INTERTEMPORAL CHANGE IN COST EFFICIENCY AND ITS DETERMINANTS USING A BASE PERIOD APPROACH: AN EVIDENCE FROM KOREAN RICE FARMS

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Abstract: The objective of our study is to propose a procedure for intertemporal comparison of technical and cost efficiencies across years. The procedure measures the efficiency change while excluding the frontier shift effect using the base period approach. Our first contribution to the literature is to develop a procedure that can allow intertemporal comparison for cost efficiency (*CE*). The newly developed procedure first decomposes the change in the standard *CE*, estimated with a different frontier and input prices each year, into four factors: technology change, individual effort for technical efficiency (*TE*) change, price effect, and individual effort for allocative efficiency (*AE*) change. Then, the intertemporal change in *CE*, estimated with the base-period frontier, is calculated after eliminating technology change and price effect from the change in the standard *CE*. Our second contribution is to statistically test mean differences of efficiency scores using a sample T-test based on the asymptotic normal distribution, following Kneip, Simar, and Wilson. (2015, 2016), and Simar and Wilson (2020). The third contribution is to conduct a two-stage analysis using efficiency scores estimated from the based period approach. A few earlier studies also conduct a two-stage regression analysis to show effects of factors other than already considered to estimate efficiency scores. However, earlier studies use the standard efficiency scores estimated with changing frontiers each year, which makes difficult the scores comparable over time. We compare regression results estimated from our base period approach with those estimated with the standard approach.

Overall, our study finds that the two methods produced different results. Technical and cost efficiency in 2017 are less than 2008 and 2013 when the standard method with different base-frontier approach. However, when the base period approach is used, technical and cost efficiencies in 2017 improved from 2008 and 2013, while two efficiency scores from the conventional approach decreased in 2017 from 2008 and 2013. The two distinctively different results show that the conventional approach with different base-frontiers could result in erroneous policy implications. Regression results with estimated efficiency scores from standard and base period approach show no distinct difference except year dummies.

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CHAPTER I

INTRODUCTION

Efficiency scores have been widely used to measure performance of operating units such as public and private firms, agricultural farms, government, health care providers, and other businesses. Estimated efficiency scores are often used to compare the operating units' performances to a target performance or compare these efficiencies intertemporally. The outcome of these comparisons should be essential to develop strategies and policies that can help improve efficient use of resources at both firm and government levels.

Many previous studies in the literature empirically estimate efficiency scores and compare them between different time periods (e.g., Fare et al. 1994, Kwon and Lee 2004, Maniadakis and Thanassoulis 2004, O'Donnell, Rao, and Battese 2008, Flokou, Aletras, and Niakas 2017, Chen, Huang, and Chiu 2017). For example, Fare et al. (1994) examines efficiency change as the ratio of two technical efficiencies which are evaluated under different frontiers. However, comparing efficiency change is problematic if the two efficiencies are measured based on two different base frontiers. O'Donnell, Rao, and Battese (2008), Flokou, Aletras, and Niakas (2017), and Chen, Huang, and Chiu. (2017) suggest that the comparison of efficiencies under different frontiers is invalid. The meta-frontier approach by O'Donnell, Rao, and Battese (2008) and the window approach in

Flokou, Aletras, and Niakas (2017) try to make a common frontier in the same group to compare efficiency scores. Chen, Huang, and Chiu (2017) set a base frontier for the base period and attempt to catch the efficiency change, while excluding frontier movement.

The objective of our study is to propose a procedure for intertemporal comparison of both technical and cost efficiency across years. The procedure measures the efficiency change while excluding the frontier shift effect using the base period approach. Our first contribution to the literature is to develop a procedure that can allow intertemporal comparison for cost efficiency (*CE*). Extending Chen, Huang, and Chiu (2017), the newly developed procedure first decomposes the change in the standard *CE*, estimated with a different frontier each year, into four factors: technology change, individual effort for technical efficiency (TE) change, price effect, and individual effort for allocative efficiency (*AE*) change. Then, the intertemporal change in *CE*, estimated with the base period frontier, is calculated after eliminating technology change and price effect from the change in the standard *CE*. To demonstrate the importance of using the based period approach, we compare the based period approach *CE*s with those from the standard approach. The meta-frontier and the window Data Envelopment Analysis (DEA) approaches also assume a common frontier so that one can compare efficiency change. However, it is impossible to find common input or output price in different years, and the window DEA approach fails to compare efficiency score in a distinct window.

Our second contribution is to statistically test mean differences of efficiency scores using a sample T-test based on the asymptotic normal distribution, following Kneip, Simar, and Wilson. (2015, 2016), and Simar and Wilson (2020). Efficiency scores estimated by a non-parametric procedure such as DEA are biased, and the bias does not converge to zero under the ordinary central limit theorem. The adjusted central limit theorem, proposed by Kneip, Simar, and Wilson (2015) and Simar and Wilson (2020), can remove the bias and to derive the asymptotic normal distribution for estimated efficiency scores.

The third contribution is to conduct a two-stage analysis using efficiency scores estimated from the based period approach. A few earlier studies also conduct a two-stage regression analysis to show effects of factors other than already considered to estimate efficiency scores, which includes farm owners' socio-demographic characteristics, and environmental and policy factors (e.g., Ray 1991; Simar and Wilson 2007; Banker and Natarajan 2008; Souza and Gomes 2015). However, earlier studies use the standard efficiency scores estimated with changing frontiers each year, which makes difficult the scores comparable over time. We compare regression results estimated from our base period approach with those estimated with the standard approach.

CHAPTER II

LITERATURE REVIEW

Although there have been many studies on estimating firm efficiency, only a limited number of studies focus on intertemporal comparison of these efficiencies. We review previous studies on the intertemporal comparison here. Fare et al. (1994) introduce the Malmquist productivity index that is decomposed into *TE* change and technology change; then, the *TE* change is divided to scale efficiency change and pure *TE* change. Efficiency scores from the Malmquist productivity index and those from the standard, different base-frontier, approaches are compared in Fare et al.'s study. The study shows that the two approaches produce different results because efficiency scores are affected by both technology change and individual effort. One limitation of the Malmquist productivity index approach is that it still fails to net out the individual effort effect from the *TE* change. Another attempt to compare the efficiency scores intertemporally is the window DEA approach proposed by Flokou, Aletras, and Niakas (2017). The window DEA assumes no technology change during the comparison period, which allows one to compare the efficiency in the same window. However, because of the assumption of no technology change under the same window, the window DEA is not applicable when the time difference is big. The third attempt is the meta-frontier approach developed by Hayami and Rutan (1970) and O'Donnell, Rao, and Battese (2008). The meta-frontier approach combines many frontiers from different groups or time periods to create one common frontier so that one can compare efficiency scores across groups or time periods. One drawback of the meta-frontier approach is that it assumes technology progress with time, which always expands the upward shift of the frontier line. As result, it does not include the possibility of technology regress. Although the possibility may be rare for intertemporal comparison, it is possible that the meta-frontier could shift downward when adding or removing groups for cross-sectional comparison. Finally, Chen, Huang, and Chiu (2017) provide two indicators: technology progress ratio and individual progress ratio to investigate the frontier shift effect and the individual effort, respectively, on *TE* change. The individual progress ratio is the ratio of two *TE*s using the two efficiency scores evaluated under different frontiers. Since the study focuses on *TE*, the proposed procedure is not applicable to compare the economic efficiencies. As far as we know, no adequate procedure has been proposed for the intertemporal comparison of economic efficiencies in the literature.

We extend previous studies, particularly Chen, Huang, and Chiu (2017) to develop a procedure that can compare economic efficiencies, specifically *CE*s. Unlike the standard approach and Chen, Huang, and Chiu. (2017), the base period approach developed in the study allows one to compare *CE*s across different time periods by netting out individual effort for change in *TE* and *AE* from the change in standard *CE*s. One drawback of the DEA estimator is that it is biased (Kniep, Simar, and Wilson 2015; Simar and Wilson 2020). The DEA estimator is biased because efficiency scores are estimated based on the frontier estimated not from the true population but a sample, which typically causes a positive bias. To address the biasedness, Simar and Wilson (1998, 2000) suggest a bootstrapping approach to reduce bias. The DEA procedure is also a non-parametric estimator with no distribution attached. Therefore, no statistical inference, for example, comparing efficiency scores over time, can be drawn from estimated efficiency scores. One could assume that the mean of DEA scores follows the normal distribution by the central limit theorem. However, the bias does not converge to zero, which makes the ordinary central limit theorem not applicable (Kniep, Simar, and Wilson 2015; Simar and Wilson 2020; Cameron and Trivedi 2005). Kniep, Simar, and Wilson (2015) and Simar and Wilson (2020) provide the adjusted central limit theorem to address this problem by improving the convergence rate. Following Simar and Wilson (1998) and Kniep, Simar, and Wilson (2015) and Simar and Wilson (2020), our study first reduces the bias from DEA scores using a bootstrapping procedure and then compare their mean values after adjusting standard deviations, which allows the unbiased DEA estimator to follow the adjusted central limit theorem.

CHAPTER III

THEORETICAL FRAMEWORK

To derive the intertemporal change in efficiency, we first define *TE*, *CE*, *AE*, and their relationship. Consider a production possibility set:

(1) $T = \{(x, y): x \textit{ can produce } y\}$,

where $x \in R_{+}^{P}$ is input vector and $y \in R_{+}^{R}$ is output vectors. It is assumed that the production possibility set is nonempty, closed, convex, bounded from above for all input vector, $(x, 0) \in T$,$(0, y) \notin T$ for $y \geq 0$, and satisfies disposability of x and y (Chambers 1988). The input requirement set $(V(y))$ is defined as:

(2) $V(y) = \{x : (x, y) \in T\}$.

We assume that the input requirement set is convex, closed, nonempty, bounded from below, $V(y_1) \subseteq V(y_2)$ for $y_1 \geq y_2$, and $x_2 \in V(y)$ when $x_2 \geq x_1$ and $x_1 \in V(y)$ (Chambers 1988; Varian 1992). The boundary of the input requirement set plays a role for technical frontier in efficiency analysis. Based on disposability of x and y in T and the latest properties in $V(y)$ there exist inefficient production plan for a certain firm.

Following Farrell (1957), the input oriented *TE* is defined as the ratio of input use on frontier to observed input use. Mathematically, the input-oriented *TE* for x to produce y is defined as (Fried, Lovell, and Schmidt 2008):

(3) $TE = min\{\theta : \theta\, x \in V(y)\}$[1].

Graphically, the technically efficient input use for a point of A is B which is an intersection of radial line from O to A and isoquant curve SS' in Figure 1. So, in Figure 1, the input oriented *TE* is:

(4) $TE = \frac{||x^T||}{||x||} = \frac{OB}{OA}$,

where x^T is the technically efficient point of input quantity on frontier and the point B in figure 1, and $||x^T||$ and $||x||$ is the Euclidean distance from origin to each point. By definition, $0 < TE \leq 1$. If $TE = 1$, then a farm produces technically efficient way. A firm is technically inefficient when *TE* is less than one.

Coelli et al. (2005) shows that the Shephard input distance function is inverse of Farrell input-oriented *TE*. Here the input distance function is defined as:

(5) $D(y, x) = sup\{\rho : \frac{x}{\rho} \in V(y)\}$.

By definition $D(y, x) \geq 1$, and the input distance function is one when a farm produces efficiently. The input distance function is nondecreasing in input and

[1] *TE* and *CE* are calculated at the farm level. For simplicity, we decide not to include the farm specific notation throughout the paper.

nonincreasing in output. The input distance function is homogeneous degree of one in x. The function is concave in input use and quasi concave in output (Coelli et al. 2005).

The cost oriented economic efficiency (*CE*) is defined as the ratio of the minimized cost to observed cost (Coelli et al. 2005). Then, the *CE* can be written as:

$$(6) \qquad CE = \frac{w'x^*}{w'x} = \frac{C(w,y)}{w'x} = \frac{OC}{OA},$$

where x and w represent input and price of input vectors, while a vector x^* denotes the optimized input quantity given input prices. $C(w, y)$ is a cost function with given input price w and output y and $w'x$ is an observed cost. In Figure 3, OC is radial distance from origin to optimized input mixture. *CE* is greater than 0 and below 1 likewise *TE*. When a farm is efficient under given input price and technology, then $CE = 1$. Unless a farm is economically efficient, *CE* is less than 1. In Figure 3, points for x, x^* are A and D, and minimized cost line with input price w is W.

Next, *AE* is defined as the ratio of minimized cost to cost at technically efficient point. Then, mathematically, *AE* is (Maniadakis and Thanassoulis 2004):

$$(7) \qquad AE = \frac{w'x^*}{w'x^T} = \frac{C(w,y) \times D(y,x)}{w'x} = \frac{OC}{OB}.$$

AE also ranges between 0 to 1. *AE* is less than one when its input mix does not reflect input price, even if it operates technically efficient way. If the minimized cost is equal to cost of production on frontier, then *AE* is one.

Following Coelli et al. (2005), *CE* is also defined by the multiplication of *TE* and *AE*:

(8) $$CE = \frac{OC}{OA} = \frac{OB}{OA} \times \frac{OC}{OB} = TE \times AE.$$

CHAPTER IV

METHODOLOGY

This chapter first shows the decomposition of *CE* change into four factors: technology change (*TC*), individual effort for *TE* change (*IETC*), price effect (*PE*), individual effort for AE change (*IEAC*). Input-oriented *TE* is the ratio of efficient input use on frontier and observed input quantity. Change in *TE* is caused by technology change, more efficient production[2], or both of them. Technology change means frontier shift of production set. Frontier improves or regresses by time (Chen, Huang, and Chiu, 2017). A farm faces different frontier at distinct time. Even if a farm uses the same input to produce the same output, *TE* of a certain farm diminishes when the technology improves (frontier shift upward). Comparison of *TE* under different frontiers is invalid (O'Donnell, Rao, and Battese 2008; Flokou, Aletras, and Niakas 2017). Excluding effect of technology change is needed to compare *TE* and *CE* across time periods. The *IETC* is the *TE* change after excluding the effect of frontier change. Our study first estimates the standard *TE* and *CE* for each year, then net out the *TC* and *PE* using the base-year frontier, which is the year,

[2] More efficient production means less use of input factor given output level, more outputs under a given input set, or both of them.

2013 in this study to make the estimated *TE*s and *CE*s comparable across years. The second part of this chapter presents a procedure to compare efficiency score means across years following Kneip, Simar, and Wilson (2015, 2016) and Simar and Wilson (2020). Lastly, a two-stage analysis is discussed in this chapter to show how other factors such as the units' demographic characteristics, business and risk behaviors, location, and farm size could affect farm efficiencies.

Decomposition of Intertemporal Cost Efficiency Change[3]

Equation (8) shows that the *CE* is the *TE* multiplied by the *AE*. Using equation (8), we first decompose change in *TE* into frontier shift and change in individual effort. Then, change in *AE* is decomposed into price effect and change in individual effort for input mix. We combine all four explanatory factors for the purpose of intertemporal *CE* change. Then, we compare individual effort for efficiency change by using two out of four factors.

Change in *CE* between time period *t+s* and *t* is defined as the product of change in *TE* and *AE*. Then, the *CE* change from time period *t+s* and *t* is:

$$(9)\qquad \Delta CE = \frac{CE_{t+s,t+s}^{t+s}}{CE_{t,t}^{t}} = \Delta TE \times \Delta AE,$$

where ΔCE, ΔTE, and ΔAE is intertemporal change in *CE*, *TE*, and *AE*. A superscript means time period of observed input and output tuple. The first subscript in *CE* is time

[3] Please see Appendix I for detailed derivations.

period of frontier under which efficiency is evaluated. The second subscript in *CE* stands for time period of input price which is given to a farm. For example, $CE_{t,t}^{t}$ is CE of (x^t, y^t) evaluated under frontier and input price at time *t*.

TE is a ratio of technically efficient input to observed input use, so *TE* is changeable by the frontier change, the change in observed input use, or both. Chen, Huang, and Chiu (2017) state that change in *TE* is affected by frontier shift and individual effort to improve *TE*. Our research decomposes *TE* change between time *t* and *t*+*s* as[4]:

$$(10) \qquad \Delta TE = \frac{TE_{t+s}^{t+s}}{TE_t^t} = \frac{D^t(y^t, x^t)}{D^{t+s}(y^{t+s}, x^{t+s})},$$

where the superscript in *TE* is time period of input and output which is evaluated, and the subscript in *TE* indicates time of frontier under which input use is evaluated. For example, TE_{t+s}^{t+s} is a *TE* of (x^{t+s}, y^{t+s}) evaluated under frontier at time *t*+*s*. The superscript in distance function stands for time period of frontier. $D^t(y^{t+s}, x^{t+s})$ is input distance function of (x^{t+s}, y^{t+s}) under the frontier at time *t*. In Figure 2, $\Delta TE = \frac{OD/OB}{OC/OA}$, where the point A and B correspond to input use at time *t* and *t*+*s*. If ΔTE is bigger than one, then *TE* of a farm is better in time *t*+*s* than *t*. When ΔTE is less than unity, *TE* declines. Chen, Huang, and Chiu (2017) propose Efficiency Progress Ratio (EPR), which is similar to ΔTE. EPR equals $\Delta TE - 1$. When TE improves or declines between time *t*+*s* and *t*, ΔTE is greater or less than one and EPR is bigger or smaller than zero.

Similar to ΔTE in (10), *TC* at time period *t*+*s* and *t* is defined as:

[4] Input distance function is homogeneous degree of one in input (Fare and Primont 1995).

(11) $TC = \frac{x_{t+s}^{t+sT}}{x_t^{t+s}} = \frac{D^t(y^{t+s},x^{t+s})}{D^{t+s}(y^{t+s},x^{t+s})}$,

where x_{t+s}^{t+s} is technically efficient input use of x^{t+s} on frontier at *t*+*s*, and x_t^{t+sT} is technically efficient input quantity of x^{t+s} on frontier at time *t*. In figure 2, $TC = \frac{OD}{OE}$. The TC is change of frontier across time *t* and *t*+*s*. If TC is less than one, then technology improves (frontier shift upward) between *t*+*s* and *t*. $TC > 1$ implies deterioration in technology (frontier shift downward). When the value of TC is unity, technology does not change. Unlike *TE* in (4) which evaluated under frontier at the same time period, $0 < TE_t^{t+s} = \frac{1}{D^t(y^{t+s},x^{t+s})}$. Therefore, there may exist $TE_t^{t+s} > 1$ and $D^t(y^{t+s},x^{t+s}) < 1$.

TC in (11) is similar to Technology Progress Ratio (TPR) in Chen, Huang, and Chiu (2017). TPR at *t*+*s* equals $1 - TC$. TPR is the ratio of gap between two frontiers of x^{t+s}at *t*+*s* and *t* to input use at time *t*+*s* ($\frac{x_t^{t+sT} - x_{t+s}^{t+sT}}{x_t^{t+sT}}$). When TPR is greater or less than zero, then it means technology improvement or regress, respectively. It responds to $TC < 1$ or $TC > 1$. If TPR is zero, then the value of TC is one. It indicates there does not exist frontier shift. The TC is the same with measure of technology change based on observation at *t*+*s* in Malmquist productivity analysis (Fare et al. 1992; Maniadakis and Thanassoulis 2004). In the Malmquist productivity analysis technology change is measured by geometric mean of TC of input and output at *t*+*s* and *t*. Technical change in Malmquist productivity index has the same direction with *TC*. When there is technical improvement, *TC* and the measure of technical change in Malmquist productivity index is less than one. They show the same sign around one in the other two cases for frontier shifts.

As stated in Chen, Huang, and Chiu (2017) *TE* is changed not only frontier shift but also individual effort to catch frontier. They define Individual Progress Ratio (IPR) as the difference between EPR and TPR. Likewise, we define *IETC* at time period t+s as the other part in ΔTE in equation (11):

$$(12) \qquad IETC = \frac{x_t^{t+sT}}{x^{t+s}/D^t(y^t,x^t)} = \frac{D^t(y^t,x^t)}{D^t(y^{t+s},x^{t+s})}.$$

In (12), *IETC* is an adjusted *TE* at time t+s and *t* evaluated with the frontier at time period *t*. The denominator of the first term in (12) is input quantity at time t+s deflated by *TE* of input at time *t* evaluated under frontier at *t*. In the denominator, $x^{t+s}/D^t(y^t,x^t)$, is a hypothetical input use at time t+s if the input use at t+s is reduced as much as input at *t* to be efficient (TE_t^t). The *IETC* implies the change in input quantity to reduce input use as much as the usage on the base period frontier. We apply *IETC* to compare *TE* of input in current and previous periods based on frontier in base year. In Figure 2, $IETC = \frac{OE}{OF}$. If *IETC* is bigger than one, then individual effort improves between t+s and *t*. When *IETC* is less than unity, individual effort regresses.

Using equations (10), (11), and (12), ΔTE is defined as multiplication of TC and $IETC$:

$$(13) \qquad \Delta TE = \frac{TE_{t+s}^{t+s}}{TE_t^t} = \frac{D^t(y^{t+s},x^{t+s})}{D^{t+s}(y^{t+s},x^{t+s})} \times \frac{D^t(y^t,x^t)}{D^t(y^{t+s},x^{t+s})} = TC \times IETC.$$

ΔTE is decomposed into *TC* and *IET*C. *TC* is technology change. *IETC* implies how close to frontier at *t* for x^{t+s} and x^t. One example is $y^{t+s} = y^t$ and $x^{t+s} < x^t$.

Since x^{t+s} is closer to frontier than x^t, TE_t^{t+s} is bigger than TE_t^t. $TE_t^{t+s} > TE_t^t$ means famer's *TE* improves except technology change.

The IPR indicator in Chen, Huang, and Chiu (2017) is positive when individual efficiency makes progress. *IETC* is greater than one, if individual efficiency is better in time *t+s* than *t*. *IETC* < 1 responds to negative IPR. Chen, Huang, and Chiu (2017) defined IPR is zero when TE at each period is one ($TE_{t+1}^{t+1} = TE_t^t = 1$). However, *IETC* is bigger than one with technical improvement (*TC* < 1) and the same level of *TE* ($\Delta TE =$ 1). When technology deteriorate (*TC* > 1), *IETC* is less than one.

AE is the ratio of the minimized cost under input price and technology to cost at technically efficient input use. It implies that ratio of cost reduction by choosing input mix in response to input price. When observed input and cost minimized input are on the same radial line from origin, *AE* is one. Maniakadis and Thanassoulis (2004) state that the change in cost Malmquist productivity index is composed of change in *TE* and *AE*, technology change, and effect of input price change. Diewert (2014) decomposes observed cost change into output change, input price change, technology progress, and *CE* change. Based on equation (7) *AE* change is affected by input price change and individual effort for choice of input mix to minimize cost. We decompose *AE* between time period *t* and *t+s* as:

$$(14) \qquad \Delta AE = \frac{AE_{t+s,t+s}^{t+s}}{AE_{t,t}^{t}} = \frac{\frac{C^{t+s}(y^{t+s},w^{t+s})\times D^{t+s}(y^{t+s},x^{t+s})}{w^{t+s\prime}x^{t+s}}}{\frac{C^{t}(y^{t},w^{t})\times D^{t}(y^{t},x^{t})}{w^{t\prime}x^{t}}},$$

where the superscript is time period of input and output to be evaluated in *AE*. The first subscript stands for time of frontier, and the second subscript means time of input price.

For example, $AE_{t+s,t+s}^{t+s}$ is AE of input and output at time $t+s$ evaluated under frontier and input price at time $t+s$. The superscript in cost function is the time period of frontier. For instance, $C^{t+s}(y^{t+s}, w^{t})$ is cost function of (x^{t+s}, y^{t+s}) with input price w^{t} and frontier at $t+s$. In figure 3, $\Delta AE = \frac{OD/OC}{OE/OF}$. The point D is on iso-cost line in time $t+s$, so cost at the point D is the same with $C^{t+1}(y^{t+s}, w^{t+s})$. The point E is on iso-cost line at time t and its cost equals to optimal cost at time t like the point D at time $t+s$. If ΔAE is bigger than one, then AE of a farm is better off in time $t+s$ than t. When ΔAE is less than unity, AE decreases.

Diewert (2014) defines effect of input price change on minimized cost based on period $t+s$ technique to produce y^{t+s} as $\frac{C^{t+s}(y^{t+s},w^{t+s})}{C^{t+s}(y^{t+s},w^{t})}$. Maniadakis and Thanassoulis (2004) decomposes Malmquist productivity index based on cost minimization assumption[5]. As a result Maniadakis and Thanassoulis (2004) shows price effect on the movement of the minimum cost boundary given (x^{t+s}, y^{t+s}) as $\frac{\frac{w^{t\prime}x^{t+s}}{C^{t}(y^{t+s},w^{t})\times D^{t+s}(y^{t+s},x^{t+s})}}{\frac{w^{t\prime}x^{t+s}}{C^{t+s}(y^{t+s},w^{t})\times D^{t+s}(y^{t+s},x^{t+s})}}$.

In the light of Diewert (2014) PE at time $t+s$ is defined as:

$$(15) \quad PE = \frac{\frac{C^{t+s}(y^{t+s},w^{t+s})\times D^{t+s}(y^{t+s},x^{t+s})}{w^{t+s\prime}x^{t+s}}}{\frac{C^{t+s}(y^{t+s},w^{t})\times D^{t+s}(y^{t+s},x^{t+s})}{w^{t\prime}x^{t+s}}} = \frac{AE_{t+s,t+s}^{t+s}}{AE_{t+s,t}^{t+s}} .$$

PE means change of AE evaluated at (x^{t+s}, y^{t+s}) under current frontier at $t+s$ by input price change. In other words, PE indicates change of ability to reduce cost by input price change with given input use (x^{t+s}) and technology at time $t+s$ to produce y^{t+s}. In

[5] Fare et al. (1992, 1994) and other previous literature made the Malmquist productivity index by distance function.

figure 3, $PE = \frac{OD/OC}{OE/OC}$. When PE is greater than one, AE at x^{t+s} is better off with current input price than previous price level to guaranteey^{t+s}. PE is one, when change of input price does not make any relative difference in ability to reduce cost. If a farm has bigger room to reduce cost given previous input price, then PE is less than one.

AE is changed not only by price change but also by choice of input mix by a farm. Previously this research decomposes ΔTE into *TC* and *IETC*. *TC* means frontier shift. Each farm is hard for technology change, so we can consider *TC* is exogenous factor in change of *CE* and *TE*[6]. *IETC* is individual effort for *TE* change of each farm. A farm can decide about input use in each time period. *IETC* is endogenous factor in cost and *TE* change. If we assume that no farm has any market power in the input market, then input price in each time period is given to each farm. Based on the assumption about market structure, we can consider *PE* is exogenous factor in cost and allocative efficiency change. A certain farm can choose input mix to produce certain level of output by themselves. Change in input mix can affect change in *AE* change. We define *IEAC* at time period *t+s* to capture effect of change in input mix by a farm as:

$$(16) \qquad IEAC = \frac{\frac{C^{t+s}(y^{t+s},w^t)\times D^{t+s}(y^{t+s},x^{t+s})}{w^{t\prime}x^{t+s}}}{\frac{C^t(y^t,w^t)\times D^t(y^t,x^t)}{w^{t\prime}x^t}} = \frac{AE^{t+s}_{t+s,t}}{AE^t_{t,t}}.$$

Measure of *IEAC* is change of AE evaluated at different input mix x^{t+s} and x^t and different frontier at time *t+s* and *t* given the same previous input price. Since *PE* investigates effect of change in input price, *IEAC* as the remainder term in ΔAE is

[6] The true frontier is unknown. As a result, it is estimated by DEA in our study. If a firm is on the frontier, the firm's change in input use can affect frontier shift and technical change.

evaluated price level at time *t*. *IEAC* represents the change in input mix in response to input price in the base year. In figure 3, $IEAC = \frac{OE/OC}{OE/OF}$. AE at x^{t+s} is better off at given previous input price with *IEAC* > 1. *IEAC* > 1 means cost of input mix at x^{t+s} is relatively smaller than cost of input mix at x^t comparing to their minimized cost when input price is w^t. *IEAC* < 1 means cost of previous input mix is closer than current input mix.

We have decomposed change of *CE* into four explanatory factors: technology change, individual effort for technical efficiency change, price effect, and individual effort for allocative efficiency change. The first two factors are components for ΔTE, and the last two are for ΔAE. We can consider *TC* and *PE* as exogenous factors and *IETC* and *IEAC* as endogenous factors for ΔCE. To summarize all four explanatory factors ΔCE is redefined as:

(17) $$\Delta CE = \frac{CE_{t+s,t+s}^{t+s}}{CE_{t,t}^{t}} = \Delta TE \times \Delta AE = TC \times IETC \times PE \times IEAC.$$

IETC at *t*+*s* and *t* is $\frac{D^t(y^t,x^t)}{D^t(y^{t+s},x^{t+s})}$, and IETC at *t*+*h* and *t* is $\frac{D^t(y^t,x^t)}{D^t(y^{t+h},x^{t+h})}$. Then, two *IETCs* are comparable as:

(18) $$IETC_{t+s,t+h} = \frac{\frac{D^t(y^t,x^t)}{D^t(y^{t+s},x^{t+s})}}{\frac{D^t(y^t,x^t)}{D^t(y^{t+h},x^{t+h})}} = \frac{D^t(y^{t+h},x^{t+h})}{D^t(y^{t+s},x^{t+s})}.$$

Equation (18) implies the change in *TE* from *t*+*s* to *t*+*h* without *TC* are compared after setting the base period at *t*.

Individual Effort for Cost Efficiency Change (*IECC*) is the product of $IETC$ and $IEAC$ excluding *TC* and *PE*. Then, *IECC* can be extended as:

(19) $$IECC = IETC \times IEAC$$

$$= \frac{\frac{C^{t+s}(y^{t+s},w^t)}{w^{t\prime}x^{t+s}} \times \frac{D^{t+s}(y^{t+s},x^{t+s})}{D^t(y^{t+s},x^{t+s})}}{\frac{C^t(y^t,w^t)}{w^{t\prime}x^t}}.$$

The denominator in the last equation of (19) is $CE_{t,t}^{t}$. In the same equation, the first term of the numerator is $CE_{t+s,t}^{t+s}$, and the second term reflects the of the frontier from *t+s* to *t*. Therefore, the entire product term in the numerator of the last equation of (19) is $CE_{t,t}^{t+s}$. *IECC* from *t+s* to *t+h* can be compared as:

(20) $$IECC_{t+s,t+h} = \frac{\frac{\frac{C^{t+s}(y^{t+s},w^t)}{w^{t\prime}x^{t+s}} \times \frac{D^{t+s}(y^{t+s},x^{t+s})}{D^t(y^{t+s},x^{t+s})}}{\frac{C^t(y^t,w^t)}{w^{t\prime}x^t}}}{\frac{\frac{C^{t+h}(y^{t+h},w^t)}{w^{t\prime}x^{t+h}} \times \frac{D^{t+h}(y^{t+h},x^{t+h})}{D^t(y^{t+h},x^{t+h})}}{\frac{C^t(y^t,w^t)}{w^{t\prime}x^t}}} = \frac{\frac{C^{t+h}(y^{t+h},w^t)}{w^{t\prime}x^{t+h}} \times \frac{D^{t+h}(y^{t+h},x^{t+h})}{D^t(y^{t+h},x^{t+h})}}{\frac{C^{t+s}(y^{t+s},w^t)}{w^{t\prime}x^{t+s}} \times \frac{D^{t+s}(y^{t+s},x^{t+s})}{D^t(y^{t+s},x^{t+s})}}.$$

Equation (20) shows the change in *CE* from *t+s* to *t+h* without the change in *TC* and *PE* after setting the base period at *t*.

Using the aforementioned derivations, we compare the change in *TE* estimated from the standard approach from *t+s* to *t+h* as $\frac{TE_{t+h}^{t+h}}{TE_{t+s}^{t+s}}$, which still include technology change. The change in *TE* estimated from the base period approach from *t+s* to *t+h* is represented by $IETC_{t+s,t+h}$, in (18), which now does not include technology change. We estimate *TE* at time *t+s* by on a base period at time *t* by using $TE_t^{t+s} = \frac{1}{D^t(y^{t+s},x^{t+s})}$ in (18).

Comparing CE estimated from the standard approach from $t+s$ to $t+h$ b can be done as $\frac{CE_{t+h,t+h}^{t+h}}{CE_{t+s,t+s}^{t+s}}$, which still includes technology change and price effect. However, the change in CE estimated from the base-year approach derived in (20) as $IECC_{t+s,t+h}$ now eliminates technology change and price effect. CE at time $t+s$ based on base period at time t is estimated as $CE_{t,t}^{t+s}$ in (19).

Using a DEA procedure, the input oriented TE for the standard approach at time t is estimated for each farm (Coelli et al. 2005)[7] from:

(21) $$\min_{\theta^t,\lambda_j^t} \theta^t$$

$$s.t. \sum_{j=1}^{N^t} \lambda_j^t x_{jp}^t \leq \theta^t x_p^t$$

$$\sum_{j=1}^{N^t} \lambda_j^t y_{jr}^t \geq y_r^t$$

$$\lambda_j^t \geq 0,$$

where θ_i^t is TE at time t, x_{jp}^t is p^{th} input quantity for j^{th} farm at time t, y_{jr}^t is r^{th} output quantity for j^{th} farm at time t, λ_j^t is j^{th} element in weight vector at time t and $\lambda_j^t \geq 0$ for all j, and $j = 1, \ldots N^t$, $p = 1, \ldots P$, $r = 1, \ldots, R$, N^t is the number of farm at time t, and time $t = 1, \ldots T$. The weight vector is used to make benchmark point of the farm. Weight vector and efficient farms make frontier. The last constraint means the technology is constant return to scale (CRS). If one uses $\sum_{j=1}^{N^t} \lambda_j^t = 1$ and $\lambda_j^t \geq 0$, then technology visits

[7] For simplicity, the subscript for a farm specific notation is not included.

variable return to scale (VRS). One assumes non-increasing return to scale production process by using constraint as $\sum_{j=1}^{N^t} \lambda_j^t \leq 1$. The optimized solution from (21) is $TE_t^t = \frac{1}{D^t(y^t,x^t)}$. The estimator is used for technical efficiency score under different frontier. Input and output data at time *t* are used to construct frontier at time *t*. $TE_{t+s}^{t+s} = \frac{1}{D^{t+s}(y^{t+s},x^{t+s})}$ is estimated by using observations at time period *t+s* instead of data at time *t*.

Estimating $D^t(y^{t+s}, x^{t+s})$ in (11) and (12) for *TC* and *IETC* for the base period approach using input and output data at time *t* and *t+s* can be represented as:

(22) $$\min_{\theta_t^{t+s},\lambda_j^{t+s}} \theta_t^{t+s} = \frac{1}{D^t(y^{t+s},x^{t+s})}$$

$$s.t. \sum_{j=1}^{N^t} \lambda_j^t x_{jp}^t \leq \theta_t^{t+s} x_p^{t+s}$$

$$\sum_{j=1}^{N^t} \lambda_j^t y_{jr}^t \geq y_r^{t+s}$$

$$\lambda_{sj}^t > 0.$$

CE from the standard approach is obtained by minimizing farm cost under technology and input price at time *t* as (Coelli et al. 2005):

(23) $$\min_{\lambda_j^t,x_p^{t*}} \sum_{p=1}^{P} w_p^t x_{ip}^{t*}$$

$$s.t. \sum_{j=1}^{N^t} \lambda_{ij}^t x_{jp}^t \leq x_{ip}^{t*}$$

$$\sum_{j=1}^{N^t} \lambda_j^t y_{jr}^t \geq y_r^t$$

$$\lambda_j^t > 0,$$

where x_p^{t*} is the optimized input quantity of p^{th} input under input price and technology at time t, and w_p^t is p^{th} input price at time t. *CE* for each farm is estimated by the ratio of minimized cost from (23) to observed cost. We use equation (23) to estimate $CE_{t,t}^t$ in (9), (17), and (19).

Finally, *CE* from the base period approach is estimated by minimizing farm cost at *t*+*s* with input price at the base period *t* as:

(24) $$\min_{\lambda_j^t, x_p^{t*}} \sum_{p=1}^{P} w_p^t x_p^{t+s*}$$

$$s.t. \sum_{j=1}^{N^t} \lambda_j^t x_{jp}^t \leq x_p^{t+s*}$$

$$\sum_{j=1}^{N^t} \lambda_j^t y_{jr}^t \geq y_r^{t+s}$$

$$\lambda_j^t > 0.$$

In (24), the frontier is constructed with (x^t, y^t) as the frontier at time *t*. Therefore, the solution represents the minimized cost at time *t*+*s* under the base-year frontier with input price and frontier at time *t*. Equation (24) is employed to estimate $CE_{t,t}^{t+s}$ in (19).

Statistical Test of Mean Difference from Estimated Efficiencies

The DEA estimator is biased because efficiency scores are estimated based on frontiers estimated from a sample not from the true population. Therefore, estimated *TE* and *CE* from (21) to (24) are biased, and the bias does not converge to zero when firms operate with multiple inputs and outputs under the central limit theorem (Kneip, Simar, and Wilson 2015; Simar and Wilson 2020). Therefore, an adjusted central limit theorem was introduced by Kneip, Simar, and Wilson (2015) and Simar and Wilson (2020) to remove the bias and to derive the asymptotic normal distribution for mean of estimated efficiency scores. Using the asymptotic normal distribution of estimated *TE* and *CE*, we conduct a sample T-test to compare the *TE* and *CE* scores estimated from standard and base period approaches. A t-statistic for a sample T-test following the asymptotic normal distribution can be written to compare samples 1 and 2 as:

$$(25) \qquad T = \frac{(\hat{\mu}_1 - \hat{\mu}_2) - (B_1 - B_2)}{\sqrt{\frac{\widehat{S_1^2}}{N1_k} + \frac{\widehat{S_2^2}}{N2_k}}} \sim t_{N1_k + N2_k - 2},$$

where T is t-statistic; $\hat{\mu}_1$ and $\hat{\mu}_2$ are mean efficiency scores for samples 1 and 2; B_1 and B_2 are estimated biases, estimated from a bootstrapping procedure applied to the two samples; S_1 and S_2 are standard deviations from the samples[8]; $N1_k = N1^{2k}$; $N2_k =$

[8] Specifically, the central limit theorem cannot be applied when the sum of input and output numbers is more than 4. In this case, the bias goes to infinity as sample size goes to infinity. Kneip, Simar, and Wilson (2015), and Simar and Wilson (2020) propose an adjusted central limit theorem to address the bias problem. The earlier studies reduce the degree of freedom by limiting the sample size with smaller N^{2k} observations, which should be $N^{2k} < N$ when the sum of input and output numbers is more than 4, i.e., $\mathrm{k} < 1/2$. For the bias correction procedure, we first split the sample into two subsamples, samples 1 and 2. Observations are drawn randomly from subsamples without replacement. Then, efficiency scores are estimated from each subsample. A h*th* bootstrap mean is the average of estimated efficiency from each of bootstrapped subsamples. Finally, the bias is calculated as the difference between the mean of all efficiency scores from bootstrap samples and the average of estimated efficiency scores ($\hat{\mu}$ in (25)) divided by $(2^k -$

$N2^{2k}$; $N1$ and $N2$ are the number of observations for samples 1 and 2, respectively; $k = \frac{2}{a+b}$ from (21) to (24) under CRS, *a* is the number of input variables, and *b* is the number of outputs; t-statistic follows t-distribution with degree of freedom with $N1_k + N2_k - 2$. We use 200 bootstrap samples to correct the bias.

Two Stage Analysis

The efficiency scores represent how much each of decision-making units is efficient relative to the benchmark units, the best-practice frontier ranging between 0 and 1. However, other factors such as the units' demographic characteristics, business and risk behaviors, location, and farm size could affect farm efficiencies. Earlier studies use a two-stage regression analysis to investigate these factors in the form of Tobit regression, truncated maximum likelihood (MLE), ordinary least squares (OLS) with log transformed estimated efficiency score, or generalized method of moments (GMM) with instrumental variable (IV).

Our econometric model for the two-stage analysis is written as:

(26) $\hat{\theta} = Z\beta + \varepsilon,$

where $\hat{\theta}$ is estimated efficiency score; Z represents environmental variables such as location, farmer's age and education level, etc.; β is a parameter vector; ε is a random error term.

1). See Kneip, Simar, and Wilson (2015), and Simar and Wilson (2020) for detailed discussions on the adjusted central limit theorem and the bootstrapping procedure.

The efficiency score has the limited range. Previous papers in the related literature proposed ways to address the limited range of dependent variable: Tobit regression (Ray, 1991), truncated MLE (Simar and Wilson, 2007), and OLS with log-transformed efficiency score (Banker and Natarajan, 2008). Potential correlation problem between environmental variables and the error term, the endogeneity problem, in the second-stage equation could require an additional attention in estimating the model. Simar and Wilson (2007) claim that the endogeneity problem could disappear asymptotically under a certain condition, the separability condition[9]. However, it is not likely that the separability condition is satisfied in most real-world situations. Banker and Natarajan (2008) estimate the OLS regression assuming no endogeneity problem between environmental variables and the regression error term. Souza and Gomes (2015) use the GMM procedure with IV to address the potential endogeneity problem.

Following earlier studies, we estimate the second-stage equation using three regression procedures: truncated MLE, OLS with log-transformed efficiency score, and GMM with IV. Unlike Souza and Gomes (2015), we log-transform the dependent variable, estimated efficiency scores, to account for the limited range of dependent variable, following Banker and Natarajan (2008). Therefore, our GMM with IV procedure addresses both limited dependent variable and endogenous environmental variable problems. Our study estimates robust standard errors for the GMM/IV procedure, following Baum, Schaffer, and Stillman (2003). For the truncated MLE, 1000

[9] The separability condition mentioned in Simar and Wilson (2007) refers to no effect of environmental variables on frontier shift.

bootstrap samples are used. We use PROC Qlim for truncated MLE, PROC Reg for OLS, and PROC Model for GMM with IV in SAS.

CHAPTER V

DATA

Our study uses a dataset from the Agricultural Production Cost Survey (ALPCS) conducted by the Microdata Integrative Service in the Korean Statistics Bureau for four years, 2003, 2008, 2013, and 2017. The dataset includes labor input quantity and cost, fertilizer usage and cost, pesticide usage and cost, amount of capital input, other input costs, production quantity, revenue, and information about farm owner's demographic characteristics (age, gender, education, number of family members, etc.). The ALPCS data focus on farms producing rice, chili pepper, bean, garlic, and onion. Out of the five products, rice is the main agricultural product in Korea.

Table 1 reports descriptive statistics of input and output used to estimate farm efficiencies. Output, Rice (lbs.) is average rice production of net grain in pounds each year. Labor is total family and hired labor input in hours. Land is the sum of own and rented crop land area used for rice production in acre. Average arable land use for rice production does not change much in 2003 to 2017. Capital is the sum of depreciation of all capital inputs each year. Other inputs include total cost for pesticide, seed, fertilizer, heat and light use. Both capital and other input are deflated by average Korean Won per

U.S. dollar exchange rate each year. Numbers of farms are 1333, 950, 1148, and 1118 individual farms for 2003, 2008, 2013, and 2017, respectively.

Overall, average rice production per farm is increasing as farm size (land size) increases and total number of farms decreases over time. Table 1 also shows that Korean rice farms use less labor force over time, probably because the rice farms substitute labor with capital and other inputs due to increased wage. The use of capital and other inputs, particularly other inputs, increases in general.

Table 2 shows descriptive statistics of output and input prices. Our study uses unit prices for input and output prices because the ALPCS dataset does not collect market prices of input and output from farmers. Prices of capital and other inputs are set at one in Korea Won, which is equivalent to approximately $0.001. It is noticeable that wage in the Korean agricultural sector has increased significantly lately. Rice and land price are stable over time.

This study compares average efficiencies of Korean rice farms by size and possession of crop insurance. Average rice farm size in Korea is around 1.5ha in 2015. Therefore, in Table 3, we decided to classify the farm size into three categories: less than 1ha, 1~3ha, and more than 3ha. Korean crop insurance program started in 2001. At that time, only two agricultural product, apple and pear were covered by the crop insurance. By 2010, 25 products were included in crop insurance program. Rice was included in the crop insurance program from 2013. Some rice producers who operated farms for rice and other fruits together bought crop insurance in 2003, but the number of farmers with crop insurance were small before 2013. As can be seen Table 3, the number of rice farms that participate in the crop insurance increased significantly from 2013. Our study uses the enrollment of the crop insurance as a proxy variable for rice farmers' risk preference.

Table 4 presents descriptive statistics of environmental variables for rice production that are used as explanatory variables for our econometric analysis, two-stage analysis. Data for these variables have been collected from three sources: precipitation in each province (using a representative city for each province) is collected from the Korea Statistical Information Service (KOSIS). The data for other variables such as No education (1 if the farm household head has less than an elementary school diploma; 0 otherwise), Elementary (1 if the farm household head has an elementary school diploma; 0 otherwise), Middle school (1 if the farm household head has a middle school diploma; 0 otherwise), High school (1 if the farm household head has a high school diploma; 0 otherwise), Age (household head's age), Male (1 if household head is male; 0 otherwise), Capital includes Seoul, Incheon, and Gyeonggi province (1 if farm is located in the capital region; 0 otherwise); Central includes Daejeon, Chungbuk province, and Chungnam province (1 if farm is located in the central region; 0 otherwise); Northern represents Gangwon province (1 if farm is located in the northern region; 0 otherwise); Southeastern includes Gwangju, Jeonbuk province, and Jeonnam province (1 if farm is located in the southeastern region; 0 otherwise); The farm location data and total sales are obtained from the Farm Household Economy Survey (FHES) in the Microdata Integrative System of the Korean Bureau of Statistics. The data of farmland ownership and the ratio of family labor force to the total labor input are from the Agricultural Production Cost Survey (ALPCS); Rented (1 if farm uses only rental land; 0 otherwise), Own and rental (1 if farm uses both own and rental lands; 0 otherwise). Debt ratio is calculated as debt divided by asset for each farm household, and non-farm income ratio is non-farm income over total income. Data for debt, asset, non-farm income, and total income are collected from FHES. The same key for farm household in the ALPCS and FHES means the same household at each year. In detail, the data from ALPCS are Rented (1 if farm uses only rental land; 0 otherwise), Own and rental (1 if farm uses both own and rental lands; 0 otherwise).

CHAPTER VI

RESULTS

Two *TE* estimates are reported in Figure 4: *TE* with different base-frontier each year and *TE* with a base year frontier The *TE* based on a changing frontier each year is estimated under the frontier made by production possibility set formed each year. The mean of *TE* in 2017 is lower than the mean of *TE* in 2013 when compared with *TE*s estimated using a different base-frontier approach. Based on the traditional efficiency estimation method, i.e., the different base-frontier approach, average *TE* of Korean rice farms increases from 2003 to 2013 and then decreases from 2013 to 2017. Change in efficiency can be caused by technology shift (frontier shift) or farms' own efficiency change. Therefore, one cannot conclude that the efficiency decreased in 2017 compared to 2013 because one cannot be sure if the efficiency change is the result of change in the base-frontier or change in farm's own *TE* under the different base-frontier approach.

TE with a base year frontier is estimated by setting a frontier at each year. In our paper, we set 2013 as the base year. As mentioned, advantage of the base period approach effectively eliminates the frontier shifting effect while catching a decision-making unit's *TE* change as one's own effort. For example, *TE* with a base period frontier in Figure 4 in 2017 is 0.817. In this case, the overall *TE* in 2017 is higher than the scores from any previous years unlike the *TE*s estimated from the different base-frontier approach. The *TE*s estimated using the base year frontier show that the Korean rice production farms' *TE* was enhanced gradually from 2003 to 2017, while there was a decline of *TE* from 2008 to 2013.

Table 5 shows pairwise comparisons of means of *TE* from each year using a simple two sample T-test. Hypotheses are $H_0: \mu^t = \mu^s$, and $H_1: \mu^t \neq \mu^s$, where $\mu^{t(s)}$ is the mean of *TE* at year *t(s)*, and $\mathrm{t} \neq \mathrm{s}$. Mean of *TE* in 2003 is lower than those from 2007, 2013, and 2017 at the 1% significance level based on the different base-frontier approach. Mean of *TE* in 2008 is lower than the 2013 efficiency at the 5% significance level, and higher than one from 2017 at the 1% significance level. The *TE* estimated for 2013 is higher than one from 2017 at the 1% significance level on average. Test results for *TE*s from the base period approach looks somewhat different. Mean of *TE* of Korean rice production farms in 2008 excluding the frontier-shift effect is higher than efficiency scores from 2003 and 2013 at the 1% significance level. However, it fails to reject the null hypothesis when TEs of 2008 and 2017 are compared. The T-test results show that mean of *TE* in 2017 is the highest based on efficiency estimates from the base year frontier approach.

Figure 5 shows estimation result of *CE*. Mean of Korean rice farms' *CE* using a standard approach is 0.533, 0.550, 0.554, and 0.454 in 2003, 2008, 2013, and 2017 respectively. Estimates of *CE* are lower than those of *TE*, because *TE* is determined by the difference between input use and output produced, but *CE* is also affected by input mix under input price condition. The results show that *CE* improved from 2003 to 2013, then decreased in 2017.

However, the change in *CE* could have been affected by decision making unit's own effort to change *TE*, frontier shift, input mixture under input price information. *CE* estimates based on a base period frontier and price should be better for intertemporal comparison. Results reported in Figure 5 show that when the base year frontier method is used, *CE* was improved in 2008 compared to 2003. There was a small decline in 2013, but it went up in 2017. Confidence intervals of *CE* do not contain mean values, which indicates estimates are all significant at the 5% level. The base period frontier approach gives a different result compared to the different frontier method. Unlike the standard estimation method with different base-frontier, the *CE* estimated from the base year frontier approach produces the highest *CE* in 2017.

Change in *CE* is statistically tested using a pairwise sample T-test, and results are reported in Table 6. Based on the different frontier approach the mean of *CE* in 2017 is the lowest at the 1% significance level. The difference between *CE* in 2003 and 2008 is not statistically significant. Test result shows that *CE* improved in 2013 compared to 2008 based on the different frontier approach at the 1% significance level. Test result from the base period frontier approach shows the mean of *CE* in 2017 is the highest at the 1% significance level. When the same base year was used, *CE* in 2003 is the lowest at the 1% significance level. The difference between 2008 and 2013 is not statistically different[10].

[10]In addition to intertemporal comparison, we conduct a sample T-test on mean difference of two efficiencies: one from the standard approach and the other from the base period approach each year. The null hypothesis is $H_0: \mu_S - \mu_B = 0$ and the alternative hypothesis is $H_1: \mu_S - \mu_B \neq 0$, where μ_S and μ_B are means of efficiency scores from standard and base-year approaches, respectively. Test results are reported in the Table AII. Because the base year is 2013, estimates for *TE* and *CE* from both approaches are equal in 2013, which results in zero mean differences. However, the sample T-test clearly show that the two approaches, standard and base period approaches, produce quite different efficiency scores in all other years. That is, all differences are statistically significant at the 1% level.

Table 7 presents statistical test for intertemporal *TE* and *CE* changes of small farms with land size less than 1 ha. Mean of *TE* in 2003 is the lowest, and *TE* in 2013 is the highest at the 1% significance level when the different frontier approach is used. The statistical test results show individual effort for *TE* from the base year frontier approach improved from 2003 to 2008, 2013, and 2017 at the 1% significance level, then decreased from 2008 to 2013. The individual effort also improved in 2017 compared to 2013.

For the same small farms, test results on *CE* change from the different frontier approach show that *CE* in 2013 is the highest and the lowest in 2017. TE in 2003 is lower than 2017, but *CE* in 2017 is higher at the 1% significance level. Unlike the different frontier approach, the base period frontier approach shows that the *CE* in 2017 is the highest and lowest in 2003. The result could be due to the improvement in individual effort for *TE* change as farm owners' individual effort for *AE* change increases. Mean of intertemporal *TE* and *CE* change for medium and large farms with arable land of 1 to 3ha and more than 3ha shows similar results (see Tables 8 and 9).

We also examined if efficiencies between different farm size differ in a given year, and results are reported in Table 10. In 2003, *TE* based on both approaches (base period frontier and different frontier) increases with farm size. *TE* of farms with more than 3ha is the highest, and *TE* of small farms with less than 1ha is the lowest. However, farm size does not affect TE in 2008, 2013, and 2017, which implies that small farms tend to make effort to catch the efficiency of larger farms. In case of *CE*, small farms were inefficient in most years. According to base year frontier and different frontier approaches, *CE* from large farms with more than 3ha is higher than those of small farms. Except 2013, *CE* of medium size farm is better than small farms. The result shows that small farm with less than 1ha arable land is insensitive with change in input prices. On the other hand, farm owners with bigger arable land are better in minimizing their production cost subject to change in input prices.

Tables 11 and 12 show statistical test result on intertemporal change of mean efficiency for farmers who do not participate in the crop insurance program and for farmers who participate in the crop insurance program. This implies that farmer who possesses crop insurance is more risk averse than those who does not have. Test result on *TE* and *CE* change shows similar results from both farmers. The result implies that efficiency change is not affected by farmer's risk preference.

Table 13 confirms our findings from Tables 11 and 12. Table 13 tests if efficiencies differ by risk preference in a same year. A sample T-test fails to reject the null hypothesis in most cases, which indicates that we do not have enough evidence on differences of efficiencies between the two farmer groups with different risk preferences. The result could be led by the data limitation because the crop insurance program was not implemented until 2012. Therefore, the number of farmers who buy crop insurance is small in 2003 and 2008. These farmers had a chance to participate in the insurance program because they grew fruits and other crops that were already allowed to participate in the insurance program.

Tables 14 and 15 present two-stage analysis estimation results with *TE* and *CE* as dependent variables, respectively. We use three estimation methods: truncated MLE, OLS, and GMM with IV. Before running the GMM/IV procedure, the Hausman test is conducted for all five economic variables, rented land, own and rental land, ratio of family labor force, debt ratio, and non-farm income ratio. The test rejected the null hypothesis of no correlation between each of economic variable and error term, implying the endogeneity problem. The selected instrumental variables include ratios of agricultural income, revenue from all agricultural products, and revenue from grain divided by total income and proportions of agricultural subsidy such as direct payment over total net income, total income, total revenue from agricultural products, and revenue from grain only. We also included square of each of the seven selected instrumental variables. Hansen's J-test (Hansen 1982) show the validity of over identifying restrictions for all for models, *TE_S*, *TE_B*, *CE_S*, and *CE_B* at least at the 10% level.

In Table 14, from five out of six columns, precipitation has a negative correlation with the change in efficiency, and the coefficient is significant at least at the 5% level. Farm owners' age is not a significant factor affecting efficiencies. However, education level, particularly, no education vs. college degree shows that it is likely that farmers with college degree have more efficient farms than those with no education. Gender is also an important factor; farms owned by female are less efficient. In terms of farm locations, farmers in northern and southeastern regions are less efficient than those located in the capital, central and southwestern regions in Korea. Results from truncate MLE and OLS show that farms with owned arable land has higher efficiency than farms with rented land and own and rental land. To account for year effect, we included year dummy variables in the model, and coefficients of year dummies shows that *TE* in 2013 is better than 2008 and 2017, which is consistent with findings from in Table 5.

Results of the two-stage analysis estimation with *CE* as the dependent variable is reported in Table 15. Again, overall results from all six columns look similar regardless of estimations methods of *CE* and estimation methods of two-stage analysis. When *CE* is used as the dependent variable, precipitation has a negative relationship with *CE*. Negative sign on precipitation implies more rain leads additional input use. This result may reflect that most Korean rice farms already have sufficient water through irrigation system and heavy rain might cause more damage to farms. Again, regression results show that owners' education level is an important factor affecting *CE*. Farm owners with college degree is better than those with less education level in improving *CE*, which suggests that farm owners with higher education tend to be more adaptable and flexible to input rice changes than those with less education level. Coefficients of farm locations are similar with results in Table 14. Farmers in northern and southeastern regions are still less efficient than those located in central and southwestern regions. Farm owners who operate on their own land shows higher cost efficiency than those only on rental land. Estimation result on year dummies is mostly consistent with findings in Figure 5.

CHAPTER VII

CONCLUSION

Our study presents a procedure for intertemporal comparison of both technical and cost efficiencies across years. Using a base period approach, our procedure is able to compare efficiency scores after excluding the frontier shift and input price change effect. Our procedure is applied to Korean rice production data from four separate years: 2003, 2008, 2013, and 2017. Results from our base-year procedure are compared to efficiency scores estimated with the different base-frontier approach. Average *TE* by traditional approach in 2003, 2008, 2013, and 2017 are 0.642, 0.724, 0.746, and 0.696, respectively. *TE* of rice producers increases from 2003 to 2013, then decreases in 2017. Mean of *TE* based on the base period approach are 0.682, 0.796. 0.746, and 0.817 in 2003, 2008, 2013, and 2017, respectively. Average cost efficiencies of Korean rice producers are 0.533, 0.550, 0.554, and 0.454 in 2003, 2008, 2013, and 2017, respectively from the traditional approach, and 0.393, 0.564, 0.554, and 0.636 from the base period approach. Then, we conduct a sample T-test to examine intertemporal change in farm efficiencies across years. Our results show that technical and cost efficiency in 2007, 2013, and 2017 improved from 2003 from both methods. However, two methods produced different results in other years. Technical and cost efficiency in 2017 are less than 2008 and 2013 when the standard method with different base-frontier approach. However, when the base period approach is used, technical and cost efficiencies in 2017 improved from 2008 and 2013, while two efficiency scores from the conventional approach decreased in 2017 from 2008 and 2013. The two distinctively different results show that the conventional approach with different base-frontiers could result in erroneous policy implications. For example, our study finds that both *TE* and *CE* were deteriorated from 2013 to 2017 based on the standard approach, while the same efficiency scores were improved when the base period approach was used. Therefore, results from the two approaches should lead to opposite directions of policy implications. Results from the standard approach suggest the change in farm policy to improve farm efficiency, while findings from the base period approach indicate that the current farm policy is and working and appropriate in helping farmers improve their efficiencies.

Regression results with estimated efficiency scores from standard and base period approach show no distinct difference except year dummies. Overall, less educated farm owners show lower *CE* than those with a college degree, which implies more educated farmers are more adaptable to change in market situation, for example, change in input price than less educated farm owners. We also find regional differences in farm efficiency. Farmers located in the northern and southeastern areas are less efficient than those located in the central and southwestern regions. Many parts of the northern and southeastern regions are mountainous. Therefore, these areas may not be good for rice production. Farmers in these areas may be better off by switching their operation from rice production to other crops such as fruits, wheat, or vegetables. Also, Korean government could invest more research money in developing new crops which are suitable for mountainous area.

One direction of future research might be to do a sensitivity analysis using alternative base periods. The current study uses the year 2013 as the base period. However, the changing base period could lead to different outcomes. For example, if we change the base year from 2013 to 2008, we expect to have a different reference group, i.e., a group of benchmarking farms. Therefore, efficiency scores estimated based on year 2008 could be different from those with the base year 2013. We believe sensitivity analysis could help improve the base-year approach. Another research that could be resolved in a future study might be to estimate efficiency score s and two-stage regressions using a panel approach. Our study was not able to conduct a panel regression because the farm-level ID was not available. In this case, one can further improve the base period approach combining with the meta frontier approach.

Table 1. Means and Standard Deviations of Input and Output Quantities

Variable	2003	2008	2013	2017
Rice (lbs.)	14,940.90 (20,980.61)	14,468.47 (18.256.77)	17,029.76 (24,093.29)	19,283.34 (26,801.80)
Labor (hr)	292.94 (296.40)	151.93 (152.88)	159.25 (193.59)	133.26 (165.49)
Land (ac)	2.84 (3.71)	2.33 (2.85)	2.96 (4.27)	3.10 (4.28)
Capital ($)	415.61 (907.03)	376.10 (786.76)	508.40 (941.32)	430.05 (938.07)
Other ($)	647.17 (816.51)	770.97 (986.03)	1,083.25 (1,483.97)	1,160.81 (1,753.39)
No. of Farms	1333	950	1148	1118

Numbers in parenthesis are standard deviations.
Source: Agricultural Production Cost Survey each year

Table 2. Means and Standard Deviations of Input and Output Prices

Variable	2003	2008	2013	2017
Rice ($/lbs.)	0.55 (0.03)	0.55 (0.05)	0.61 (0.05)	0.51 (0.05)
Labor ($/hr)	4.11 (0.66)	5.40 (0.75)	12.55 (0.41)	14.73 (0.52)
Land ($/ac)	835.34 (250.35)	901.55 (295.80)	955.89 (397.69)	851.39 (354.85)
Capital ($)	0.001 (0.0)	0.001 (0.0)	0.001 (0.0)	0.001 (0.0)
Other ($)	0.001 (0.0)	0.001 (0.0)	0.001 (0.0)	0.001 (0.0)
No. of Farms	1333	950	1148	1118

Numbers in parenthesis are standard deviations.
Source: Agricultural Production Cost Survey each year

Table 3. Number of Farms by Size and Participation of Crop Insurance

Type		2003	2008	2013	2017
Total		1333	950	1148	1118
Size	Less than 1ha	853	684	748	725
	1 - 3ha	404	229	306	298
	Over 3ha	76	37	94	95
Insurance	Participating	45	32	573	731
	Non-participating	1288	918	575	387

Source: Agricultural Production Cost Survey and Farm Household Economy Survey each year

Table 4. Descriptive Statistics of Explanatory Variables for Two Stage Analysis Model

Variable	2003	2008	2013	2017
Precipitation (mm)	1828.0 (162.9)	998.5 (166.3)	1178.5 (126.3)	961.2 (109.0)
Age	75.5 (10.7)	74.6 (10.2)	71.6 (9.6)	70.5 (8.9)
No Education	0.097 (0.296)	0.102 (0.303)	0.064 (0.244)	0.062 (0.240)
Elementary School	0.443 (0.497)	0.398 (0.490)	0.408 (0.492)	0.393 (0.489)
Middle School	0.200 (0.400)	0.225 (0.418)	0.234 (0.424)	0.237 (0.425)
High School	0.226 (0.418)	0.236 (0.425)	0.255 (0.436)	0.263 (0.440)
Male	0.976 (0.153)	0.963 (0.188)	0.956 (0.206)	0.945 (0.229)
Capital	0.143 (0.350)	0.149 (0.356)	0.103 (0.303)	0.100 (0.300)
Central	0.242 (0.429)	0.247 (0.432)	0.252 (0.434)	0.250 (0.433)
Northern	0.129 (0.335)	0.089 (0.286)	0.084 (0.278)	0.074 (0.262)
Southeastern	0. 223 (0.416)	0.248 (0.432)	0.294 (0.456)	0.305 (0.461)
Rental Land	0.146 (0.354)	0.178 (0.383)	0.183 (0.387)	0.192 (0.394)
Own and Rental Land	0.404 (0.491)	0.407 (0.492)	0.436 (0.496)	0.440 (0.497)
Family Labor (%)	0.792 (0.120)	0.876 (0.132)	0.907 (0.120)	0.904 (0.132)
Debt Ratio (%)	0.138 (0.235)	0.076 (0.182)	0.078 (0.197)	0.062 (0.127)
Non-farm Income Ratio (%)	0.274 (2.505)	0.366 (0.990)	0.291 (0.477)	0.256 (0.464)
No. of Farms	1333	950	1148	1118

Numbers in parenthesis are standard deviations.
Source: KOSIS; Farm Household Economy Survey; Agricultural Production Cost Survey each year

Table 5. Mean Differences and Sample T-Test Results on Change in *TE*

	TE_S	TE_B
2003 - 2008	-0.082***	-0.115***
2003 - 2013	-0.104***	-0.064***
2003 - 2017	-0.054***	-0.135***
2008 - 2013	-0.022**	0.050***
2008 - 2017	0.028***	-0.021
2013 - 2017	0.050***	-0.071***

TE_S and *TE_B* denote *TE* with a standard approach based on different frontier each year and *TE* with base period frontier, respectively.
*, **, and *** indicate that mean differences are significantly different from zero at 90%, 95%, and 99% levels, respectively

Table 6. Mean Differences and Sample T-Test Results on *CE* Change

	CE_S	CE_B
2003 - 2008	-0.017	-0.171***
2003 - 2013	-0.021***	-0.161***
2003 - 2017	0.079***	-0.243***
2008 - 2013	-0.004***	0.010
2008 - 2017	0.096***	-0.073***
2013 - 2017	0.100***	-0.083***

CE_S and *CE_B* denote *CE* with a standard approach based on a different frontier and price each year and *CE* with a base period frontier and price, respectively.
*, **, and *** indicate that mean differences are significantly different from zero at 90%, 95%, and 99% levels, respectively.

Table 7. Mean Differences and Sample T-Test Results on Change in *TE* and *CE* by Farm Size (Less than 1ha)

Hypothesis	TE_S	TE_B	CE_S	CE_B
$\mu_{2003} - \mu_{2008} = 0$	-0.083^{***}	-0.123^{***}	-0.021	-0.172^{***}
$\mu_{2003} - \mu_{2013} = 0$	-0.110^{***}	-0.072^{***}	-0.027^{***}	-0.169^{***}
$\mu_{2003} - \mu_{2017} = 0$	-0.060^{***}	-0.157^{***}	0.077^{***}	-0.247^{***}
$\mu_{2008} - \mu_{2013} = 0$	-0.027^{***}	0.051^{***}	-0.006^{**}	0.003
$\mu_{2008} - \mu_{2017} = 0$	0.023^{***}	-0.034^{*}	0.098^{***}	-0.074^{***}
$\mu_{2013} - \mu_{2017} = 0$	0.050^{***}	-0.086^{***}	0.104^{***}	-0.078^{***}

TE_S and *TE_B* denote *TE* with a standard approach based on different frontier each year and *TE* with base period frontier, respectively; *CE_S* and *CE_B* denote *CE* with a standard approach based on a different frontier and price each year and *CE* with a base period frontier and price, respectively.
*, **, and *** indicate that mean differences are significantly different from zero at 90%, 95%, and 99% levels, respectively.

Table 8. Mean Differences and Sample T-Test Results on Change in *TE* and *CE* by Farm Size (1~3ha)

Hypothesis	TE_S	TE_B	CE_S	CE_B
$\mu_{2003} - \mu_{2008} = 0$	-0.088***	-0.019***	-0.025	-0.187***
$\mu_{2003} - \mu_{2013} = 0$	-0.099***	-0.054***	-0.013*	-150***
$\mu_{2003} - \mu_{2017} = 0$	-0.047***	-0.128***	0.079***	-0.244***
$\mu_{2008} - \mu_{2013} = 0$	-0.011	0.064***	0.012	0.037*
$\mu_{2008} - \mu_{2017} = 0$	0.041***	-0.010	0.104***	-0.057**
$\mu_{2013} - \mu_{2017} = 0$	0.052***	-0.074***	0.092***	-0.095***

TE_S and *TE_B* denote *TE* with a standard approach based on different frontier each year and *TE* with base period frontier, respectively; *CE_S* and *CE_B* denote *CE* with a standard approach based on a different frontier and price each year and *CE* with a base period frontier and price, respectively.
*, **, and *** indicate that mean differences are significantly different from zero at 90%, 95%, and 99% levels, respectively.

Table 9. Mean Differences and Sample T-Test Results on Change in *TE* and *CE* by Farm Size (More than 3ha)

Hypothesis	TE_S	TE_B	CE_S	CE_B
$\mu_{2003} - \mu_{2008} = 0$	-0.063^{***}	-0.096^{**}	0.026	-0.150^{***}
$\mu_{2003} - \mu_{2013} = 0$	-0.061^{***}	-0.025	0.010	-0.120^{***}
$\mu_{2003} - \mu_{2017} = 0$	-0.015^{***}	-0.103^{***}	0.104^{***}	-0.217^{***}
$\mu_{2008} - \mu_{2013} = 0$	0.002	0.071^{*}	-0.016	0.030
$\mu_{2008} - \mu_{2017} = 0$	0.048^{**}	-0.007	0.078^{***}	-0.067
$\mu_{2013} - \mu_{2017} = 0$	0.046^{***}	-0.078^{***}	0.094^{***}	-0.097^{***}

TE_S and *TE_B* denote *TE* with a standard approach based on different frontier each year and *TE* with base period frontier, respectively; *CE_S* and *CE_B* denote *CE* with a standard approach based on a different frontier and price each year and *CE* with a base period frontier and price, respectively.
*, **, and *** indicate that mean differences are significantly different from zero at 90%, 95%, and 99% levels, respectively.

Table 10. Mean Differences and Sample T-Test Results on Change in *TE* and *CE* by Farm Size Each Year

Year	Hypothesis	TE_S	TE_B	CE_S	CE_B
	$\mu_{1ha} - \mu_{1\sim3ha} = 0$	-0.009	-0.016	-0.029**	-0.036***
2003	$\mu_{1ha} - \mu_{3ha} = 0$	-0.057**	-0.055**	-0.074***	-0.087***
	$\mu_{1\sim3ha} - \mu_{3ha} = 0$	-0.048*	-0.039*	-0.044*	-0.051***
	$\mu_{1ha} - \mu_{1\sim3ha} = 0$	-0.014	-0.012	-0.033**	-0.050***
2008	$\mu_{1ha} - \mu_{3ha} = 0$	-0.037	-0.028	-0.027	-0.065*
	$\mu_{1\sim3ha} - \mu_{3ha} = 0$	-0.023	-0.016	0.006	-0.015
	$\mu_{1ha} - \mu_{1\sim3ha} = 0$	0.001	0.001	-0.016	-0.016
2013	$\mu_{1ha} - \mu_{3ha} = 0$	-0.008	-0.008	-0.037*	-0.037*
	$\mu_{1\sim3ha} - \mu_{3ha} = 0$	-0.010	-0.010	-0.022	-0.022
	$\mu_{1ha} - \mu_{1\sim3ha} = 0$	0.004	0.013	-0.027**	-0.033*
2017	$\mu_{1ha} - \mu_{3ha} = 0$	-0.012	-0.001	-0.047**	-0.057**
	$\mu_{1\sim3ha} - \mu_{3ha} = 0$	-0.016	-0.014	-0.020	-0.024

TE_S and *TE_B* denote *TE* with a standard approach based on different frontier each year and *TE* with base period frontier, respectively; *CE_S* and *CE_B* denote *CE* with a standard approach based on a different frontier and price each year and *CE* with a base period frontier and price, respectively.
*, **, and *** indicate that mean differences are significantly different from zero at 90%, 95%, and 99% levels, respectively.

Table 11. Mean Differences and Sample T-Test Results on Change in *TE* and *CE* by Risk Preference (Farmers Who Do Not Participate in the Crop Insurance Program)

Hypothesis	TE_S	TE_B	CE_S	CE_B
$\mu_{2003} - \mu_{2008} = 0$	-0.083***	-0.120***	-0.019	-0.173***
$\mu_{2003} - \mu_{2013} = 0$	-0.105***	-0.065***	-0.027***	-0.167***
$\mu_{2003} - \mu_{2017} = 0$	-0.053***	-0.152***	0.081***	-0.242***
$\mu_{2008} - \mu_{2013} = 0$	-0.022**	0.055***	-0.008**	0.007
$\mu_{2008} - \mu_{2017} = 0$	0.029***	-0.031	0.100***	-0.069***
$\mu_{2013} - \mu_{2017} = 0$	0.052***	-0.086***	0.108***	-0.076***

TE_S and *TE_B* denote *TE* with a standard approach based on different frontier each year and *TE* with base period frontier, respectively; *CE_S* and *CE_B* denote *CE* with a standard approach based on a different frontier and price each year and *CE* with a base period frontier and price, respectively.
*, **, and *** indicate that mean differences are significantly different from zero at 90%, 95%, and 99% levels, respectively.

Table 12. Mean Differences and Sample T-Test Results on Change in *TE* and *CE* by Risk Preference (Farmers Who Participate in the Crop Insurance Program)

Hypothesis	TE_S	TE_B	CE_S	CE_B
$\mu_{2003} - \mu_{2008} = 0$	-0.055***	-0.084*	0.024	-0.113**
$\mu_{2003} - \mu_{2013} = 0$	-0.106***	-0.059	-0.020	-0.156***
$\mu_{2003} - \mu_{2017} = 0$	-0.058***	-0.140***	0.073***	-0.247***
$\mu_{2008} - \mu_{2013} = 0$	-0.051**	0.025	-0.044**	-0.043
$\mu_{2008} - \mu_{2017} = 0$	-0.002	-0.055*	0.048***	-0.134***
$\mu_{2013} - \mu_{2017} = 0$	0.049***	-0.081***	0.093***	-0.091***

TE_S and *TE_B* denote *TE* with a standard approach based on different frontier each year and *TE* with base period frontier, respectively; *CE_S* and *CE_B* denote *CE* with a standard approach based on a different frontier and price each year and *CE* with a base period frontier and price, respectively.
*, **, and *** indicate that mean differences are significantly different from zero at 90%, 95%, and 99% levels, respectively.

Table 13. Mean Differences and Sample T-Test Results on Change in *TE* and *CE* by Risk Preference (Farmers Who Do Not Participate vs. Farmers Who Participate in the Crop Insurance Program) Each Year

Year	TE_S	TE_B	CE_S	CE_B
2003	0.004	-0.004	0.005	0.001
2008	0.031	0.032	0.048*	0.062*
2013	0.003	0.003	0.011	0.011
2017	0.000	0.008	-0.004	-0.004

TE_S and *TE_B* denote *TE* with a standard approach based on different frontier each year and *TE* with base period frontier, respectively; *CE_S* and *CE_B* denote *CE* with a standard approach based on a different frontier and price each year and *CE* with a base period frontier and price, respectively.
*, **, and *** indicate that mean differences are significantly different from zero at 90%, 95%, and 99% levels, respectively.

Table 14. Result from Two-stage Analysis Estimation with *TE*

Variable	TE_S			TE_B		
	Truncated MLE	OLS	GMM-IV	Truncated MLE	OLS	GMM-IV
Intercept	0.913***	-0.094	-0.235	0.864***	-0.168	-0.326
	(0.082)	(0.121)	(0.361)	(0.085)	(0.121)	(0.341)
Precipitation	-0.203***	-0.227***	-0.406**	-0.158***	-0.157	-0.315**
	(0.056)	(0.083)	(0.169)	(0.057)	(0.082)	(0.159)
Precipitation Squared	0.008	-0.013	0.059	-0.029	-0.036	0.026
	(0.019)	(0.028)	(0.069)	(0.021)	(0.028)	(0.066)
Age	0.030*	0.037	-0.134	0.029	0.036	-0.122
	(0.020)	(0.030)	(0.131)	(0.021)	(0.030)	(0.133)
Age Squared	-0.002	-0.002	0.010	-0.002	-0.002	0.009
	(0.001)	(0.002)	(0.008)	(0.001)	(0.002)	(0.008)
No education	-0.054***	-0.078***	-0.141***	-0.044***	-0.063***	-0.119***
	(0.011)	(0.016)	(0.046)	(0.012)	(0.016)	(0.044)
Elementary school	-0.022**	-0.030**	-0.073**	-0.013	-0.018	-0.056*
	(0.010)	(0.014)	(0.030)	(0.010)	(0.014)	(0.029)
Middle school	-0.020**	-0.027**	-0.058*	-0.012	-0.016	-0.043*
	(0.010)	(0.014)	(0.028)	(0.010)	(0.014)	(0.026)
High school	-0.005	-0.008	-0.031	0.003	0.003	-0.019
	(0.009)	(0.014)	(0.024)	(0.010)	(0.013)	(0.023)
Sex	-0.032***	-0.044***	-0.139***	-0.040***	-0.048***	-0.134***
	(0.009)	(0.013)	(0.042)	(0.010)	(0.013)	(0.043)
Capital	0.015**	0.027**	0.086**	0.013*	0.022**	0.080*
	(0.007)	(0.011)	(0.039)	(0.008)	(0.011)	(0.039)
Central	0.038***	0.053***	0.094***	0.035***	0.047***	0.086***
	(0.006)	(0.008)	(0.025)	(0.006)	(0.008)	(0.025)
Northern	-0.014*	-0.018*	0.065	-0.013	-0.015	0.064
	(0.007)	(0.011)	(0.042)	(0.008)	(0.010)	(0.043)
Southwestern	0.025***	0.042***	0.072***	0.022***	0.034***	0.062***
	(0.005)	(0.007)	(0.021)	(0.005)	(0.007)	(0.022)
Rental land	-0.016***	-0.023***	0.253	-0.019***	-0.025***	0.211
	(0.005)	(0.007)	(0.250)	(0.005)	(0.007)	(0.240)
Own and rental land	-0.001*	-0.008	0.203	-0.009**	-0.010*	0.172
	(0.001)	(0.006)	(0.150)	(0.004)	(0.006)	(0.156)
Ratio of Family Labor Force	-0.028**	-0.039*	0.918**	-0.007	-0.011	0.902**
	(0.010)	(0.021)	(0.400)	(0.015)	(0.020)	(0.412)
Debt Ratio	-0.016*	-0.029**	-0.720	-0.014	-0.026*	-0.632
	(0.010)	(0.014)	(0.556)	(0.010)	(0.014)	(0.551)
Ratio of Non-farm Income	-0.001	-0.002	-0.001	-0.002*	-0.003*	-0.002
	(0.001)	(0.002)	(0.003)	(0.001)	(0.002)	(0.004)
Year Dummy for 2003	-0.007	0.014	0.153***	0.058***	0.081***	0.213***
	(0.010)	(0.015)	(0.058)	(0.010)	(0.015)	(0.059)
Year Dummy for 2008	-0.057***	-0.077***	-0.049**	0.023***	0.029***	0.054***
	(0.006)	(0.009)	(0.021)	(0.006)	(0.009)	(0.021)
Year Dummy for 2017	-0.094***	-0.127***	-0.146***	0.043***	0.049***	0.031**
	(0.006)	(0.009)	(0.016)	(0.007)	(0.009)	(0.016)

Sigma	0.113 (0.001)	0.168	0.256	0.121 (0.001)	0.166	0.240
Hansen' J-statistic			11.82 (0.224)			11.93 (0.217)
No. of farms	4549	4549	4549	4549	4549	4249

TE_S and *TE_B* denote *TE* with a standard approach based on different frontier each year and *TE* with base period frontier, respectively.
Numbers in parenthesis are standard errors. For the GMM-IV, numbers in parentheses are adjusted standard errors.
*, **, and *** indicate that mean differences are significantly different from zero at 90%, 95%, and 99% levels, respectively.

Table 15. Result from Two-stage Analysis Estimation with *CE*

Variable	CE_S			CE_B		
	Truncated MLE	OLS	GMM-IV	Truncated MLE	OLS	GMM-IV
Intercept	0.708***	-0.202	-0.353	0.739***	-0.225	-0.242
	(0.083)	(0.181)	(0.405)	(0.091)	(0.188)	(0.433)
Precipitation	-0.138**	-0.334***	-0.430**	-0.240***	-0.389***	-0.522***
	(0.056)	(0.123)	(0.197)	(0.062)	(0.128)	(0.201)
Precipitation Squared	-0.002	0.019***	0.055	0.039*	0.023	0.077
	(0.019)	(0.042)	(0.078)	(0.022)	(0.044)	(0.080)
Age	0.006	-0.014	-0.039	0.016	0.018	-0.071
	(0.021)	(0.045)	(0.152)	(0.023)	(0.047)	(0.156)
Age Squared	0.000	0.001	0.003	-0.001	-0.001	0.004
	(0.001)	(0.003)	(0.010)	(0.002)	(0.003)	(0.010)
No education	-0.054***	-0.102***	-0.142***	-0.058***	-0.119***	-0.154***
	(0.011)	(0.024)	(0.050)	(0.013)	(0.025)	(0.052)
Elementary school	-0.033***	-0.061***	-0.083**	-0.037***	-0.080***	-0.098***
	(0.010)	(0.020)	(0.035)	(0.011)	(0.021)	(0.035)
Middle school	-0.029***	-0.057*	-0.078**	-0.035***	-0.072***	-0.087***
	(0.010)	(0.021)	(0.032)	(0.011)	(0.022)	(0.033)
High school	-0.018*	-0.035*	-0.046	-0.022**	-0.046**	-0.060**
	(0.010)	(0.020)	(0.029)	(0.011)	(0.021)	(0.029)
Sex	-0.031***	-0.064***	-0.096***	-0.035***	-0.058***	-0.098**
	(0.009)	(0.020)	(0.053)	(0.010)	(0.020)	(0.054)
Capital	0.062***	0.138***	0.143***	0.071***	0.164***	0.185***
	(0.007)	(0.016)	(0.050)	(0.008)	(0.017)	(0.052)
Central	0.054***	0.110***	0.117***	0.059***	0.116***	0.133***
	(0.006)	(0.012)	(0.032)	(0.006)	(0.012)	(0.032)
Northern	-0.008	-0.012	0.012	-0.007	-0.005	0.044
	(0.008)	(0.016)	(0.053)	(0.008)	(0.016)	(0.053)
Southwestern	0.031***	0.076***	0.083***	0.031***	0.007***	0.090***
	(0.005)	(0.011)	(0.025)	(0.006)	(0.011)	(0.025)
Rental land	-0.014***	-0.030***	0.265	-0.016***	-0.033***	0.166
	(0.005)	(0.011)	(0.270)	(0.006)	(0.011)	(0.291)
Own and rental land	0.002	0.008	0.051	0.005	0.014	0.082
	(0.004)	(0.008)	(0.179)	(0.004)	(0.009)	(0.176)
Ratio of Family Labor Force	-0.006	0.027	0.364	0.015	0.015	0.527
	(0.015)	(0.031)	(0.520)	(0.016)	(0.032)	(0.525)
Debt Ratio	-0.015	-0.028	-0.379	-0.009	-0.017	-0.531
	(0.010)	(0.020)	(0.614)	(0.011)	(0.021)	(0.607)
Ratio of Non-farm Income	-0.001	-0.003	-0.003	-0.001	-0.002	-0.002
	(0.001)	(0.003)	(0.004)	(0.001)	(0.003)	(0.004)
Year Dummy for 2003	0.075***	0.154***	0.216***	-0.079***	-0.132***	-0.052
	(0.010)	(0.022)	(0.071)	(0.011)	(0.023)	(0.072)
Year Dummy for 2008	-0.030***	-0.053**	-0.045*	-0.018***	-0.044	-0.029
	(0.006)	(0.014)	(0.026)	(0.007)	(0.014)	(0.026)
Year Dummy for 2017	-0.131***	-0.268***	-0.284***	0.049***	0.065***	0.048**
	(0.006)	(0.014)	(0.021)	(0.007)	(0.014)	(0.021)

Sigma	0.118 (0.001)	0.250	0.278	0.130 (0.001)	0.261	0.288
Hansen' J-statistic			13.00 (0.163)			13.00 (0.163)
No. of farms	4549	4549	4549	4549	4549	4549

CE_S and *CE_B* denote *CE* with a standard approach based on a different frontier and price each year and *CE* with a base period frontier and price, respectively.
Numbers in parenthesis are standard errors. For the GMM-IV, numbers in parentheses are adjusted standard errors.
*, **, and *** indicate that mean differences are significantly different from zero at 90%, 95%, and 99% levels, respectively.

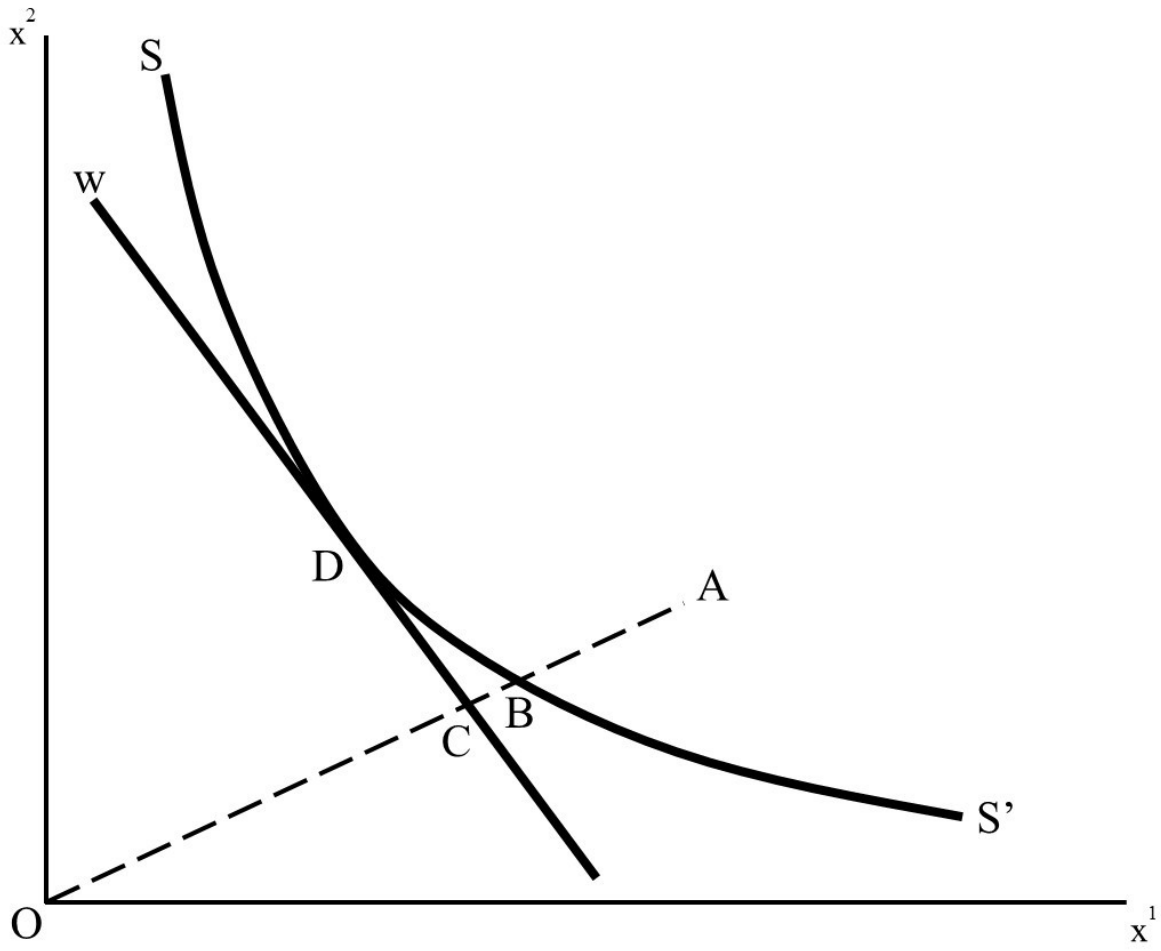

Figure 1. Geometrical Representation of *TE*, *AE*, and *CE*

Source: Farrell (1957)

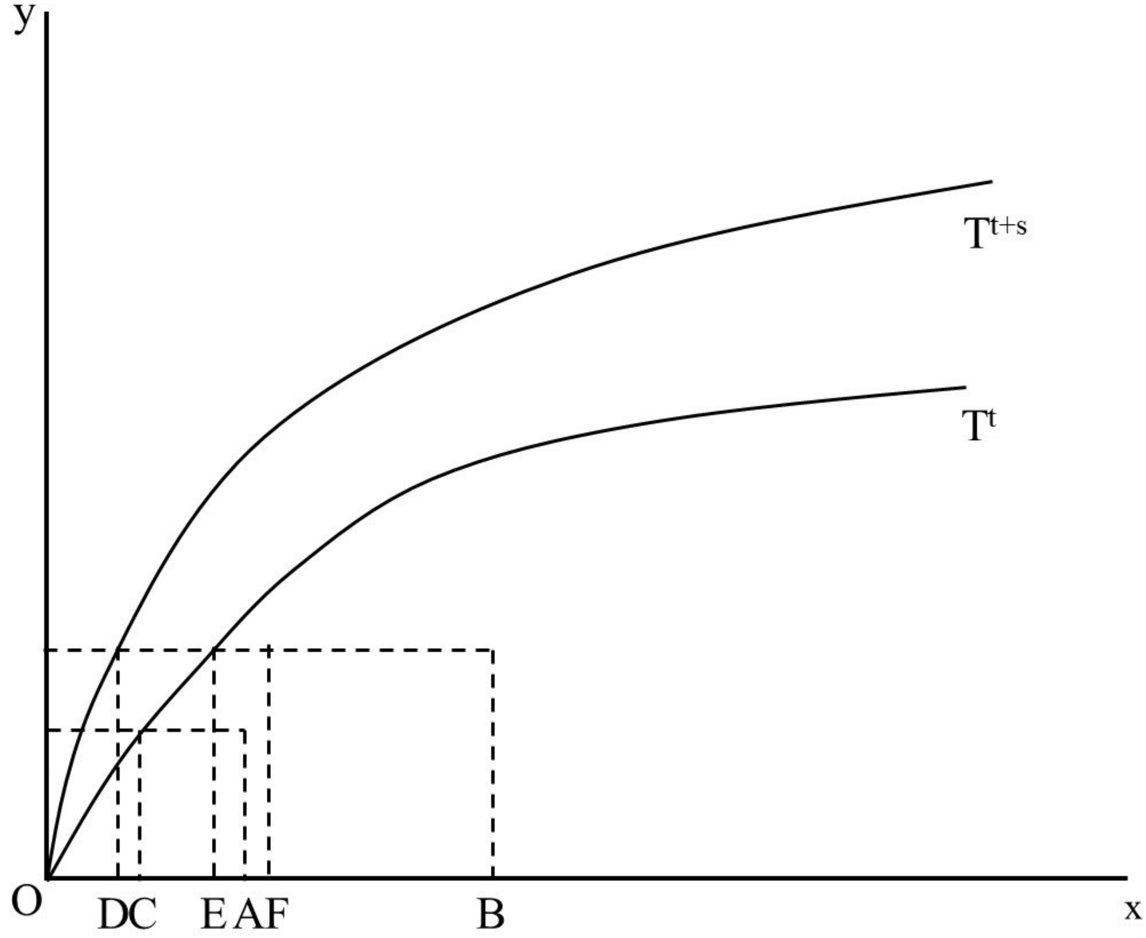

Figure 2. Geometrical Representation of ΔTE, *TC*, and *ITEC*

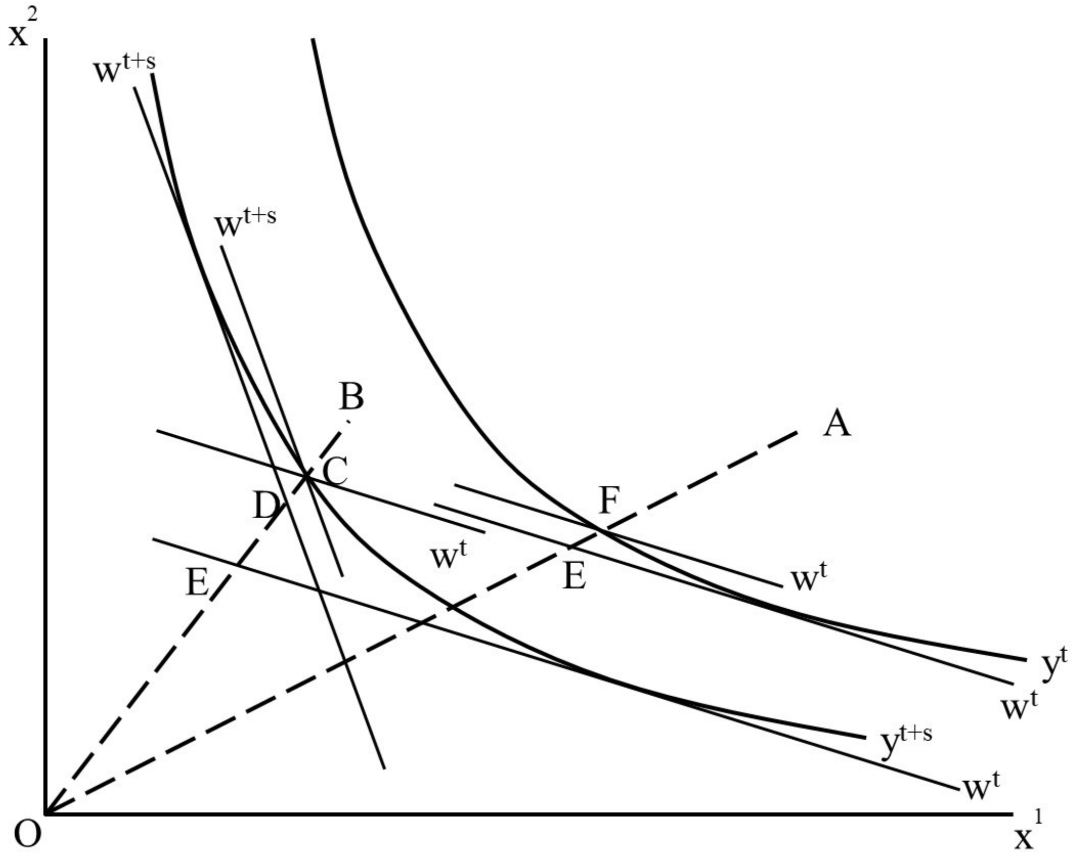

Figure 3. Geometrical Representation of Δ*AE*, *PE*, and *IEAC*

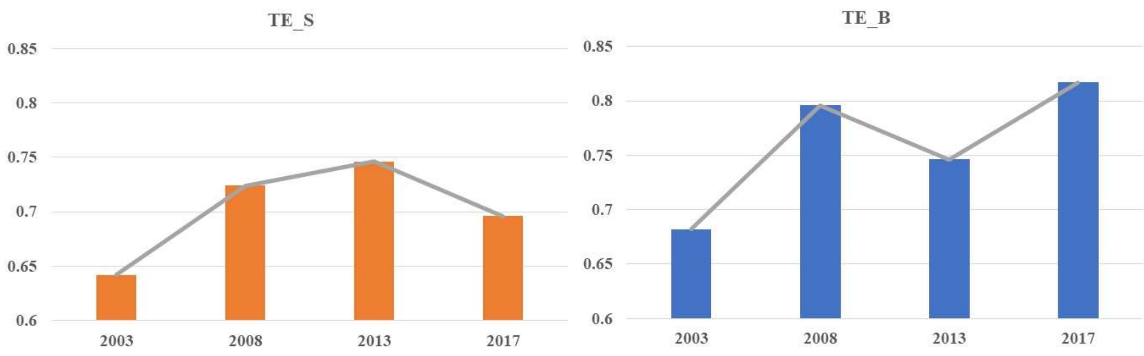

Figure 4. Mean of Technical Efficiency

TE_S and *TE_B* denote *TE* with a standard approach based on different frontier each year and *TE* with base period frontier, respectively.

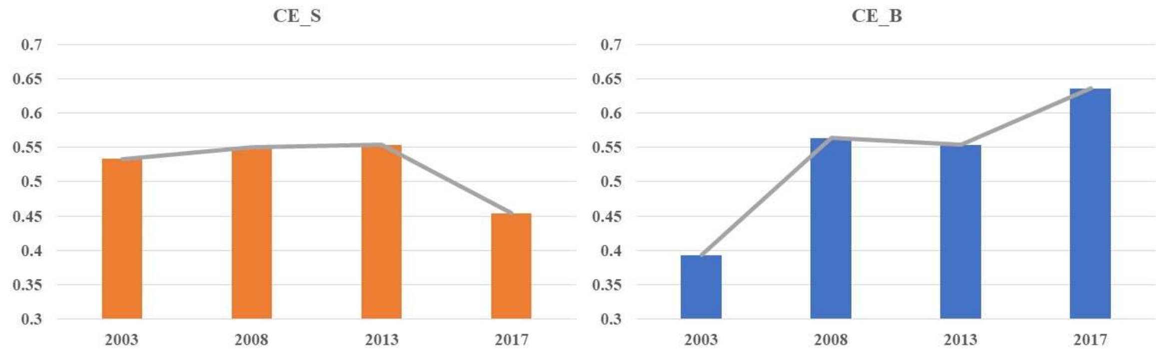

Figure 5. Mean of Cost Efficiency

CE_S and *CE_B* denote *CE* with a standard approach based on a different frontier and price each year and *CE* with a base period frontier and price, respectively.

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APPENDICES

Appendix I

The appendix shows detailed derivations for the decomposition procedure presented in Chapter 4.

Equation (9) is decomposed into ΔTE and ΔAE as:

(A1) $\Delta CE = \frac{CE_{t+s,t+s}^{t+s}}{CE_{t,t}^{t}} = \Delta TE \times \Delta AE.$

Since the distance function is homogeneous degree of one in input, (10) is:

(A2) $\Delta TE = \frac{TE_{t+s}^{t+s}}{TE_{t}^{t}} = \frac{D^{t}(y^{t},x^{t})}{D^{t+s}(y^{t+s},x^{t+s})} = \frac{1}{D^{t+s}(y^{t+s},\frac{x^{t+s}}{D^{t}(y^{t},x^{t})})} = \frac{x_{t+s}^{t+sT}}{x_{t}^{t+sT}} \times \frac{x_{t}^{t+sT}}{x^{t+s}/D^{t}(y^{t},x^{t})}.$

In the last product term of (A2), the first ratio is a fraction of technically efficient point of x^{t+s} evaluated on the frontier estimated at time *t+s* and *t.* The second ratio in the last product term is the fraction of *TE* for x^{t+s} and x^{t} which are evaluated on the frontier at time *t*. Then, (A2) is written with the distance function as:

(A3) $\Delta TE = \frac{x_{t+s}^{t+sT}}{x_{t}^{t+sT}} \times \frac{x_{t}^{t+sT}}{x^{t+s}/D^{t}(y^{t},x^{t})} = \frac{D^{t}(y^{t+s},x^{t+s})}{D^{t+s}(y^{t+s},x^{t+s})} \times \frac{D^{t}(y^{t},x^{t})}{D^{t}(y^{t+s},x^{t+s})}.$

In the last product term of (A3), the first ratio is *TC*, and the second ratio is *IETC* from (11) and (12). Combining (11), (12), and (A3), we have ΔTE as the multiplication of *TC* and *IETC*:

(A4) $$\Delta TE = \frac{TE_{t+s}^{t+s}}{TE_t^t} = \frac{D^t(y^{t+s},x^{t+s})}{D^{t+s}(y^{t+s},x^{t+s})} \times \frac{D^t(y^t,x^t)}{D^t(y^{t+s},x^{t+s})} = TC \times IETC.$$

AE is defined as a ratio of the cost of technically efficient input quantity to the minimized cost in (7). ΔAE in (14) can be decomposed into two ratios as:

(A5) $$\Delta AE = \frac{AE_{t+s,t+s}^{t+s}}{AE_{t,t}^t} = \frac{\frac{C^{t+s}(y^{t+s},w^{t+s})\times D^{t+s}(y^{t+s},x^{t+s})}{w^{t+s\prime}x^{t+s}}}{\frac{C^t(y^t,w^t)\times D^t(y^t,x^t)}{w^{t\prime}x^t}}$$

$$= \frac{\frac{C^{t+s}(y^{t+s},w^{t+s})\times D^{t+s}(y^{t+s},x^{t+s})}{w^{t+s\prime}x^{t+s}}}{\frac{C^{t+s}(y^{t+s},w^t)\times D^{t+s}(y^{t+s},x^{t+s})}{w^{t\prime}x^{t+s}}} \times \frac{\frac{C^{t+s}(y^{t+s},w^t)\times D^{t+s}(y^{t+s},x^{t+s})}{w^{t\prime}x^{t+s}}}{\frac{C^t(y^t,w^t)\times D^t(y^t,x^t)}{w^{t\prime}x^t}}.$$

The last equation in (A5) is the multiplication of *PE* and *IEAC* from (15) and (16), respectively. Then, ΔAE can be decomposed into *PE* and *IEAC* as:

(A6) $$\Delta AE = \frac{AE_{t+s,t+s}^{t+s}}{AE_{t,t}^t} = \frac{\frac{C^{t+s}(y^{t+s},w^{t+s})\times D^{t+s}(y^{t+s},x^{t+s})}{w^{t+s\prime}x^{t+s}}}{\frac{C^{t+s}(y^{t+s},w^t)\times D^{t+s}(y^{t+s},x^{t+s})}{w^{t\prime}x^{t+s}}} \times \frac{\frac{C^{t+s}(y^{t+s},w^t)\times D^{t+s}(y^{t+s},x^{t+s})}{w^{t\prime}x^{t+s}}}{\frac{C^t(y^t,w^t)\times D^t(y^t,x^t)}{w^{t\prime}x^t}}$$

$$= \frac{AE_{t+s,t+s}^{t+s}}{AE_{t+s,t}^{t+s}} \times \frac{AE_{t+s,t}^{t+s}}{AE_{t,t}^t} = PE \times IEAC.$$

Combining (A1), (A4), and (A6) yields the decomposition of ΔCE into four factors: *TC, IETC, PE*, and *IEAC*, which is:

(A7) $$\Delta CE = \frac{CE_{t+s,t+s}^{t+s}}{CE_{t,t}^t} = \Delta TE \times \Delta AE = \frac{TE_{t+s}^{t+s}}{TE_t^t} \times \frac{AE_{t+s,t+s}^{t+s}}{AE_{t,t}^t}$$

$$= \frac{D^t(y^t,x^t)}{D^{t+s}(y^{t+s},x^{t+s})} \times \frac{\frac{C^{t+s}(y^{t+s},w^{t+s})\times D^{t+s}(y^{t+s},x^{t+s})}{w^{t+s\prime}x^{t+s}}}{\frac{C^t(y^t,w^t)\times D^t(y^t,x^t)}{w^{t\prime}x^t}}$$

$$= \frac{D^t(y^{t+s},x^{t+s})}{D^{t+s}(y^{t+s},x^{t+s})} \times \frac{D^t(y^t,x^t)}{D^t(y^{t+s},x^{t+s})}$$

$$\times \frac{\frac{C^{t+s}(y^{t+s},w^{t+s})\times D^{t+s}(y^{t+s},x^{t+s})}{w^{t+s\prime}x^{t+s}}}{\frac{C^{t+s}(y^{t+s},w^{t})\times D^{t+s}(y^{t+s},x^{t+s})}{w^{t\prime}x^{t+s}}} \times \frac{\frac{C^{t+s}(y^{t+s},w^{t})\times D^{t+s}(y^{t+s},x^{t+s})}{w^{t\prime}x^{t+s}}}{\frac{C^{t}(y^{t},w^{t})\times D^{t}(y^{t},x^{t})}{w^{t\prime}x^{t}}}.$$

$$= \frac{D^t(y^{t+s},x^{t+s})}{D^{t+s}(y^{t+s},x^{t+s})} \times \frac{D^t(y^t,x^t)}{D^t(y^{t+s},x^{t+s})} \times \frac{AE^{t+s}_{t+s,t+s}}{AE^{t+s}_{t+s,t}} \times \frac{AE^{t+s}_{t+s,t}}{AE^{t}_{t,t}}.$$

$= TC \times IETC \times PE \times IEAC.$

(A7) is detailed derivation procedure for (17).

IECC in (19) is a product of *IETC* and *IEAC*. Result of (19) is derived as:

(A8) $IECC = IETC \times IEAC$

$$= \frac{D^t(y^t,x^t)}{D^t(y^{t+s},x^{t+s})} \times \frac{\frac{C^{t+s}(y^{t+s},w^{t})\times D^{t+s}(y^{t+s},x^{t+s})}{w^{t\prime}x^{t+s}}}{\frac{C^{t}(y^{t},w^{t})\times D^{t}(y^{t},x^{t})}{w^{t\prime}x^{t}}}$$

$$= \frac{\frac{C^{t+s}(y^{t+s},w^{t})}{w^{t\prime}x^{t+s}} \times \frac{D^{t+s}(y^{t+s},x^{t+s})}{D^{t}(y^{t+s},x^{t+s})}}{\frac{C^{t}(y^{t},w^{t})}{w^{t\prime}x^{t}}}.$$

Appendix II

Table AII. Sample T-Test Results on Mean Differences of TE and CE from Standard and Base Period Approaches Each Year

Year	TE_S - TE_B	CE_S - CE_B
2003	-0.039^{***}	0.140^{***}
2008	-0.072^{***}	-0.014^{***}
2013	0.000	0.000
2017	-0.121^{***}	-0.182^{***}

TE_S and *TE_B* denote *TE* with a standard approach based on different frontier each year and *TE* with base period frontier, respectively.

CE_S and *CE_B* denote *CE* with a standard approach based on a different frontier and price each year and *CE* with a base period frontier and price, respectively.

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