# The economic and environmental performance of farms: The impact of migration

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Abstract: Both economic and environmental performance of farms has received widespread attention. Migration of rural labour force is another growing phenomenon of many developing countries, including China. Theoretically, migration is considered as an important influencing factor of farms' economic and environmental performance. The objectives of this paper are therefore to estimate the technical and fertilizer use efficiency scores of rice production, and to examine the causal effect of migration and migration intensity on technical and fertilizer use efficiency. Applying the stochastic frontier analysis (SFA) and propensity score matching (PSM) analysis to survey data collected in four provinces, we found the average of technical efficiency among interviewed rice production households is 0.92, while the average of fertilizer use efficiency is only 0.22. The results of PSM suggest a negative impact of migration on both economic and environmental performance of farms, and the impact is amplified for households participated in migration more intensively.

Key words: China; fertilizer use efficiency; migration; technical efficiency

## 1. Introduction

Sustainability is one of the major concerns in present agricultural policies making (Guesmi and Serra, 2015; Abdulai, 2011), hence both economic and environmental performance of farms has received widespread attention (e.g. Skevas et al., 2018; Coelli et al., 2007; Reinhard et al., 1999; Zhu and Lansink, 2010; Zhu et al., 2011). Increasing application of fertilizer is demonstrated as a key factor in improving agricultural productivity (Beaman et al., 2013; Duflo et al., 2011). Meanwhile, the excessive use of fertilizer has resulted in serious threats and losses on ecological environment (Wu et al., 2018; Abdulai and Abdulai, 2017; Ma et al., 2014; Thanh Nguyen et al., 2012).

Migration of rural labour force is another growing phenomenon of many developing countries, including China (Zhao, 1999). Migration plays an important role in the rural development of China, especially in terms of reducing rural poverty and inequality (Rozelle et al., 1999). Therefore, much of literature on migration naturally focus on its positive impact on the welfare or income of rural households (De Janvry et al., 2015; De Brauw and Rozelle, 2008; Du et al., 2005). Less attention, however, has been paid to the impact of migration on the economic and environmental performance of farms.

Theoretically, migration is considered as an important factor influencing farms' economic and environmental performance. First, the remittance from migrated household members, on the one hand, relaxes the credit constraint of the family and allows them to invest in assets that improving productivity, but on the other hand, migration weakens other household members' incentive to make money from farming (Sauer et al., 2015). Second, migration implies reduced time availability for working on farm, which makes farming households less resilient to changing farm conditions or harder to adopt time-intensive farming techniques (Phimister and Roberts, 2006).

Empirically, some empirical studies explored the impact of migration on technical efficiency on the economic performance of farm, i.e., technical efficiency or productivity. The results, however, are rather inconclusive. Migration is found to have a negative impact on technical efficiency in Kosovo (Sauer et al., 2015). By contrast, a positive impact of migration on technical efficiency has been found for cereal production in Burkina Faso (Wouterse, 2010). In China, Yang et al. (2016) and Li et al. (2013) find no significant impact of migration on technical efficiency or productivity, While Chen et al. (2009) indicates that village migration ratio has a positive impact on technical efficiency.

Few studies have focused on the impact of migration on the environmental performance of farms, which is usually measured by fertilizer application. Migration or off-farm work is illustrated to be negatively influencing factor of chemical fertilizer application in England and Wales (Phimister and Roberts, 2006). Little evidence has been shown about on the impact of migration on environmental performance in China. Wu et al. (2018) argues that restrictive rural-urban migration policies contribute to the prevalence of small sized farms, and farm size is estimated to be negatively correlated to fertilizer use intensity. Other empirical studies include income sourced from off-farm or farming activities as a control variable. Ma et al. (2014) finds a positive impact of off-farm income on fertilizer use efficiency. On the contrary, Wu et al. (2011) finds the share of income sourced from farming activities has a positive impact on fertilizer use efficiency.

There are several shortcomings of previous empirical studies. First, migration is measured by the dummy variable of whether migrate or not (e.g. Wouterse, 2010), while the intensity of migration is seldom considered, except Sauer et al. (2015). Second, migration or off-farm income has been considered as an influencing factor of technical efficiency or fertilizer use efficiency, but the causal effect of migration and migration intensity has not been evaluated. Third, the environmental performance of farms is commonly measured by the amount of fertilizer use (e.g. Phimister and Roberts, 2006), which might ignore the variation of other inputs. Hence, the objectives of this paper are therefore to: (i) estimate the technical and fertilizer use efficiency scores of rice production; (ii) examine the causal effect of migration and migration intensity on technical and fertilizer use efficiency. The major contributions of this paper are of two aspects. First, we will estimate the causal effect of both migration and its intensity on the performance of farms. Second, we link migration with environmental performance of farms, i.e., fertilizer use efficiency, defined as the ratio of minimum feasible fertilizer use to observed fertilizer use, conditional on output level and other inputs.

A cross-sectional dataset containing 1486 households in 124 villages across 4 provinces from China, is used for this purpose. Stochastic frontier analysis (SFA) and translog production function is employed to estimate technical and environmental efficiency scores. Propensity score matching (PSM) approach is then applied to examine the causal effect of migration and migration intensity on technical and fertilizer use efficiency. Specifically, first, the logit regression of migration or migration intensity is estimated to obtain the propensity score. The households in treatment group (households with migrants) is then matched with those in the control group (households without migrants) based on the propensity score. Next, we obtain the technical efficiency and fertilizer use efficiency of matched groups and the treatment effect of migration.

The rest of this paper is organized into five sections. The next section presents method, while the third section presents data and descriptive statistics. The estimation results of empirical models are presented in section 4, and the last sections offers a set of concluding remarks and policy implications.

## 2. Method

### *2.1 Estimate technical efficiency and fertilizer use efficiency*

We employ a parametric stochastic frontier analysis (SFA) rather than a non-parametric approach such as data envelopment analysis (DEA) because SFA models offer a richer specification where agricultural production is stochastic due to unpredictable weather conditions and disease and pest infestation (Zhu and Lansink, 2010).

Translog production function

$$ln\, Y_i = \beta_0 + \sum_j \beta_j \, ln\, X_{ij} + \beta_f \, ln\, F_i + \frac{1}{2}\sum_j \sum_k \beta_{jk} \, ln\, X_{ij} \, ln\, X_{ik} + \frac{1}{2}\beta_{ff} \, (ln\, F_i)^2 + \sum_j \beta_{jf} \, ln\, X_{ij} \, ln\, F_i + v_i - u_i$$

where $Y_i$ are the output of household *i*; $X_1, \ldots, X_4$ represent inputs, i.e., labour, machine, pesticide and land; $F$ is fertilizer input, measured by the sum of three active ingredients, including nitrogen (N), phosphorus (P) and potassium (K); $v_i$ is the standard white noise with 0 mean and constant variance; $u_i$ is non-negative random errors accounting for TE in production, i.e., $TE_i = \exp(-u_i)$.

Following Reinhard et al. (1999) and Cuesta et al. (2009), the translog production function of households who use fertilizer efficiently, could be written as:

$$ln\, Y_i = \beta_0 + \sum_j \beta_j\, ln\, X_{ij} + \beta_f\, ln\, F_i^M + \frac{1}{2}\sum_j \sum_k \beta_{jk}\, ln\, X_{ij}\, ln\, X_{ik} + \frac{1}{2}\beta_{ff}\,(ln\, F_i^M)^2 + \sum_j \beta_{jf}\, ln\, X_{ij}\, ln\, F_i^M + v_i$$

Households who use fertilizer efficiently are technically efficient, so $u_i$ is equal to zero. $F_i^M$ represent the minimum feasible fertilizer input given the production function and observed values of output and other inputs.

$$(\beta_f + \sum_j \beta_{jf} \ln X_{ij})\,(\ln F_i - \ln F_i^M) + \frac{1}{2}\beta_{ff}((\ln F_i)^2 - (\ln F_i^M)^2) - u_i = 0$$

$$\frac{1}{2}\beta_{ff}(\ln F_i^M - \ln F_i)^2 + (\beta_f + \sum_j \beta_{jf} \ln X_{ij} + \beta_{ff} \ln F_i)\,(\ln F_i^M - \ln F_i) + u_i = 0$$

Fertilizer use efficiency (FE) is defined as a ratio of minimum fertilizer use over observed fertilizer use. It could be expressed as:

$$\ln FE_i = \ln(\frac{F_i^M}{F_i})$$

$$\ln FE_i = \frac{-(\beta_f + \sum_j \beta_{jf} \ln X_{ij} + \beta_{ff} \ln F_i) \pm ((\beta_f + \sum_j \beta_{jf} \ln X_{ij} + \beta_{ff} \ln F_i)^2 - 2\beta_{ff}u_i)^{0.5}}{\beta_{ff}}$$

Fertilizer efficiency is calculated using the "+$()^{0.5}$".This is because a technically efficient farm is necessarily to use fertilizer efficiently, and when $u_i = 0$, $\ln FE_i = 0$, only if "+$()^{0.5}$" is used.

$$FE_i = \exp\left(\frac{-(\beta_f + \sum_j \beta_{jf} \ln X_{ij} + \beta_{ff} \ln F_i) \pm ((\beta_f + \sum_j \beta_{jf} \ln X_{ij} + \beta_{ff} \ln F_i)^2 - 2\beta_{ff} u_i)^{0.5}}{\beta_{ff}}\right)$$

$$FE_i = \alpha_0 + \sum_z \alpha_z Z_{zi} + e_i$$

where $Z_z$ is a vector of variables that affect fertilizer use efficiency; $\alpha$

*2.2 Impact assessment: propensity score matching*

The second step of the empirical analysis is to apply propensity score matching (PSM) and to estimate the average treatment effect of migration on technical efficiency and fertilizer use efficiency. For each household, in treatment group (M=1) or in control group (M=0), they have potential outcomes $Y_0$ and $Y_1$. The average treatment effect should be E($Y_1$| M=1)- E($Y_0$| M=1) for treatment group or E($Y_1$| M=0)- E($Y_0$| M=0) for control group. However, for households in treatment group, we only observed E($Y_1$| M=1), while only E($Y_0$| M=0) is only observed for control group. Thus, E($Y_0$| M=1) and E($Y_1$| M=0) are missing with survey data. PSM matches each household in treatment group with a household control group based on observed characteristics, and then estimate the missing situation of each treatment household.

*2.3 Variables used in estimating propensity score*

The outcome variables must be independent of treatment conditional on the propensity score (conditional independence assumption, CIA). Caliendo and Kopeinig (2008) suggests two criterions for selecting variables in estimating propensity score based on CIA. First, only variables that influence both the treatment variables and the outcome variables should be included. Second, only variables unaffected by participation should be included. That is, variables should either be fixed over time or measured before participation.

We use the variables in Table 2 as matching controls. Following Sauer et al. (2015), we include characteristics of both household head and household members. The age and education level of household head, average age and education of adults in the household, village official, household size, number of adults, dependency ratio, and female ratio of household. Besides, natural capital (i.e., contracted land area per capita and number of contracted plots), physical capital (i.e., possession of house, possession of machine), access to market (i.e., distance to the centre of nearest town), and provincial dummies for Jiangsu, Liaoning and Chongqing are included.

## 3. Data and Descriptive Statistics

### *3.1 Research area*

The data employed were collected data in four provinces in 2015 in Jiangsu province and Jiangxi province and in 2016 in Liaoning province and Chongqing municipality, China (see Figure A.1). They are located in four major agro-ecological zones of China. The survey obtained information about agricultural production, occupation of household members and basic household characteristics. Using structured village leader and household questionnaires and face-to-face interviews, we collected data of 124 villages and 1,486 households in total. We used the data of 810 households producing rice in this paper.

### *3.2 Descriptive statistics of variables in production function*

The description of variables in production function are shown in Table 1. The average rice yield in research area is 8254.94 jin (4127.47 kg). Fertilizer use, measured by adding up the active ingredients (nitrogen, phosphate and potassium), is 515.14 jin (257.57 kg) on average, with the minimum and maximum levels of 7.36 jin and 44082.3 jin respectively. The average land input per household is 8.33 mu (0.56 ha). Machine and pesticide inputs are measured in monetary terms, with the average levels of 696.78 and 764.30 yuan respectively. Labour input is measured in terms of labour day, the average level in our sample is 40.32 days. Soil quality and irrigation condition is 3.27 and 3.22 on average, with a scale from 1 (= low quality) to 5 (= high quality).

Table 1 Descriptive statistics of variables in production function

| Variable | Unit | Mean | S.D. | Min. | Max. |
|---|---|---|---|---|---|
| Yield | Jin | 8254.94 | 14007.99 | 270 | 112000 |
| Fertilizer | Jin | 515.14 | 1723.27 | 7.36 | 44082.3 |
| Land | Mu | 8.33 | 13.56 | 0.3 | 112 |
| Machine | Yuan | 696.78 | 1478.19 | 0 | 16855 |

| | | | | | |
|---|---|---|---|---|---|
| Labour | Labour day | 40.32 | 131.51 | 0.33 | 3120 |
| Pesticide | Yuan | 764.30 | 1520.31 | 0 | 22400 |
| Soil quality | | 3.27 | 0.92 | 1 | 5 |
| Irrigation condition | | 3.22 | 1.12 | 1 | 5 |

Note: 1 jin=0.5 kg; 1 labour day=8 working hours; 15 mu=1 ha

3.3 *Descriptive statistics of variables in estimating propensity score*

The descriptive statistics of variables in estimating propensity score are shown in Table 2. Regarding our treatment variable, we found 43% of households in our sample have at least one member participated in migration. Lots of control variables show a significant difference between treatment and control groups. For instance, compared to non-migrated households, migration households are with an elder household head. What's more, for households with migrants, the adults of the household tend to be younger, higher educated or with off-farm experience. Migration households are of larger household size or with more adults. Besides, migration households tend to be with less land, less likely to possess machinery or live further from the township centre.

Table 2 Descriptive statistics and comparison of variables in estimating propensity score

| Variables | Control Migration=0 | Treatment Migration=1 | Difference[1] | Mean | Std. Dev. | Min | Max |
|---|---|---|---|---|---|---|---|
| Migration | -- | -- | -- | 0.43 | 0.49 | 0 | 1 |
| Household head age | 56.15 | 57.79 | -1.64** | 56.85 | 9.45 | 23 | 83 |
| Household head education level | 2.66 | 2.59 | 0.07 | 2.63 | 0.99 | 1 | 6 |
| Average age of adults | 51.01 | 46.19 | 4.82*** | 48.95 | 8.71 | 29.33 | 74.33 |
| Average education level of adults | 0.54 | 0.61 | -0.07*** | 0.57 | 0.33 | 0 | 1 |

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| Average off-farm employment experience of adults | 0.54 | 0.66 | -0.13*** | 0.59 | 0.31 | 0 | 1 |
| Household size | 3.83 | 4.89 | -1.06*** | 4.29 | 1.74 | 1 | 15 |
| Female ratio | 0.49 | 0.48 | 0.01 | 0.49 | 0.12 | 0 | 1 |
| Number of adults | 2.98 | 3.87 | -0.88*** | 3.36 | 1.16 | 1 | 9 |
| Dependency ratio | 0.22 | 0.24 | -0.02 | 0.23 | 0.19 | 0 | 0.75 |
| Village official | 0.26 | 0.25 | 0.01 | 0.26 | 0.44 | 0 | 1 |
| Land area per capita | 2.28 | 1.22 | 1.06*** | 1.83 | 2.63 | 0 | 35 |
| Number of land plots | 8.36 | 8.22 | 0.13 | 8.31 | 7.22 | 0 | 45 |
| Houses | 1.19 | 1.16 | 0.03 | 1.18 | 0.44 | 0 | 4 |
| Machinery | 0.34 | 0.25 | 0.09** | 0.30 | 0.46 | 0 | 1 |
| Distance to town | 5.11 | 5.67 | -0.56* | 5.35 | 4.19 | 0 | 26 |
| Jiangsu | 0.21 | 0.22 | -0.01 | 0.21 | 0.41 | 0 | 1 |
| Liaoning | 0.09 | 0.07 | 0.03 | 0.08 | 0.27 | 0 | 1 |
| Chongqing | 0.24 | 0.32 | -0.07** | 0.27 | 0.45 | 0 | 1 |

Note: 1 Differences are tested by a two-sided unpaired t-test of means or proportion. *** Significant at the 1% level; ** Significant at the 5% level; * Significant at the 10% level.

## 4. Results

### *4.1 Production function estimates*

Table 3 presents the results of production function. Fertilizer input has a positive impact, while the squared term of fertilizer input has a negative impact on yield. This implies that more fertilizer applied has is a nonlinear input in the production of rice. Land input and its squared term have significant positive effects on yield. The squared term of labour input has a significant positive impact, suggesting that labour is a nonlinear input in the production of rice. The coefficients of interaction terms between land and pesticide and between land and labour are both negative and significant, implying that labour and machine are substitutes for land. The interaction term between pesticide and machine has a positive impact on the yield. Land quality and irrigation condition both have positive impacts on rice production.

Table 3 Production function results

| Variables | Coef. | z | Variables | Coef. | z |
|---|---|---|---|---|---|
| ln(Fertilizer) | 0.13** | 1.97 | ln(Fertilizer)× ln(Machine) | 0.001 | 0.15 |
| ln(Land) | 1.01*** | 7.32 | ln(Fertilizer)× ln(Labour) | 0.005 | 0.33 |
| ln(Pesticide) | -0.03 | -0.54 | ln(Land)× ln(Pesticide) | -0.03** | -2.39 |
| Pesticide | -0.04 | -0.28 | ln(Land)× ln(Machine) | -0.01 | -0.72 |
| ln(Machine) | -0.03 | -0.93 | ln(Land)× ln(Labour) | -0.03** | -2.01 |
| Machine | -0.003 | -0.04 | ln(Pesticide)× ln(Machine) | 0.003* | 1.67 |
| ln(Labour) | -0.06 | -1.28 | ln(Pesticide)× ln(Labour) | 0.01 | 1.11 |
| $0.5(\ln(\text{Fertilizer}))^2$ | -0.04* | -1.76 | ln(Machine)× ln(Labour) | 0.003 | 0.67 |
| $0.5(\ln(\text{Land}))^2$ | 0.11* | 1.9 | Soil quality | 0.02** | 1.99 |
| $0.5(\ln(\text{Pesticide}))^2$ | 0.001 | 0.08 | Irrigation condition | 0.01** | 2.18 |
| $0.5(\ln(\text{Machine}))^2$ | 0.003 | 0.5 | Jiangsu | 0.25*** | 10.21 |
| $0.5(\ln(\text{Labour}))^2$ | 0.01* | 1.69 | Liaoning | 0.21*** | 5.3 |
| ln(Fertilizer)× ln(Land) | 0.01 | 0.39 | Chongqing | 0.11*** | 4.11 |
| ln(Fertilizer)× ln(Pesticide) | 0.01 | 1.01 | Constant | 6.57*** | 34.36 |
| Sample size | 810 | | Log likelihood | 329.88 | |
| Wald Chi2(27) | 31097.92*** | | | | |

Note: *** Significant at the 1% level; ** Significant at the 5% level; * Significant at the 10% level. We cluster standard errors at the village level.

The kernel density distribution of the technical efficiency and environmental efficiency scores is shown in figure 1 and 2, respectively. As shown in table 4, the technical efficiency score of our sample ranges from 0.78 to 0.97, with an average of 0.92. This is similar to the results of Tan et al. (2010), which were 0.91, 0.80 and 0.89 for early rice, one-season rice and late rice respectively for three villages in Jiangxi of the year 2000. The median technical efficiency is 0.92; the 25$^{th}$ and 75$^{th}$ percentiles are 0.91 and 0.94, respectively.

The fertilizer use efficiency score of our sample is 0.22 on average, ranging from 0.05 to 0.48. This suggests that nearly 80% of fertilizer use applied is excessive. This is similar with Ma et al. (2014), which found that fertilizer use efficiency is 0.25 for rice production of Taihu Basin in Jiangsu in 2008, while is lower than the score of 0.33 estimated by Wu (2011) for grain production in five provinces in China in 2007. The median fertilizer use efficiency is 0.22; the 25$^{th}$ and 75$^{th}$ percentiles are 0.17 and 0.26, respectively.

Table 4 Technical efficiency and fertilizer use efficiency scores

| | Technical efficiency | Fertilizer use efficiency |
|---|---|---|
| Mean[1] | 0.92 (0.02) | 0.22 (0.06) |
| Minimum | 0.78 | 0.05 |
| 25$^{th}$ percentile | 0.91 | 0.17 |
| 50$^{th}$ percentile | 0.92 | 0.22 |
| 75$^{th}$ percentile | 0.94 | 0.26 |
| Maximum | 0.97 | 0.48 |

Note: [1].The standard deviations are in parentheses.

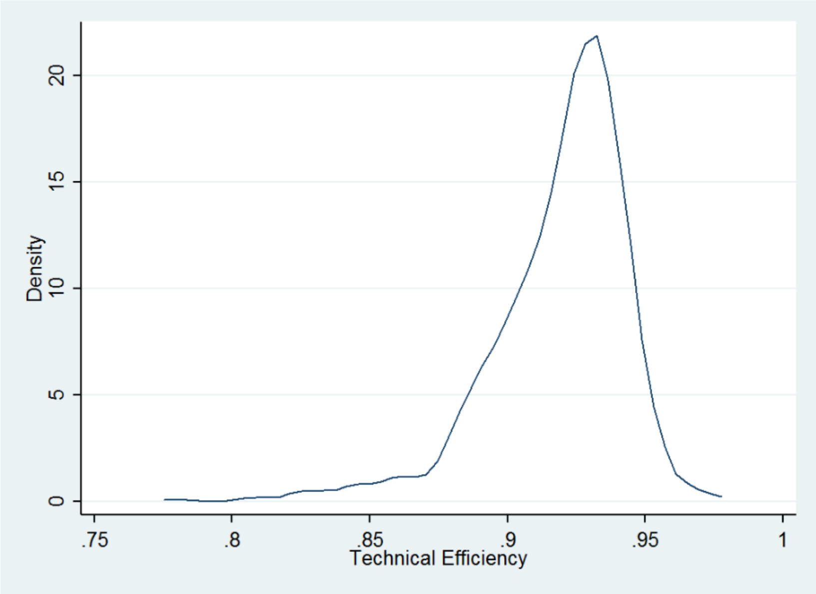


Figure 1 Kernel density distribution of technical efficiency

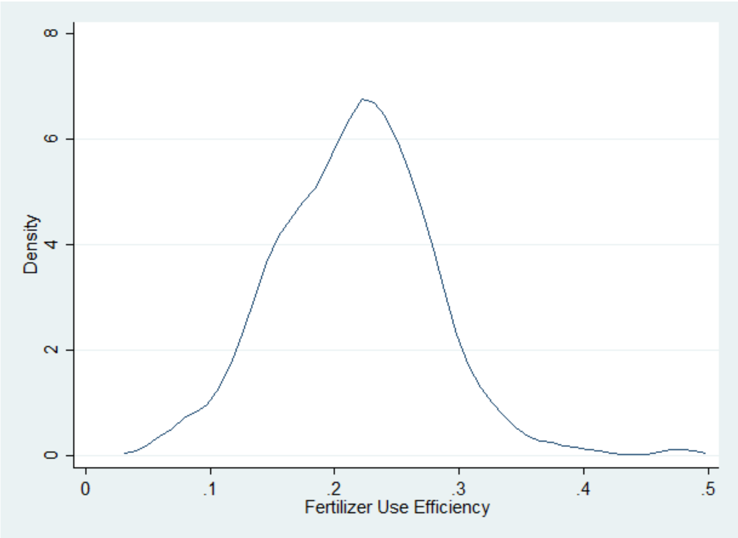


Figure 2 Kernel density distribution of fertilizer use efficiency

*4.2 The influencing factors of migration*

Table 5 shows the results of logit regression explaining influencing factors of participation in migration. The age of household head has a positive impact on migration, while the average age of adults in the family has a negative impact. Average off-farm employment experience of adults is found to have a positive impact on migration. Household size has a negative effect on migration, whereas number of adults has a positive effect on migration. Land endowment has a negative impact on migration. Besides, possession of both houses and machinery have negative impacts on migration.

Table 5 Influencing factors of migration

| Variables | Coef. | Z |
|---|---|---|
| Household head age | 0.05*** | 3.52 |
| Household head education level | -0.02 | -0.14 |
| Average age of adults | -0.09*** | -5.06 |
| Average education level of adults | -0.02 | -0.05 |
| Average off-farm employment experience of adults | 0.87** | 2.59 |
| Household size | -0.31** | -2.44 |
| Female ratio | 0.23 | 0.34 |
| Number of adults | 0.90*** | 5.13 |
| Dependency ratio | 0.57 | 0.99 |
| Village official | -0.16 | -0.72 |
| Land area per capita | -0.16** | -2.02 |
| Number of land plots | -0.01 | -0.31 |
| Houses | -0.52** | -2.26 |
| Machinery | -0.33* | -1.65 |
| Distance to town | 0.04 | 1.41 |
| Jiangsu | 0.08 | 0.28 |
| Liaoning | 0.50 | 1.12 |
| Chongqing | 0.53 | 1.62 |
| Constant | -0.30 | -0.28 |
| Observations | 747 | |
| Log likelihood | -405.15 | |

Note: *** Significant at the 1% level; ** Significant at the 5% level; * Significant at the 10% level. We cluster standard errors at the village level.

*4.3 The impact of migration on technical efficiency and fertilizer use efficiency*

Table 6 (3rd and 4th rows) reports the technical efficiency and fertilizer use efficiency distinguishing between households with and without migrants. The outcome variables include technical efficiency, fertilizer use efficiency and output per mu. The treatment variable is migration of last year (2014 for Jiangsu and Jiangxi households; 2015 for Liaoning and Chongqing households). The results reveal the significant efficiency lower effect of migration. Households participated in migration are with a technical efficiency of 0.9166 on average, which is significantly lower than that of non-migrated households (0.9193 on average). Households with migrants are with a lower level of fertilizer use efficiency as well, which is 0.2103 on average and 3.97% lower than households who did not participate in migration. It contradicts Ma et al. (2014)'s finding that off-farm income has a positive impact on fertilizer use efficiency in Taihu Basin, China. But this is somehow consistent with Guesmi and Serra (2016), which found income sourced from non-agriculture has a negative impact on technical efficiency and fertilizer use efficiency in Catanla.

Although there is a significant treatment effect of migration on technical and environmental efficiency, the magnitude is quite small. Thus the impact of migration on output per mu is also reported in Table 6 to retest the treatment effect. Households with migrants are also with a lower level of output, which is 967.27 jin/mu averagely. This is 40.01 jin/mu lower than that of households without migrants. This is consistent with Rozelle et al. (1999)'s finding that yield falls sharply as more household members migrate.

We further look into the impact of migration intensity on technical efficiency, fertilizer use efficiency and productivity. We divided treatment households into two groups, including less intensive migration group (households spent less than 30% of total working time on migration activities) and more intensive (households spent more than 30% of total working time on migration activities). As we discussed, the negative impact of migration on technical efficiency and fertilizer use efficiency might be explain by that less labour are available for farming in migration households. We found no evidence of significant differences in technical efficiency and fertilizer use efficiency between the control group and the less intensive group. By contrast, the differences in technical efficiency, fertilizer use efficiency and productivity are amplified for more intensive migration group. That is, only households participated in migration more intensively, are likely to be less efficient in terms of fertilizer use and productivity.

Table 6 The impact of migration on technical efficiency, fertilizer use efficiency and output

| | Treated | Control | Difference | S. E. | T-statistic |
|---|---|---|---|---|---|
| *Treatment: migration* | | | | | |
| Technical efficiency | 0.9166 | 0.9193 | -0.0028 | 0.0024 | -1.14* |
| Fertilizer use efficiency | 0.2103 | 0.2189 | -0.0087 | 0.0060 | -1.45** |
| Output per mu | 967.27 | 1007.37 | -40.10 | 19.93 | -2.01*** |
| Observations | 428 | 319 | | | |
| *Treatment: less intensive migration, <=0.3* | | | | | |
| Technical efficiency | 0.9163 | 0.9204 | -0.0041 | 0.0043 | -0.93 |
| Fertilizer use efficiency | 0.2103 | 0.2220 | -0.0117 | 0.0102 | -1.15 |
| Output per mu | 972.11 | 1017.87 | -45.76 | 32.54 | -1.41* |
| Observations | 428 | 78 | | | |
| *Treatment: more intensive migration, >0.3* | | | | | |
| Technical efficiency | 0.9166 | 0.9203 | -0.0037 | 0.0026 | -1.42** |
| Fertilizer use efficiency | 0.2104 | 0.2219 | -0.0116 | 0.0063 | -1.83*** |
| Output per mu | 965.70 | 1012.81 | -47.11 | 20.83 | -2.26*** |
| Observations | 428 | 241 | | | |

Note: *** Significant at the 1% level; ** Significant at the 5% level; * Significant at the 10% level.

### *4.4 Robustness check*

To check the robustness of our results, we presented the results using Cobb-Douglas production function in Table A.2 and Table A.3. The results of production function and estimated technical efficiency are generally consistent with our primary results. The estimated fertilizer use efficiency is 0.12, which is lower than that estimated from translog production function. The reason could be that Cobb-Douglas production function underestimates the elasticity of fertilizer.

## 5. Conclusions

We applied the stochastic frontier analysis (SFA) and propensity score matching (PSM) analysis to survey data collected in four provinces, to estimate the technical efficiency and fertilizer use efficiency for households conducted rice production, and to examine the impact of migration and its intensity on households' technical efficiency and fertilizer use efficiency.

The results of SFA show that the average of technical efficiency among interviewed rice production households is 0.92, which implies that an improvement of 8% of rice production could be achieved given the present inputs level. The average of fertilizer use efficiency is 0.22, which indicates there is a scope of 78% in reducing fertilizer application given the current technology and output level.

The results of PSM suggest a negative impact of migration on both economic and environmental performance of farms, and the impact is amplified for households participated in migration more intensively. Thus our results reveal that migration, especially more time spent on migration, has a negative impact on both economic and environmental performance of farms, although the magnitude of treatment effect is not big.

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Appendix

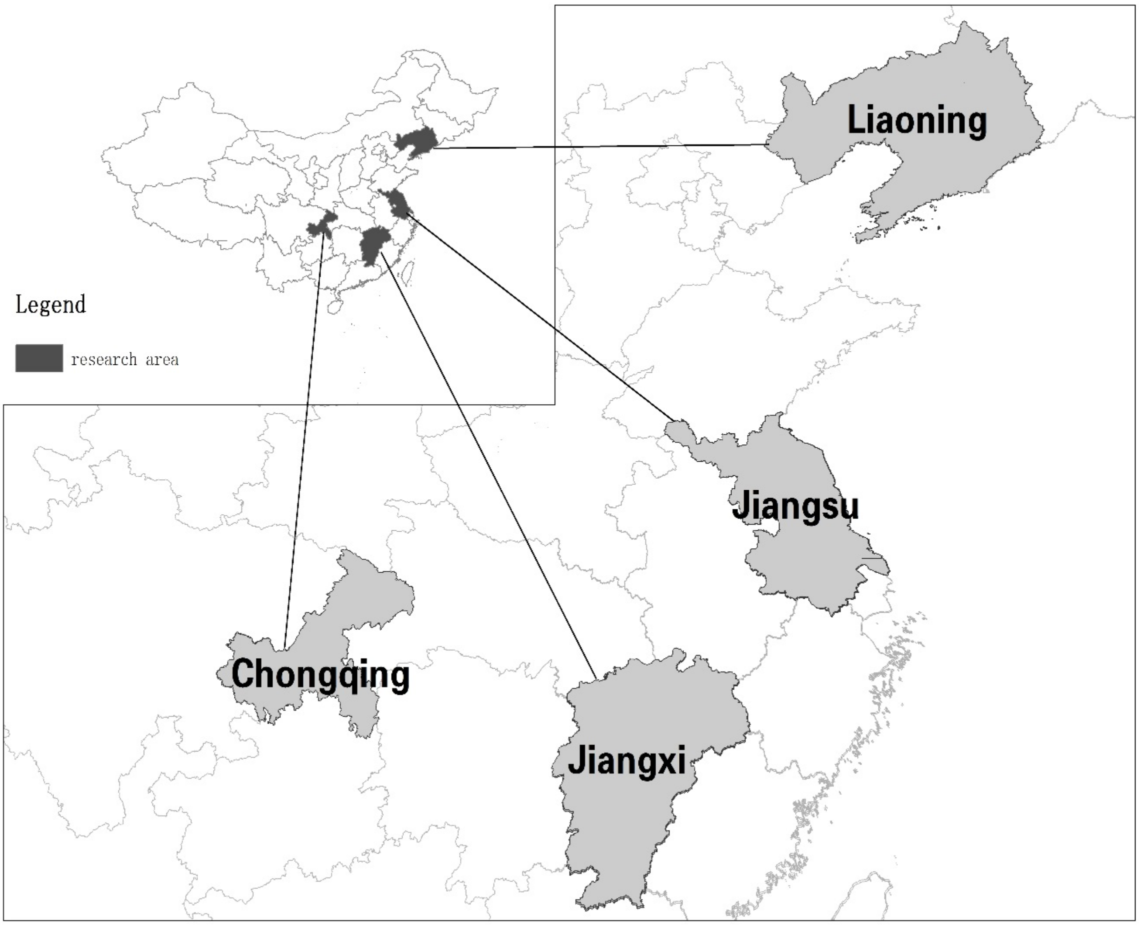


Figure A.1 Study area location

Data source: National Catalogue Service For Geographic Information (2017).

Table A.1 Definition of variables in estimating propensity score

| Variables | Definition |
|---|---|
| Migration | =1 if the household has at least one member living outside the county at least six months for employment purposes; =0 otherwise |
| Household head age | Age of household head |
| Household head education level | Education level of household head |

| | |
|---|---|
| Average age of adults | Average age of adults (aged up 16 years old and excluding those are still students) |
| Average education level of adults | Ratio of adults taken junior high school or higher to all adults in the household |
| Average off-farm employment experience of adults | Ratio of adults with off-farm experience the year before last year to all adults in the household |
| Household size | Number of household members |
| Female ratio | Ratio of female adults |
| Number of adults | Number of household members aged up 16 years old |
| Dependency ratio | The number of family members aged over 65 or below 16 divided by family size |
| Village official | Household head is or was a village official |
| Land area per capita | Area of contracted land per capita (mu) |
| Number of land plots | Number of contracted land plots |
| Houses | The number of houses the household owns the year before last year |
| Machinery | =1 if the household possesses a machinery the year before last year; =0 otherwise |
| Distance to town | Distance to township centre (km) |
| Jiangsu | =1 if the household is from Jiangsu; =0 otherwise |
| Liaoning | =1 if the household is from Liaoning; =0 otherwise |
| Chongqing | =1 if the household if from Chongqing; =0 otherwise |

Table A.2 Stochastic frontier analysis using Cobb-Douglas production function

| Variables | Coef. | Z |
|---|---|---|
| ln(Fertilizer) | 0.04** | 2.07 |
| ln(Land) | 0.96*** | 41.32 |
| ln(Pesticide) | 0.003 | 0.28 |
| Pesticide | -0.06 | -1.02 |
| ln(Machine) | 0.01** | 2.04 |
| Machine | 0.05 | 1.52 |

| | | |
|---|---|---|
| ln(Labour) | -0.01 | -0.77 |
| Land quality | 0.01* | 1.71 |
| Irrigation condition | 0.01** | 2.21 |
| Jiangsu | 0.25*** | 10.69 |
| Liaoning | 0.23*** | 5.05 |
| Chongqing | 0.12*** | 4.16 |
| Constant | 6.57 | 66.59 |
| Observation | 747 | |
| Log likelihood | -405.15 | |
| Wald Chi$^2$ (18) | 269.21 | |

Note: *** Significant at the 1% level; ** Significant at the 5% level; * Significant at the 10% level.

Table A.3 Technical efficiency using Cobb-Douglas production function

| | Technical efficiency | Fertilizer use efficiency |
|---|---|---|
| Mean[1] | 0.92 (0.02) | 0.12 (0.07) |
| Minimum | 0.78 | 0.001 |
| 25$^{th}$ percentile | 0.91 | 0.07 |
| 50$^{th}$ percentile | 0.92 | 0.11 |
| 75$^{th}$ percentile | 0.93 | 0.15 |
| Maximum | 0.97 | 0.45 |

Note: [1]. The standard deviations are in parentheses.