit was getting worse over years, which has the similar pattern as compared to the graph between agricultural and non-agricultural banks. It is difficult to distinguish which group of banks is doing better, but a slight efficiency improvement for both groups was observed in 2005. $k_{23}$ for critically insolvent banks fluctuated around one as compared to surviving banks. Surprisingly, surviving banks have brought in more financial capital instead of adding fixed assets since 2001. Recent argument about bank regulation declared that banks should hold more capital and used them as a buffer against financial crisis (Hoenig, 2012). So this might be the reason that banks prefer to hold more capital, especially for those banks that eventually survived the banking crisis. Similar to the graph of $k_{14}$, $k_{24}$ is less than 1 over years regardless of bank’s solvency condition. Even though this ratio is far below the efficient way to utilize the physical capital and deposit, it is observed that surviving banks were facing an upper slope of $k_{24}$ since 2002, which indicates these banks’ strong efforts to adjust these two inputs. Graph $k_{34}$ showed the index between financial capital
and deposits, which show the general tendency to overutilize financial capital vis-a-vis deposits among this study’s sample banks.

**Summary and Conclusion**

This study has introduced the application of the Input Distance function to measure the banks’ operating efficiency and the subsequent analyses of the effects of bank’s solvency condition and product specialization on efficiency measures. Product specialization categories allow the comparative assessments of efficiency between agricultural and non-agricultural banks. The solvency condition allows the comparative assessments of efficiency between those critically insolvent banks that either eventually failed or have been placed under the FDIC watchlist for highly risky or critically insolvent banks during the recent recession and the banks that survived the late 2000s financial crises.

The estimation of the input distance function supports the hypotheses that the bank characteristics have impacts on technical efficiency levels. Specifically, Agricultural Banks have been found to be more technically efficient than Non Agricultural Banks. The TE of Agricultural Banks is 4% higher than the TE calculated for Non Agricultural banks. Meanwhile, the technical efficiency measures showed that the whole banking industry tends to drift away from the technically efficient norm of operations. And the nature of the time-invariant input distance function gives the evidence that this scenario did not improve between 2000 and 2005.

The relative allocative efficiency measures disclosed that inefficiency due to the improper input allocation exists pervasively in the industry. Some efficiency measures showed consistency of such trend among banks of various characteristics and solvency condition. There are however some exceptions. For one thing, it is notable that all results implied that the deposits
are under utilized in the sample banks. Banks should better use this relative cheaper fund to achieve the input allocative efficiency. Moreover, the comparison between surviving and critically insolvent banks indicates that the reason why those banks eventually survived the financial crisis might because they have maintained a fairly balanced utilization of their labor expense, physical capital and financial capital.
Reference


Table 1. ANOVA Table for TE: Bank Characteristics

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<thead>
<tr>
<th>Source of Variation</th>
<th>DF</th>
<th>Sum of Squares</th>
<th>Mean Square</th>
<th>F Value</th>
<th>Pr &gt; F</th>
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<td>Model</td>
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<td>0.37</td>
<td>39</td>
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<td>Error</td>
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<td></td>
<td></td>
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<tr>
<td>Corrected Total</td>
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<td>22.23</td>
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<table>
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<tr>
<th>Bank Characteristics</th>
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<th>Standard Error</th>
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<tr>
<td>Ag Bank</td>
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</tr>
<tr>
<td>NonAg Bank</td>
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<td>0.10</td>
</tr>
</tbody>
</table>

| Comparison           | Estimate | Standard Error | t Value | Pr > |t| |
|----------------------|----------|----------------|---------|------|
| Ag Bank – NonAg Bank | 0.03     | 0.01           | 6.24    | <.0001 |
Table 2. Summary of $k_{jh}$ by Bank Characteristics over Years

<table>
<thead>
<tr>
<th>Bank Characteristics</th>
<th>Year</th>
<th>k12</th>
<th>k13</th>
<th>k14</th>
<th>k23</th>
<th>k24</th>
<th>k34</th>
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<td>0.01</td>
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<td>0.47</td>
<td>0.11</td>
<td>0.12</td>
<td>0.57</td>
</tr>
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<td>0.79</td>
<td>0.33</td>
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</tr>
<tr>
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<td>0.02</td>
<td>0.72</td>
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<td>0.26</td>
<td>0.13</td>
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<tr>
<td></td>
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<td>0.31</td>
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Table 3. Summary of \( k_{jh} \) by Bank Operating Conditions over Years

<table>
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<th>k14</th>
<th>k23</th>
<th>k24</th>
<th>k34</th>
</tr>
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<tr>
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<td>2.21</td>
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<td>0.32</td>
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<tr>
<td></td>
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<td>1.17</td>
<td>0.03</td>
<td>0.35</td>
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<tr>
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<td>2002</td>
<td>0.19</td>
<td>1.47</td>
<td>0.31</td>
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Figure 1: Technical and Allocative Efficiency Identified by Input Distance Function
Figure 2: Technical Efficiency Trend by Bank Characteristics
Figure 2: $k_{jh}$ by Bank Characteristics over Years
Figure 3: $k_{jh}$ by Bank Operating Conditions over Years