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Changes in the technical and scale efficiency of rice production activities in the Mekong delta, Vietnam

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Abstract

I used bootstrapping data envelopment analysis (DEA) to measure changes in technical and scale efficiency in rice production in the Mekong delta region, Vietnam. The data include sample production sets from 1998 and bi-annual updates from 2002 to 2010. Technical efficiency changed significantly over this period, showing an upward trend. On the other hand, increasing return to scale is dominant trend, which reflects the need to increase the rice production scale generally and expand land use particularly. Meanwhile, the government has been trying to prevent land consolidation activities and restrict production scales using quotas and agricultural land use duration rules.

Keywords: Data envelopment analysis; Technical efficiency; Bootstrap; Returns to scale; Rice production; Mekong delta

Background

The Mekong delta region is popularly considered the rice bowl of Vietnam, as it accounts for over 50% of domestic rice production and 90% of rice exports. Over the last decade, economic growth has led to dramatic changes in the rural features and rice production activities in the Mekong delta. During the period 1995 to 2011, rice production in the Mekong delta grew by 3.89%, increasing by 1.6 and 2.22% per annum in terms of area and yield growth respectively (own calculation based on GSO (2012)) (Figure 1).

In the same time period, the number of agricultural households in Vietnam has declined significantly, from 10.15 million households in 2001, to 9.15 and then 8.89 million households in 2006 and 2011 respectively (GSO, General Statistics Office of Vietnam 2001, GSO, General Statistics Office of Vietnam 2006a, GSO, General Statistics Office of Vietnam 2011). In the Mekong delta in 2011, the number of agricultural households was about 1.83 million, and these covered more than four million hectares of rice land (GSO, General Statistics Office of Vietnam 2012). The number of agricultural households declined consistently, and the amount of agricultural land available remained quite limited.

The Vietnamese government has tried to reduce the rate of land consolidation in the country - a key cause of landlessness - by imposing quotas on agricultural land use

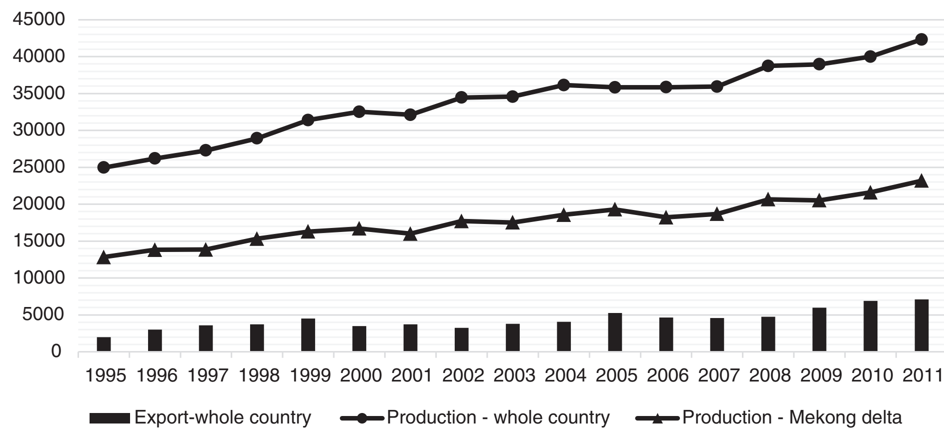

Figure 1 Rice production and exports (1000 tons). Source: Own summary from GSO, General Statistics Office of Vietnam (2012).

and limiting land use durations since the 1993 Land Law (Government of Vietnam 1993, 2003) was introduced. Article 70 of the Land Law stipulates that "*The quota on allocation to each family household or individual of land for planting annual crops, land for aquaculture and land for salt production shall be no more than three hectares of each type of land*", and specifies a twenty-year period for agricultural land use in the Mekong delta region (Government of Vietnam 2003). In 2007, this quota was increased to six hectares by Resolution No. 1126/2007/NQ-UBTVQH11 (The Standing Committee of National Assembly 2007), without any change being made to land use duration.

In practice, in 1994 11.71% of agricultural households had more than one hectare of agricultural land, but the figure increased to 15.08% by 2001 and 17.8% by 2006 (GSO, General Statistics Office of Vietnam 2001, GSO, General Statistics Office of Vietnam 2006a, GSO, General Statistics Office of Vietnam 2011). Akram-Lodhi (2001) showed that there were already 113,700 farms in excess of five hectares and 1,900 farms exceeding ten hectares by 1995. Even in some southern provinces and in the Mekong delta, it is still possible to find private farms exceeding of 1,000 hectares in size[a]. The upcoming issue is that the government's policies are limiting production scales in terms of both the area of land being used and its duration of use, and this may consequently affect the technical efficiency of rice production in the area.

Studies have analyzed technical efficiency in rice production on a nationwide scale, such as those by Minh and Long (2008), Khai and Yabe (2011), and Linh (2012). In addition, other studies used cross-section data to analyze the technical efficiency in the Mekong delta. For example, Huy (2009) analyzed the technical efficiency of 261 households during the 2006 winter-spring rice crop season, while Tuong (2010) used data from 200 households interviewed in 2010 to analyze growth rates in the area, as well as yield and production levels, and those factors affecting rice production. Thong et al. (2011) compared the economic efficiency of the summer-autumn and autumn-winter rice crop activities based on data taken from 479 households across four provinces of the Mekong delta. These studies were carried out in different years using different methods and a variety of sample sizes, making results hard to compare. Furthermore, estimates might be inconsistent due to sample size issues (Alirezaee et al. 1998; Andor & Hesse 2011; Staat 2001; Zhang & Bartels 1998).

Using a different approach, this study looked at the technical and scale efficiencies of rice production in the Mekong Delta over the period 1998 to 2010, using the same sample sizes and same study methods. Such a consistent analysis helped me to draw general conclusions and allowed me to measure changes across years in the Mekong delta's rice production activities. As a consequence, the results of this study may have policy implications for agricultural land management activities in the delta region.

Methods

Measuring technical efficiency and scale efficiency

The concept of technical efficiency was first proposed by Farrell (1957) based on the works of Debreu (1951) and Koopmans (1951). In his study, Farrell identified two forms of efficiency: *technical efficiency* and *allocative efficiency*. Technical efficiency reflects the ability of a firm to obtain maximum output based on a given set of inputs. Meanwhile, allocative efficiency measures the ability to use the optimal input set based on available prices and production techniques. Allocative efficiency is therefore also called *price efficiency*. Technical efficiency and allocative efficiency can be combined to measure the *economic efficiency* (or overall cost efficiency) of a firm.

Farrell illustrated the concepts above using the example of a firm whose work process has two inputs (x_1, x_2) and one output (q), and based on an assumption of constant returns to scale (CRS). The CRS assumption states that a given and proportionate increase in all inputs in the long run will result in an increase in outputs in the same proportion. Figure 2 shows technical efficiency based on an *input-oriented measure* which compares the actual production set (point P) and the fully-efficient production set (point Q), Q being a point which lies on the isoquant SS'. Meanwhile, in the study technical efficiency (TE) is measured using the ratio: TE = 0Q/0P, with the resulting TE values falling between zero and one. The distance QP represents technical inefficiencies, and inputs can be reduced without changing the outputs. If point P is able to move to point Q on the isoquant, the firm is said technical efficient and its TE score is unity.

In the case of the available price information, the isocost line AA' can be added to measure allocative efficiency (AE), which is calculated using the ratio: AE = 0R/0Q. By combining technical efficiency and allocative efficiency, one can generate the *overall cost efficiency*, using the following equation: CE = TE x AE = (0Q/0P) × (0R/0Q) = 0R/0P.

The analysis above illustrates Farrell's input-oriented measure of the ability of a firm to reduce inputs without changing outputs. An alternative approach, known as the *output-oriented measure*, measures the ability of a firm to increase outputs without changing inputs. In practice, the choice between input-oriented and output-oriented measures depends on whether the objective is input minimization (in which case use the input-oriented measure) or output maximization (use the output-oriented measure), without changing any of the other elements (FAO, Food and Agriculture Organization of the United Nations 2003).

The concepts mentioned above are based on an assumption of constant returns to scale. Although a firm may achieve both technical and allocative efficiency, it may not operate optimally in terms of *scale efficiency*. Using variable

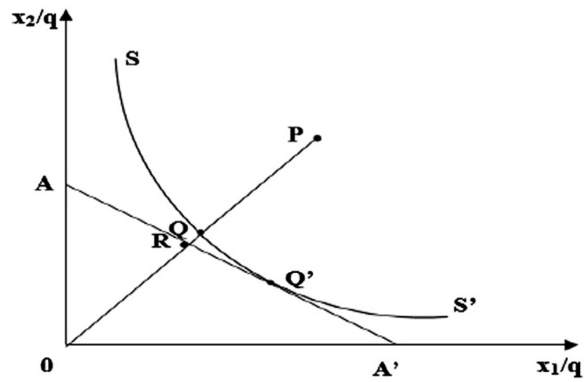

Figure 2 Technical and allocative efficiencies. Source: Coelli et al. (1998).

returns to scale (VRS) technology, the operational scale of a firm may be too small and so well within the limit of increasing returns to scale (IRS). On the other hand, a firm may be too big and operate with decreasing returns to scale (DRS), partly in the production function. If a firm operates within the IRS or DRS limit, its efficiency might be improved by changing its scale of operation (Coelli et al. 1998).

Data envelopment analysis (DEA)

Technical efficiency and scale efficiency can be measured using parametric or non-parametric approaches. In this study, a non-parametric *data envelopment analysis* (DEA) model was employed. DEA was described by Fare (1985) as creating a non-parametric piece-wise surface (or frontier) over the data (Coelli et al. 1998).

The input-oriented CRS DEA and VRS DEA models are described in Table 1. In addition to these models, I also employed an input-oriented non-increasing return to scale (NIRS) DEA model to examine the different types of returns to scale, these being CRS, IRS and DRS.

sing the DEA model, scale efficiency (SE) is given by the ratio between two corresponding efficiency scores, estimated using CRS and VRS technology, as follows:

Table 1 A summary of input-oriented DEA models

Input-oriented constant returns to scale DEA (CRS): min $_{\theta,\lambda}\theta$, subject to	Input-oriented variable returns to scale DEA (VRS): min $_{\theta,\lambda}\theta$, subject to	Input-oriented non-increasing returns to scale DEA (NIRS): min $_{\theta,\lambda}\theta$, subject to
$-q_i + Q\lambda \geq 0$	$-q_i + Q\lambda \geq 0$	$-q_i + Q\lambda \geq 0$
$\theta x_i - X\lambda \geq 0$	$\theta x_i - X\lambda \geq 0$	$\theta x_i - X\lambda \geq 0$
$\lambda \geq 0$	$N1'\lambda = 1$	$N1'\lambda \leq 1$
	$\lambda \geq 0$	$\lambda \geq 0$

Where θ is the total technical efficiency score of the ith firm and λ is a Nx1 vector of constants. The value of θ must satisfy the restriction: $0 \leq \theta \leq 1$. If $\theta = 1$; it indicates that the firm is on the production frontier and is technically efficient. When $\theta \leq 1$, the firm is technically inefficient.
In the VRS DEA model, $N1'\lambda = 1$ is added to show a convexity constraint which ensures that an inefficient firm is only benchmarked against firms of a similar size. On the other hand, in the NIRS DEA model, $N1'\lambda = 1$ is replaced by $N1'\lambda \leq 1$ to ensure that the ith firm is not "benchmarked" against firms that are substantially larger than it, but may be compared with firms smaller than it.
Source: Summarized from Coelli et al. (1998).

$$\mathrm{SE} = \mathrm{TE}_{\mathrm{CRS}}/\mathrm{TE}_{\mathrm{VRS}}$$

To determine whether a firm operates under IRS or DRS, an additional DEA problem with NIRS should be employed (Coelli et al. 1998), so:

– If $\mathrm{TE}_{\mathrm{CRS}} = \mathrm{TE}_{\mathrm{VRS}}$: the firm is operating under CRS
– If $\mathrm{TE}_{\mathrm{NIRS}} = \mathrm{TE}_{\mathrm{VRS}}$: the firm is operating under DRS, and
– If $\mathrm{TE}_{\mathrm{CRS}} \neq \mathrm{TE}_{\mathrm{VRS}}$: the firm is operating under IRS

Bootstrapping DEA

Many studies use the two-stage approach to measure efficiency. For the first stage, the DEA method is employed to calculate a technical efficiency scores, then this score is used as a dependent variable to regress with exogenous variables during the second stage, using Tobit regression or OLS. Unfortunately, Simar and Wilson (2007) has shown that DEA efficiency estimates were serially correlated in these cases and that standard approaches to inference are, therefore, invalid. As an alternative, Simar and Wilson (2007) suggested using a bootstrap method to estimate bias-corrected efficiency scores during the first step.

For the second step, regression analysis determines the influence of environmental variables on the bias-corrected efficiency scores. Based on comparative analysis, Simar and Wilson (2007) proposed a truncated regression instead of a Tobit regression, or a choice between a single and double bootstrap to measure efficiency.

Data and analysis

Sampling

This study was based a database from the Vietnam General Statistics Office (GSO), and included data from the Vietnam Living Standard Survey (VLSS) 1998 and the Vietnam Household Living Standards Surveys (VHLSS) carried out in 2002, 2004, 2006, 2008 and 2010. Since 2002, the VHLSS have been conducted every two years on a nationwide scale. The sample was composed of 9,000 households on a nationwide scale, except in 1988 when the sample size was 6,000 households and 2002 when the sample size was 30,000.

The databases used for these surveys did not include panel data, meaning a household which appears in one survey may or may not have appeared in the others. An effort could have been made to create panel data across these databases based on the demographic characteristics of the households; however, this might have proved impossible or the results might have involved a too small sample size for the panel period of 1998 to 2010 in the Mekong delta region. Despite the use of panel data, in this study I was only concerned with average technical and scale efficiency scores taken from the 1,000 household sample. As a result of taking this approach, the results could be compared across years to identify changes during the study period (Table 2).

In addition, in the DEA analysis, two issues may be debated regarding those factors affecting the efficiency scores, these being:

(1) DEA is sensitive to outliners. Since DEA relies on identifying best practice reference units, it can be sensitive to extreme points, known as outliners, especially data contaminated by measurement error as described by Kuosmanen and Post (1999) and Nam et al. (2008).

Table 2 Sample size of VHLSSs (No. of observations)

	2010	2008	2006	2004	2002	1998
Vietnam	9,399	9,189	9,198	9,198	30,000	6,000
Mekong	1,905	1,863	1,863	1,863	6,298	1,112
Random sample			1,000			

Source: Own summary from (GSO, General Statistics Office of Vietnam 1998, GSO, General Statistics Office of Vietnam 2002, GSO, General Statistics Office of Vietnam 2004, GSO, General Statistics Office of Vietnam 2006b, GSO, General Statistics Office of Vietnam 2008, GSO, General Statistics Office of Vietnam 2010).

(2) DEA efficiency scores may be affected by sample size. A study by Zhang and Bartels (1998), comparing the structural inefficiency of different sized samples, found that this can lead to biased results. In addition, Staat (2001) supported Zhang and Bartels' results, saying it not only applies to studies explicitly comparing efficiency scores derived using samples of different sizes, but also to some types of DEA models such as the FDH, hierarchical DEA and DEA models for non-discretionary variables. Specifically, Alirezaee et al. (1998) argued that when the number of decision-making units is small, the number of dominant units or efficient sets will be relatively large and the average efficiency generally high.

To reduce the probability of such factors, the sampling process in this study was carried out over two stages: (1) First, I extracted observations of the Mekong delta from the national scale data and removed observations suspected of being outliners, (2) I randomly selected 1000 observations from each year.

Analysis

In this study, a single-bootstrapping DEA model was chosen to analyze technical efficiency under the input-orientation model, the aim being to measure the ability of the sample households to minimize inputs without changing outputs (Simar and Wilson (1998). During the first stage, bias-corrected technical efficiencies from the original technical efficiencies were estimated based on the same production set across all years, including five inputs and one output recoded (see Additional file 1).

The software package FEAR 1.0 of Wilson (2008) was used to estimate the TE_{CRS}, TE_{VRS} and TE_{NIRS} scores using the *DEA* function. After that, bias-corrected TE_{VRS} values were calculated by replicating the bootstrap 2,000 times using the *boot.sw98* function with an alpha value of 0.05 to estimate the statistical sizes of the confidence intervals. However, the *boot.sw98* function resulted in a homogeneous bootstrap for the Shephard distance functions, so Farrell efficiencies were re-calculated using the reciprocals of the Shephard efficiencies.

This study follows the scale efficiency estimation using DEA-based statistics instead of bootstrap-based statistics to estimate the returns to scale and scale efficiency[b]. To explore technical inefficiency factors, during the next stage, bias-corrected TE_{VRS} was used as a dependent variable, combined with exogenous independent variables in the truncated regression models. These potential factors were basically similar by years, though some additional variables from specific years were used to expand the models' levels of significance. Variables used in the truncated regression models included one dependent variable and eight independent variables recoded (see Additional file 1).

Results and discussion

Technical efficiencies

Values for the bias-corrected technical efficiencies (VRS) were found to be in the low range, at about 3% to 5% when compared to the original technical efficiencies (VRS). For instance, the original technical efficiency score in 2010 was 0.650, while the respective bias-corrected value was only 0.606. A natural characteristic of bootstrapping processes, efficiency distribution scores became "smoother" than the original values, as shown in Figure A1 (see Additional file 1).

The mean bias-correct technical efficiency (variable returns to scale) of rice production activities in the Mekong delta increased, rising from 0.484 in 1998 to 0.606 in 2010, despite a slight downward trend after 2008 (Table 3). The proportion of higher technical efficiency scores also significantly changed over the years. In 1998, less than a half of the farms (45.6%) reached a technical efficiency level between 50 and 100%, but nearly three quarters (74.2%) had reached this level of technical efficiency by 2010.

Compared to some recent studies, including Linh (2012), Khai and Yabe (2011), and Huy (2009), the technical efficiency scores found in this study were relatively low. One of the main reasons for this may have been the difference in sample sizes. Sample size, as the studies of Smith (1993), Alirezaee et al. (1998), Zhang and Bartels (1998), and Staat (2001) showed, can have a significant impact on efficiencies when those efficiencies are evaluated using the non-parametric DEA approach. In such cases, when the number of decision making unit (DMU) is small, the average efficiency will generally be high. To examine this trend, this study used data from 2010 and randomly chose a reduced sample of 200 DMUs to calculate the technical efficiencies. The results of a Welch t-test for unequal variance samples proved that the average technical efficiency score (VRS) of the sample of 200 households was significantly different to that of the sample of 1,000; the scores coming out at 0.745 and 0.650 respectively (Additional file 1). This result tends to support the findings of Linh (2012), which used about 82 DMUs from the Mekong delta region.

Determinants of technical inefficiency variation

Basically, inefficiency factors varied year on year. However, some popular inefficiency factors could be frequently found, including household demographic characteristics such as the age, gender, ethnicity and marriage status of the household head, household size, economic status of the household and the proportion of income from growing rice as a proportion of total income.

Table 3 Summary of efficiency scores and percentage forms of returns to scale

Mean scores		1998	2002	2004	2006	2008	2010
Original technical efficiency (VRS)		0.534	0.547	0.631	0.699	0.677	0.650
Corrected technical efficiency (VRS)		0.484	0.497	0.593	0.667	0.645	0.606
Scale efficiency		0.925	0.895	0.927	0.935	0.942	0.902
Percentage	*Constant returns to scale*	*1.2*	*1.2*	*1.3*	*1.1*	*2.7*	*0.9*
	Increasing returns to scale	*52.7*	*73.9*	*69.6*	*32.6*	*75.4*	*69.3*
	Decreasing returns to scale	*46.1*	*24.9*	*29.1*	*66.3*	*21.9*	*29.8*

Source: Own calculations based on (GSO, General Statistics Office of Vietnam 1998, GSO, General Statistics Office of Vietnam 2002, GSO, General Statistics Office of Vietnam 2004, GSO, General Statistics Office of Vietnam 2006b, GSO, General Statistics Office of Vietnam 2008, GSO, General Statistics Office of Vietnam 2010).

The proportion of rice income as compared to total income affected technical efficiency in studied years. Except for a very small negative impact in 2006, those households with a higher proportion of rice income usually reached higher technical efficiency levels. Having rice as a main income source implies that household resources may be focused on rice production and, therefore, they become more efficient.

While the education level and age of the household head had no or very little impact, the ethnicity of the head reflected the higher technical efficiency of the Kinh people when compared to the other ethnic minority groups. The Kinh, the ethnic majority group in Vietnam, basically have advantages over the others. During the period 1993 to 2006, government efforts to reduce poverty lead positive but unequal effects across the ethnic groups. The general poverty rate of the Kinh ethnic group went down by 71%, while this rate fell by only 42% among the other ethnic group between 1993 and 2006 (Dang 2010). This trend, in turn, may have had a negative impact on the capacity of minority group households to adopt new technology and improve their technical efficiency. Similar evidence from this study shows that households classified as poor by the government tended to attain lower technical efficiency scores when compared to non-poor households.

The gender of the household head, seemed to impact upon technical efficiency in a variety of ways. Female household heads attained higher efficiency scores in terms of rice production in 2006 and 2008, yet lower scores in 2002 and 2010 - when compared to the male household heads. Similarly, households with improved lives in general had higher technical efficiency scores, however, the impact of this did not manifest itself very often, in this case only in 2008. On the other hand, households with both a wife and husband present had significantly higher technical efficiencies scores when compared to other married statuses.

Scale efficiency

As mentioned above, scale efficiency is calculated by the ratio between technical efficiency under constant returns to scale and technical efficiency under variable returns to scale, which indicates how optimal a farm's scale is. In this study scale efficiencies were found to be relatively stable - at around 90% over the period 1998 to 2010. The mean scale efficiency scores, which is in the range of 50 and 100%, changed slightly from 0.925 in 1998 to 0.902 in 2010. In this case, the average efficiency scale value of 90% implies that the observed rice farms in Mekong delta could have further increased their output by about 10% if they had reached an optimal scale.

However, one should ask: which scale is optimal? Efficiency scales have a relationship to the different forms of returns to scale. The results here show that increasing returns to scale was a dominant characteristic in most periods, reflecting the need to expand production scales in future years in order to attain greater efficiency. In 2010, the proportion of increasing returns to scale was 69.3%, which is much higher than the proportion of decreasing returns to scale (29.8%), while the optimal scale accounts for only a small proportion, at 0.9%.

The need to increase returns to scale would seem to reflect an economic incentive, which works in opposition to government efforts to impose land use quotas. In fact, some of the farms were found to be over-sized when compared to these limits (Additional file 1).

Being a major competitor of Vietnam in the rice export market, Thailand may be a typical example on land management policies. There have been recently changes in number of Thai farms and average farm size, whereas the number of farms has increased from 5.15 million farms in 1992 to 5.70 million farms in 2001 (ALRO, Agricultural Land Reform Office 2006). The average farm size has trended to be smaller, from 5.6 hectares per household in 1980s (LePoer 1989), to approximately 4 hectares per household in 1992 and to 3.68 hectares per household in 2001 for the whole country (ALRO, Agricultural Land Reform Office 2006). On the other hand, land is relatively concentrated. The holdings with only one parcel takes account for approximately half of total number in 2003 (NSO, National Statistical Office of Thailand 2003). Although population pressure on the land has led increasing of smaller farms, this average farm size is still much higher than the average number of farms in the Mekong delta, Vietnam.

Conclusion

In this paper, a bootstrapping DEA model with an input orientation was employed across 1,000 observations in 1998 and bi-annual updates from 2002 to 2010. Using the same method throughout in terms of sample size and production sets, allowed me to reduce the risk of bias and to demonstrate changes in technical efficiencies and scale efficiencies with respect to rice production activities in the Mekong delta.

The bias-corrected efficiency scores were "smoother" than the original scores, while being lower than some other recent studies carried out in the region. This may have been due to the difference in sample sizes used, as a small number of DMUs may result in a upward bias of the efficiency estimates.

The level of technical efficiency of the rice production activities tended to increase over the study years, while optimal scale efficiency was only achieved by a small number of farms. Scale efficiency scores changed approximately by 90%, and the proportion of those achieving increasing returns to scale was high. Using a truncated regression, the main inefficiency factors could be linked to the demographic characteristics of the households, as well as the proportion of income from rice as a proportion of total household income.

In the Mekong delta region in particular and in Vietnam in general, the government has imposed agricultural land quotas per household and set a limit on the duration of agricultural land use. The empirical results challenge for the government's land management policies, as the farmers' essential need to expand their production scale to meet increased efficiency rice production targets would seem to be in opposition to the current, more restrictive land management policies to be found in the Mekong delta.

To achieve a deeper understanding of rice technical efficiency of the Mekong delta, there is still the need to conduct more comparative studies on rice production between this region and other rice production regions in other countries which focus on the relation between technical efficiency and farm size as well as their consequence – landlessness problem. In fact, Thailand is biggest rice exporter in the world and may be considered as a good experience for policy changes on land management in the Mekong delta, Vietnam.

Endnotes

[a]The informal numbers should be verified, it however shows an upward trend in land consolidation.

[b]There are two reasons to follow the DEA-based statistics instead of the bootstrap-based statistics: (1) Based on the experiment method, Banker et al. (2009)) argued that "There is no need to use the Bootstrap-based test procedures since they yield comparable results to DEA-based procedures", and (2) both bootstrap-based estimations of returns to scale and double-bootstrapping DEA require a high performance computer to be used to carry out a large number of calculations, and this would seem to be a big challenge for an average computer, particularly when using a dataset holding 1,000 DMUs (5 inputs, 1 output), plus carrying out 2,000 replications and repeated calculations over 6 different years.

Additional file

Additional file 1: Table A1. Variables used in the estimation of technical efficiency and technical inefficiency factors. **Figure A1**. TE score distributions under VRS; comparing initial (kdensityini_vrs) and bias-corrected (kdensitycor_vrs) scores over various years. **Table A2.** Test differences between various sample sizes. Two-sample t test with unequal variances. **Table A3.** Percentage of over-sized farms per sample - compared to the Land Law 1993 and Land Law 2003 quotas. **Table A4.** Statistical results of Technical Efficiency (TE_{VRS}) and Scale Efficiency (SE) by input-oriented DEA. **Table A5.** Statistics summary of Truncated regression models. Table A5. Statistics summary of Truncated regression models.

Competing interests
The authors declare that they have no competing interests.

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References
Akram-Lodhi AH (2001) Vietnam's agriculture: is there an inverse relationship? Int Inst Soc Stud Erasmus Univ (ISS) 348:1–36
Alirezaee MR, Howland M, Van de Panne C (1998) Sampling size and efficiency bias in Data envelopment analysis. J Appl Math Decis Sci 2(1):51–64
ALRO, Agricultural Land Reform Office (2006) National Report on Agrarian Reform and Rural Development in Thailand. Paper presented at the The International Conference on Agrarian Reform and Rural Development (ICARRD), Brazil
Andor M, Hesse F (2011) A Monte Carlo Simulation comparing DEA, SFA and two simple approaches to combine efficiency estimates. CAWM Discussion Paper No. 51, University of Münster
Banker RD, Chang H, Chang SC (2009) Statistical Tests of Returns to Scale Using DEA. Paper presented at the The seventh International Conference on Data Envelopment Analysis Philadelphia, USA. http://astro.temple.edu/~banker/dea2009/paper/Fri350746B.ppt
Coelli T, Prasada Rao DS, Battese GE (1998) An introduction to efficiency and productivity analysis. Kluwer Academic Publishers, Boston
Dang HA (2010) Indigenous Peoples, Poverty and Development: A Widening Poverty Gap for Ethnic Minorities. discussion paper. World Bank, Washington
Debreu G (1951) The coefficient of resource utilization. Econometr J Econometr Soc 19(3):273–292
FAO, Food and Agriculture Organization of the United Nations (2003) Measuring and assessing capacity infisheries. 2. Issues and methods. FAO Fisheries Technical Paper. No. 433/2. FAO, Rome, p 130
Fare R (1985) The measurement of efficiency of production / by Rolf Fare, Shawna Grosskopf, and C.A. Knox Lovell. Hingham, MA, USA: Kluwer-Nijhoff Pub; Distributors for North America, Kluwer Academic Publishers, Boston
Farrell MJ (1957) The measurement of productive efficiency. J Royal Stat Soc Series A (General) 120(3):253–290
Government of Vietnam (1993) Law on Land. Hong Duc Publishing House, Hanoi
Government of Vietnam (2003) Law on Land. Hong Duc Publishing House, Hanoi
GSO, General Statistics Office of Vietnam (1998) The Viet Nam Living Standard Survey. Statistical Publishing House, Hanoi
GSO, General Statistics Office of Vietnam (2001) The Rural, Agricultural and Fishery Census in Vietnam. Statistical Publishing House, Hanoi
GSO, General Statistics Office of Vietnam (2002) The Vietnam Household Living Standards Survey. Statistical Publishing House, Hanoi
GSO, General Statistics Office of Vietnam (2004) The Vietnam Household Living Standards Survey. Statistical Publishing House, Hanoi
GSO, General Statistics Office of Vietnam (2006a) The Rural, Agricultural and Fishery Census in Vietnam. Statistical Publishing House, Hanoi

GSO, General Statistics Office of Vietnam (2006b) The Vietnam Household Living Standards Survey. Statistical Publishing House, Hanoi
GSO, General Statistics Office of Vietnam (2008) The Vietnam Household Living Standards Survey. Statistical Publishing House, Hanoi
GSO, General Statistics Office of Vietnam (2010) The Vietnam Household Living Standards Survey. Statistical Publishing House, Hanoi
GSO, General Statistics Office of Vietnam (2011) The Rural, Agricultural and Fishery Census in Vietnam. Statistical Publishing House, Hanoi
GSO, General Statistics Office of Vietnam (2012). Retrieved 12 April 2013 http://gso.gov.vn/default.aspx?tabid=717
Huy HT (2009) Technical efficiency of rice producing households in the Mekong delta of Vietnam. Asian J Agricult Dev 6(2):35–50
Khai HV, Yabe M (2011) Technical efficiency analysis of rice production in Vietnam. J. ISSAAS 17(1):135–146
Koopmans TC (1951) An analysis of production as an efficient combination of activities. In: Koopmans TC (ed) Activity Analysis of Production and Allocation. John Wiley and Sons, Inc, New York
Kuosmanen T, Post T (1999) Dealing with outliners in Data Envelopment Analysis. Rotterdam Institute for Business Economic Studies (RIBES)
LePoer BL (1989) Thailand a Country Study. Federal Research Division, Library of Congress, Washington
Linh VH (2012) Efficiency of rice farming households in Vietnam. Int J Dev Issues 11(1):60–73
Minh NK, Long GT (2008) Measuring agricultural production efficiency in Vietnam: An application of data envelopment analysis (DEA). Publishing House of Social Labour, Hanoi
Nam TA, Shively G, Preckel P (2008) A new method for detecting outliners in Data Development Analysis. Appl Econ Lett 2008:1–4
NSO, National Statistical Office of Thailand (2003) Agricultural Census. Retrieved 4 September 2013 http://service.nso.go.th/nso/nso_center/project/search_center/23project-en.htm
Simar L, Wilson PW (1998) Sensitivity analysis of efficiency scores: how to bootstrap in nonparametric frontier models. Manag Sci 44(11):49–61
Simar L, Wilson PW (2007) Estimation and inference in two-sage semi-parametric models of production processes. J Econ 136:31–64
Smith P (1993) Misspecification Bias in Data Envelopment Analysis. Discussion Paper, Department of Economics and the Related Studies. University of York, York
Staat M (2001) The effect of sample size on the mean efficiency in DEA: comment. J Prod Anal 15:129–137
The Standing Committee of National Assembly (2007) Resolution No. 1126/2007/NQ-UBTVQH11, Specifying limits for receipt of agricultural land use rights transferred to households or individuals for agricultural purpose
Thong PL, Xuan HTD, Duyen TTT (2011) So sánh hiệu quả kinh tế của vụ lúa hè thu và thu đông ở Đồng bằng sông Cửu Long (Vietnamese). Sci J Can Tho Univ 18a:267–276
Tuong DM (2010) Economic analysis on production of high quality rice in Cuulong delta, Vietnam. Omonrice 17:174–178
Wilson PW (2008) FEAR 1.0: A Software Package for Frontier Efficiency Analysis with R. Socioecon Plann Sci 42:247–254
Zhang Y, Bartels R (1998) The effect of sample size on mean efficiency in DEA with an application to electricity distribution in Australia, Sweden and New Zealand. J Prod Anal 9:187–204

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