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The Impact of Migration on Farm Performance: Evidence from Rice Farmers in China

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Abstract: Developing economies face challenges in improving the overall performance of farms. An essential challenge could be a substantial shift in the agricultural labor force to off-farm sectors during the process of economic transition. This paper estimates the causal impact of migration on the economic and environmental performance of rice farms, measured using technical efficiency and fertilizer use efficiency. A stochastic frontier analysis, based on the survey data collected in four regions of China, is applied, finding an average technical efficiency of 0.92, while the average fertilizer use efficiency is only 0.22. The results of propensity score matching suggest that migration has a marginally negative impact on both technical efficiency and fertilizer use efficiency of their rice production, while the impact is amplified for farmers who participated in migration more intensively. This would imply that the government policy on the migration of rural households might also need to consider this impact.

Keywords: migration; stochastic frontier analysis; technical efficiency; fertilizer use efficiency; China

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Citation: Ren, G.; Zhu, X.; Feng, S. The Impact of Migration on Farm Performance: Evidence from Rice Farmers in China. *Agriculture* **2023**, *13*, 708. https://doi.org/10.3390/agriculture13030708

Academic Editors: Sanzidur Rahman and Jianxu Liu

Received: 3 February 2023
Revised: 13 March 2023
Accepted: 14 March 2023
Published: 18 March 2023

1. Introduction

Improved farm performance benefits not only the welfare of agricultural households and a nation's food security but perhaps also the environmental quality when societies pursue sustainable agricultural growth. In contrast to developed economies, developing economies can face particular challenges in improving the performance of their farms [1]. A notable one could be the substantial labor force shift from agriculture to off-farm sectors during the process of economic development. This process then causes difficulties for rural households in balancing resource allocations between on-farm and off-farm activities. For example, a household with potential migrants should decide how much labor and money to invest in on-farm production and migration, respectively [2]. A natural question to ask is—does the migration of rural households lower farm performance?

China makes a good case study due to its significant increase in labor mobility since the 1990s. The primary goal of this paper is to examine the impact of migration of rural households on farm performance. Farm performance could be measured by both economic and environmental behaviors. Specifically, we use stochastic frontier analysis (SFA) with translog production function to estimate two specific measures for the economic and environmental performance of farms, i.e., *technical efficiency* and *fertilizer use efficiency*. To account for the self-selection bias of migration, we examine the effect of migration on farms' technical efficiency and fertilizer use efficiency using the propensity score matching (PSM) method. PSM allows us to address the self-selection bias of migration and construct comparable migration and non-migration groups. The effect of migration can be obtained by comparing the differences in technical efficiency and fertilizer use efficiency between migration and non-migration groups. To better understand the mechanism of estimated impact, we further identify whether more household members involved in migration lead to more efficiency loss. A cross-sectional dataset containing 809 households producing rice in 124 villages across four regions (Jiangsu, Jiangxi, Liaoning and Chongqing) in China was used for the empirical estimation.

In the literature on the economic and environmental performance of farms, several studies have used fertilizer use intensity to measure the environmental performance of farms (see, e.g., [3–5]), while few studies have considered fertilizer use efficiency. Moreover, certain important influencing factors for economic and environmental performance, such as rural-urban migration, are often neglected (see, e.g., [6]). Some studies consider the impact of migration on technical efficiency (e.g., [7–9]) but arrive at different conclusions for different contexts. For example, it has been found that migration has a negative impact on technical efficiency in Kosovo [7] and Burkina Faso [8]. Yang et al. find no significant impact of migration on technical efficiency [9], while Ma et al. find that household heads' off-farm work participation significantly increases technical efficiency in China [10]. This implies that the impact of migration on technical and environmental performance is an empirical question. Given the ongoing trend of rural-urban migration in rural China, the existing research gap motivates us to pay particular attention to the measurement of environmental performance and empirically estimate the migration effect on the economic and environmental performances of the rice farms in this study.

Our major contributions to the literature are thus two-fold. First, this study is the first attempt to examine the impact of migration on fertilizer use efficiency. Increasing the application of fertilizer is a key measure for improving agricultural productivity, but the excessive use of fertilizers has resulted in serious environmental problems [1]. Migration might induce farmers to apply all their fertilizer when sowing rather than to apply it over time, depending on the needs of plant growth due to less labor being available for on-farm work [2]. Fertilizer use efficiency measured by the ratio of the minimum feasible fertilizer use to the actual applied fertilizer use given the level of output and other inputs is a better measurement of environmental performance than the commonly used fertilizer use intensity, as the latter ignores the levels of other inputs and output. Therefore, our first contribution is to use a more appropriate measurement for environmental performance to empirically study the impact of migration on the fertilizer use efficiency of farms.

Second, our study explores the labor reduction effect of migration on technical efficiency and fertilizer use efficiency. Migration affects technical and fertilizer use efficiency mainly through its labor reduction effect. This is because it is more difficult for households with more migrants to be resilient to changes in weather conditions, plant growth and natural disasters [7]. Thus, migration can decrease farm technical efficiency by reducing labor available for agriculture production on the one hand. On the other hand, the one-time fertilization preferred by migration households due to limited agricultural labor will cause fertilizer losses and thus lead to lower fertilizer use efficiency compared to the practice of spreading fertilizer over time. Therefore, our second contribution is to show the existence of the labor-reduction effect, especially, to show whether more household members involved in the migration would lead to more efficiency loss empirically.

The rest of this paper proceeds as follows. The next section presents the theoretical analysis of how migration could affect farms' technical and fertilizer use efficiency. We then describe our empirical strategy, specify the empirical model and introduce the research area. In Section 4, we discuss the empirical results. Finally, Section 5 provides a conclusion.

2. Theoretical Analysis

The relative availability of labor and finance is significantly different between migration and non-migration households [8]. Therefore, migration entails reduced labor availability for agricultural production, while remittances sent by migrants provide households with liquidity and income security [9,11]. Migration, therefore, affects farms' productivity mainly through the decline in labor availability (i.e., labor reduction effect) and the remittances from migrated household members (i.e., remittance effect) when labor, credit and insurance markets do not function perfectly [12–14]. However, the "remittance effect" is less likely to affect the efficiency with which fertilizer and other inputs are used to produce a certain amount of output with a given technology, as remittance affects productivity through the adoption of higher-yielding, but riskier technologies [7,15]. Hence, migration primarily affects technical and fertilizer use efficiency through the "labor reduction effect".

2.1. The Impact of Migration on Farms' Technical Efficiency

As migration implies a reduction of labor available for working on the farm, it will often be more difficult for households with migrants to mobilize sufficient labor rapidly corresponding to the changes in weather, the growth of plants or the incidences of natural disasters [16]. Households with migration laborers are, therefore, less resilient to unpredictable or urgent changes in conditions [15]. Thus the "labor reduction effect" of migration on technical efficiency could be negative. This leads us to obtain our first hypothesis:

Hypothesis 1: *migration undermines technical efficiency by reducing labor available for agriculture production*.

2.2. The Impact of Migration on Farms' Fertilizer Use Efficiency

Migration makes it difficult for households to adopt time-intensive techniques and practices as a consequence of labor reduction when agricultural labor markets do not function perfectly. Households with migrants are more likely to apply large quantities of fertilizer when sowing or planting instead of spreading fertilizer over time according to plant growth requirements [2]. The one-time fertilization preferred by households with migrants might yield more fertilizer losses and a lower fertilizer use efficiency compared to the practice of spreading fertilizer over time, even with similar amounts applied. Additionally, compared to chemical fertilizer, the application of manure could be more labor-intensive [17,18]. Migration households are, therefore, less motivated to apply manure but might apply excessive chemical fertilizer. Thus the "labor reduction effect" of migration on farms' fertilizer use efficiency could be negative. Therefore, we derive the following hypothesis:

Hypothesis 2: *migration decreases fertilizer use efficiency via the labor reduction effect*.

3. Method

3.1. Measuring Technical Efficiency and Fertilizer Use Efficiency

Technical efficiency indicates the economic performance of farms, which can be measured by the ability of the farms to minimize the input use given the output level [19,20]. Fertilizer use efficiency indicates the environmental performance of the farms, which can be measured by the ratio of the minimum feasible fertilizer use to the actual applied fertilizer use, given the level of output and other inputs [21,22]. To measure technical efficiency and fertilizer use efficiency, we first define the production function. We use the translog production function because it provides a flexible functional form compared to the Cobb–Douglas production function. The translog production function is presented as

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

where Y_i is the output of household i; X_{ij} (j = 1, 2, 3 and 4) represents four inputs, i.e., labor, machine, pesticide and land; F_i is fertilizer input, measured by the sum of three active ingredients, including nitrogen (N), phosphorus (P) and potassium (K); C_i represents control variables, including land quality, irrigation condition, a dummy variable of double-season rice, and regional dummies; v_i is the two-sided noise component; u_i captures the non-negative technical inefficiency component. The technical efficiency (TE) of the farm i is calculated as

$$TE_i = \exp(-u_i), \tag{2}$$

To calculate fertilizer use efficiency, we follow the method proposed by Reinhard et al. [21]. We use F_i^M to represent the minimum feasible fertilizer input given the production function and observed values of output and other inputs. Fertilizer use efficiency (FE_i) is defined as the ratio of minimum fertilizer use (F_i^M) over observed fertilizer use (F_i). The fertilizer use efficiency could be expressed as

$$FE_i = \frac{F_i^M}{F_i}, \tag{3}$$

The translog production function of households that use fertilizer efficiently could be written as

$$\ln Y_i = \beta_0 + \sum_j \beta_j \ln X_{ij} + \beta_f \ln F_i^M + \frac{1}{2}\sum_j \sum_k \beta_{jk} \ln X_{ij} \ln X_{ik} + \frac{1}{2}\beta_{ff}(\ln F_i^M)^2 + \sum_j \beta_{jf} \ln X_{ij} \ln F_i^M + \beta_c C_i + v_i, \tag{4}$$

Households that use fertilizer efficiently are technically efficient as well, so there is no technical inefficiency component (u_i) in Equation (4) [21]. Using Equations (1) and (4), we get

$$(\beta_f + \sum_j \beta_{jf} \ln X_{ij})\left(\ln F_i - \ln F_i^M\right) + \frac{1}{2}\beta_{ff}\left((\ln F_i)^2 - \left(\ln F_i^M\right)^2\right) - u_i = 0, \tag{5}$$

where $\ln F_i^M - \ln F_i$ is equal to $\ln FE_i$ (see Equation (3)). Equation (5) can be rewritten as

$$\frac{1}{2}\beta_{ff}\left(\ln F_i^M - \ln F_i\right)^2 + (\beta_f + \sum_j \beta_{jf} \ln X_{ij} + \beta_{ff} \ln F_i)\left(\ln F_i^M - \ln F_i\right) + u_i = 0, \tag{6}$$

Solving Equation (6) yields the following:

$$\ln FE_i = \ln F_i^M - \ln F_i = \frac{-(\beta_f + \sum_j \beta_{jf} \ln X_{ij} + \beta_{ff} \ln F_i) \pm \left((\beta_f + \sum_j \beta_{jf} \ln X_{ij} + \beta_{ff} \ln F_i)^2 - 2\beta_{ff} u_i\right)^{0.5}}{\beta_{ff}}, \tag{7}$$

A technically efficient farm is necessary to use fertilizer efficiently, that is, when $u_i = 0$, $\ln FE_i = 0$. Thus "$+((\beta_f + \sum_j \beta_{jf} \ln X_{ij} + \beta_{ff} \ln F_i)^2 - 2\beta_{ff} u_i)^{0.5}$" is the only solution for calculating fertilizer efficiency. Therefore, fertilizer use efficiency could be expressed as

$$FE_i = \exp\left(\frac{-(\beta_f + \sum_j \beta_{jf} \ln X_{ij} + \beta_{ff} \ln F_i) + \left((\beta_f + \sum_j \beta_{jf} \ln X_{ij} + \beta_{ff} \ln F_i)^2 - 2\beta_{ff} u_i\right)^{0.5}}{\beta_{ff}}\right), \tag{8}$$

where "$\beta_f + \sum_j \beta_{jf} \ln X_{ij} + \beta_{ff} \ln F_i$" is exactly the output elasticity of fertilizer. That is

$$\tau_i = \beta_f + \sum_j \beta_{jf} \ln X_{ij} + \beta_{ff} \ln F_i, \tag{9}$$

where τ_i represents the output elasticity of fertilizer. We can rewrite the equation of fertilizer use efficiency as

$$FE_i = \exp\left(\frac{-\tau_i + \left(\tau_i^2 - 2\beta_{ff} u_i\right)^{0.5}}{\beta_{ff}}\right), \tag{10}$$

Hence, fertilizer use efficiency could be calculated with the output elasticity of fertilizer (τ_i), technical inefficiency component (u_i), and the coefficient of the squared term of fertilizer (β_{ff}). The stochastic frontier analysis (SFA) is used to estimate the production function to obtain β_{ff}, u_i, and the components of calculating τ_i according to Equation (9). Technical and fertilizer use efficiency scores are then calculated according to Equations (2) and (10).

3.2. Impact of Migration: Propensity Score Matching

The second step in the empirical analysis is to estimate the effect of migration on technical efficiency and fertilizer use efficiency. The outcome variables of interest are technical efficiency—measuring the economic performance of farms—and fertilizer use efficiency—measuring the environmental performance. The treatment variable is migration (M_i). According to the National Bureau of Statistics of China, a migrant is defined as an individual living outside the home county for at least six months for employment purposes during one calendar year. The treatment variable, migration (M_i), therefore, equals one if the household has at least one member migrated during the calendar year before the survey and zero otherwise. However, households' decision on migration is driven by various factors; that is, the migration decision is not random. Therefore, to estimate the causal effect of migration on farm performance, the propensity score matching (PSM) approach is applied to account for the self-selection bias of migration. PSM allows us to construct a comparable treatment and control group based on observed exogenous driving factors of migration and obtain the causal effect by comparing the differences in outcome variables between the constructed treated and non-treated groups.

Specifically, for households in the treatment group (i.e., migration households, $M_i = 1$) or in the control group (i.e., non-migration households, $M_i = 0$), they have potential outcomes Z_i^0 if non-treated, and Z_i^1 if treated. The effect of migration on outcome variables for migration and non-migration groups could be expressed as

$$E\left(Z_i^1 \middle| M_i = 1\right) - E(Z_i^0 \middle| M_i = 1), \text{ for the migration group} \tag{11}$$

$$E\left(Z_i^1 \middle| M_i = 0\right) - E(Z_i^0 \middle| M_i = 0), \text{ for the non-migration group} \tag{12}$$

However, the observed outcome (Z_i) for treated and non-treated households is $E\left(Z_i^1 \middle| M_i = 1\right)$ and $E(Z_i^0 | M_i = 0)$, respectively. The counterfactuals (i.e., $E(Z_i^0 | M_i = 1)$ and $E\left(Z_i^1 \middle| M_i = 0\right)$) are unobservable from the survey data. The PSM approach is, therefore, employed to construct the appropriate counterfactuals and estimate the causal effect of migration on technical efficiency and fertilizer use efficiency.

To find the counterfactuals, we first estimate the influencing factors of households' participation in migration by employing the Logit model:

$$M_i = \alpha_0 + \alpha_i W_i + \omega_0, \tag{13}$$

where W_i represents the influencing factors of migration. Each household's probability of participating in migration conditional on W_i (i.e., propensity score, $P_i(W_i)$) of each household is predicted. That is, $P_i(W_i) = \Pr(M_i = 1 | W_i)$. Based on the propensity score, the households in the treatment group could be matched with households in the control group. Therefore, statistically comparable treatment and control groups can be constructed. For each treated household, the counterfactual outcomes are estimated based on propensity scores and the potential outcomes of the matched households in the control group. The causal effect of migration (i.e., the average treatment effect on treated ATT) is expressed as

$$ATT = E_{P_i(W_i)|M_i=1}\left\{E\left[Z_i^1 \middle| M_i = 1, P_i(W_i)\right] - E\left[Z_i^0 \middle| M_i = 0, P_i(W_i)\right]\right\}, \tag{14}$$

To ensure that PSM identifies the causal effect of migration on efficiencies, two key assumptions must be discussed [23] (pp. 55–56). First, potential outcomes (Z_i) are independent of households' participation in migration (M_i), conditional on the set of observed characteristics (W_i). That is, $Z_i^1, Z_i^0 \perp M_i | W_i$. This is known as "conditional independence assumption". Second, there should be some overlaps between the treatment and control groups in the probability of participating in migration. This is the so-called "common support assumption". In empirical estimation, we use the most frequently used nearest neighbor (NN) matching for PSM. Specifically, we apply NN with five matching partners and restrict the matching within the common support.

3.3. Estimating Propensity Score: Influencing Factors of Migration

The conditional independence assumption states that the outcome variables must be independent of treatment, conditional on the propensity score. Caliendo and Kopeinig suggest two criteria for selecting variables in estimating the influencing factors of a treatment variable [24]. First, only variables that influence both the treatment variables and the outcome variables should be included. Second, only variables unaffected by participation in migration should be included. Hence, variables fixed over time or measured before participation in migration are preferred.

Variables in Table S1 in the Supplementary Materials are used to estimate influencing factors of participation in migration. Land certificates and land reallocation are included to capture the impact of land tenure security. Households with experiences of land reallocation are less likely to migrate due to the potential risk of losing land during land reallocation [25]. However, land reallocation might motivate migration as well. Because households with experiences of land reallocation might be less likely to invest in improving land quality and earning sufficient income from land, and therefore have a higher need to migrate [26]. Similarly, households with a land certificate are more likely to migrate since a land certificate provides legal protection against land expropriation and reallocations [27]. On the other hand, households with a land certificate are more likely to invest in improving land quality and earn sufficient income from land and, therefore, less incentivized to migrate [28]. The impacts of land certificate and land reallocation are, therefore, indeterminate.

Following Sauer et al., we include the age and education level of both household heads and household members [7]. Younger or better-educated household head or household members could be more capable of engaging in non-agricultural jobs and are, therefore, more likely to migrate [29]. Other household characteristics include whether the household head is or was a village official, household size, number of adults, dependency ratio and female household ratio are also introduced. Households with village officials will have easier access to information about off-farm jobs, on the one hand, but on the other hand, they might prefer to combine local off-farm work with the work on the village committee [30]. For households with larger household sizes, the occupation of household members is more likely to be diversified and then more likely to have migrated household members [31]. Households with more adults are more likely to have sufficient labor working on the farm and will more likely have surplus labor for migration [32]. The dependency ratio might hinder migration as more laborers are occupied taking care of dependent people, but it might also motivate laborers to migrate to meet the higher need for educational and medical costs [33]. A higher female ratio could negatively affect the probability of migration because, in rural China, it is usually the females' task to do housework and take care of children [34].

Additionally, contracted land area per capita and the number of contracted plots are introduced to reflect the role of natural capital in the household's decision on migration. A larger contracted land area per capita increases the probability that households gain sufficient livelihood security from land, thereby decreasing households' incentives to migrate [35]. On the one hand, the number of contracted plots increases the traveling costs involved in farming and raises the need for income from migration. On the other hand, it diversifies the land quality of households' land holdings, spreading the risk of natural disasters and therefore reducing the need for income from migration [36]. Physical capital, represented by the possession of houses and machinery, is expected to impact migration. It might be easier for households with more houses to overcome the credit constraint of migration [37]. However, households with more houses are wealthier and with lower needs for extra income from migration and could thus be less likely to migrate. The livelihoods of households possessing production machinery are more likely to rely on farming activities than migration [38]. Hence, possession of houses might have an indeterminate impact on migration, while possession of production machinery might have a negative impact on migration. Distance to the center of the nearest town is included to capture access to the market. Households living nearer the town center are more likely to get access to migration information, and the transportation cost is lower for them as well [39]. In contrast, households living nearer a town might be more likely to find opportunities for local off-farm work in the same town [40]. Thus, the impact of the distance to a town on migration could be either positive or negative. Provincial dummies for Jiangsu, Liaoning and Chongqing are included to capture other factors that are systematically different between provinces but influence households' incentives to migrate.

3.4. Research Area

To examine the impact of migration on technical and fertilizer use efficiency, we use the data collected in four regions of China: Jiangsu and Jiangxi provinces in 2015 and Liaoning province and Chongqing municipality in 2016. They are located in four major agroecological 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 from 124 villages with 1486 households. The detailed sample selection procedure is described in [41]. We use the subsample of households producing rice in this paper. After deleting households with missing information, the data on 809 rice-producing households is used for the empirical estimation.

4. Results

4.1. Technical Efficiency and Fertilizer Use Efficiency

The descriptive statistics of variables in the production function (see Table S2) can be found in the Supplementary Materials. The results of the estimated production function (see Tables S4 and S5) are presented in the Supplementary Materials. The kernel density distributions of the technical and environmental efficiency scores are shown in Figures 1 and 2, respectively. As shown in Table 1, the technical efficiency scores of our sample range from 0.77 to 0.97, with an average of 0.92. With the median technical efficiency of 0.92, the 25th and 75th percentiles are 0.9 and 0.93, respectively. Our average TE score is in line with the literature on rice production in China [36]. Compared with that of other crops production in other countries, our result on TE is higher than other studies; for example, the average TE score was 0.71 in Ethiopia [42], 0.63 in Benin [43], 0.64 in Germany, 0.76 in the Netherlands and 0.71 in Sweden [20]. Given that the SFA estimation strategy captures the technological distance from the within-sample production frontier, this implies that the technologies adopted by rice production in our sample are much less diversified than the production of other crops in other countries.

The fertilizer use efficiency score of our sample is 0.22 on average, ranging from 0.04 to 0.5. This suggests that only 22% of fertilizer applied to rice is utilized by plants. The rest (78%) is lost to air, soil and aquatic ecosystems. The median fertilizer use efficiency is 0.22; the 25th and 75th percentiles of fertilizer use efficiency are 0.17 and 0.26, respectively. Our result is similar to what Ma et al. found for rice production in the Taihu Basin in Jiangsu, China, in 2008 [44]. However, compared to the studies on grain production in five provinces in China, our result is slightly lower than the score of 0.33 [45]. Furthermore, compared to studies in other countries, our result is lower; for example, it was 0.49 for maize production in Zambia [46] and 0.45 for Dutch dairy farms [21]. This further confirms previous studies which indicated the overuse and low use efficiency of agricultural chemicals in China [1].

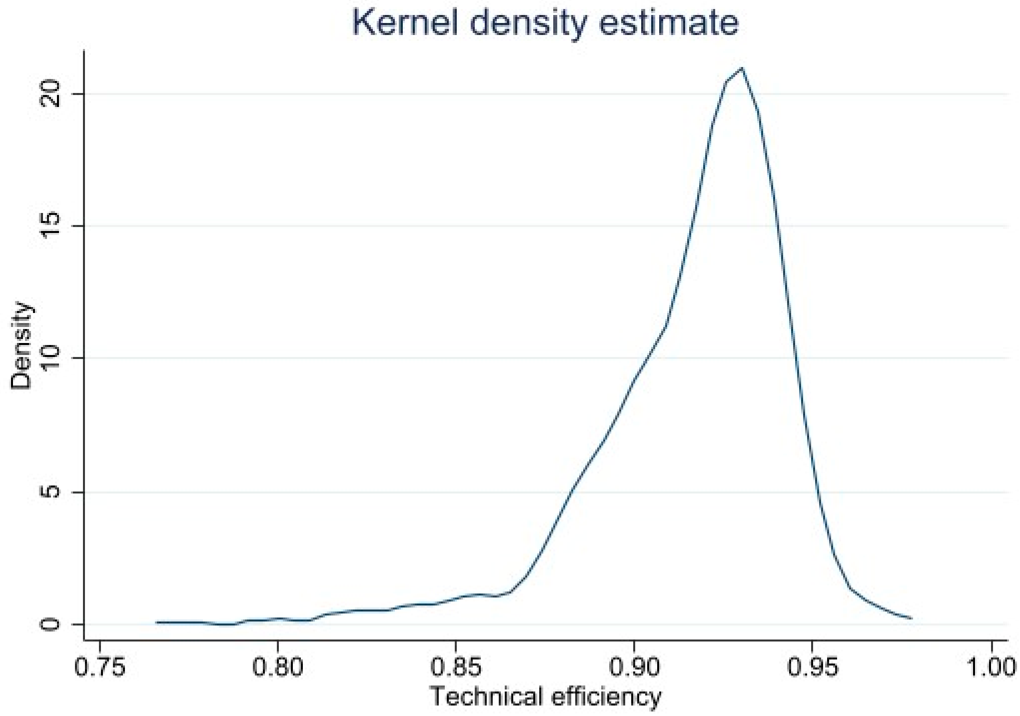

Figure 1. Kernel density distribution of technical efficiency.

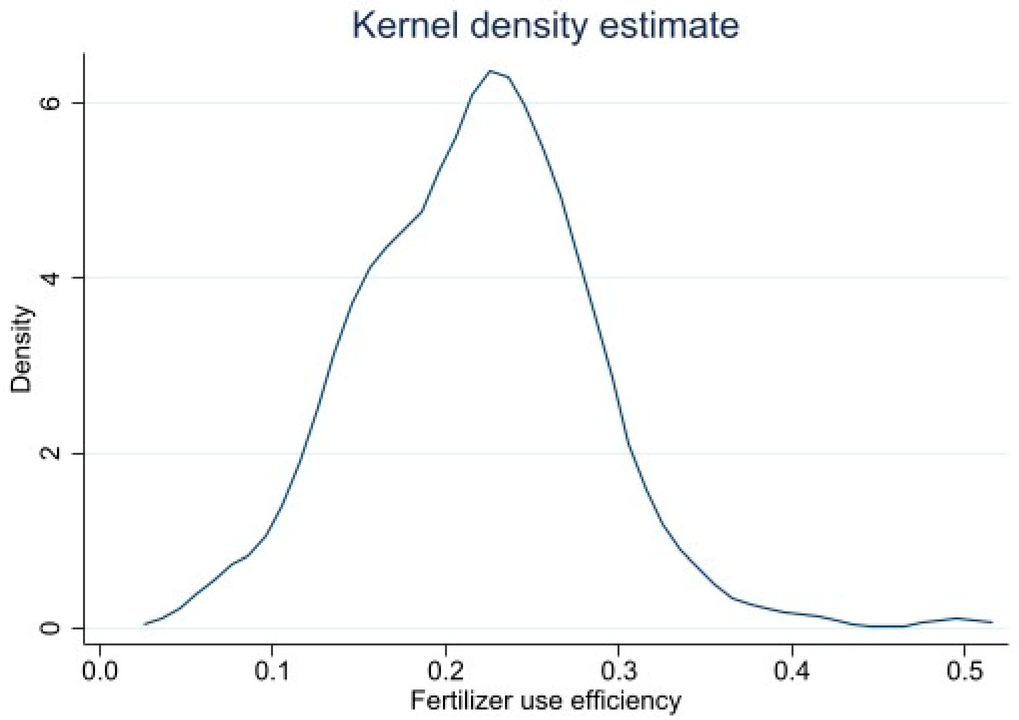

Figure 2. Kernel density distribution of fertilizer use efficiency.

Table 1. Technical efficiency and fertilizer use efficiency scores.

	Technical Efficiency	Fertilizer Use Efficiency
Mean [1]	0.92 (0.03)	0.22 (0.07)
Minimum	0.77	0.04
25th percentile	0.9	0.17
50th percentile	0.92	0.22
75th percentile	0.93	0.26
Maximum	0.97	0.5

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

4.2. The Impact of Migration on Technical Efficiency and Fertilizer Use Efficiency

To match treatment and control groups, we first estimate the Logit model of migration participation to estimate the propensity score. The descriptive statistics of the variables used (see Table S3) are presented in the Supplementary Materials. The influencing factors of participation in migration (see Table S6) are also presented in the Supplementary Materials. Figure S1 and Table S8 show that 314 treated households and 427 households in the control group are within common support (i.e., on support), while five treated households are beyond common support (i.e., off support). Table S7 presents the descriptive statistics after matching. The *t*-test suggests no significant differences in the sample means of the independent variables between the treated and control groups after matching.

Table 2 shows the technical and fertilizer use efficiency, distinguishing between treatment and control groups. The treatment variable is households' participation in migration last year (2014 for Jiangsu and Jiangxi households; 2015 for Liaoning and Chongqing households). The results reveal that migration leads to lower technical and fertilizer use efficiency. Households participating in migration have a technical efficiency of 0.9141 on average, significantly lower than that of non-migration households (0.9170 on average), which is about 0.0029, or 0.3% lower. It is consistent with Yang et al., who illustrated that migration has a negative impact on technical efficiency in five provinces (including Jiangxi) of China [9]. Similarly, migration was also found to be a cause for technical inefficiency in agricultural production in other countries such as Kosovo [7], Burkina Faso [8] and Lesotho [16]. However, the magnitude of this impact is higher than ours. For example, Sauer et al. found that the farm technical efficiency of migrants is 11% lower than that of non-migrants in Kosovo [7].

Table 2. The effect of migration on technical efficiency and fertilizer use efficiency.

	Treated	Control	Difference [1]	S. E.
	Treatment: migration			
Technical efficiency	0.9141	0.9170	−0.0029 *	0.0025
Fertilizer use efficiency	0.2113	0.2207	−0.0093 **	0.0061
Observations	314	427		

Note: [1] A *t*-test is used to identify the differences in outcomes between treatment households and their matching partners. ** Significant at the 5% level; * Significant at the 10% level.

Households with migrants also have a lower fertilizer use efficiency, which is 0.21 on average, compared to the non-migration group (0.22). Migration decreases fertilizer use efficiency by 4.5%, which is stronger than its impact on technical efficiency. This is consistent with Wu [46] and Guesmi and Serra [6], where it was found that households with farming as the major business had higher fertilizer use efficiency, and non-agricultural income negatively influenced environmental efficiency.

Consistent with the theoretical analysis in the second section, the results suggest that migration negatively affects farm performance through the changes in production behavior due to labor reduction. To directly illustrate the existence of a labor reduction effect, we divided the treatment households into two groups, comprising a less intensive migration group and a more intensive migration group (see Table 3). As farm labor is generally over-abundant in developing countries, technical efficiency and fertilizer use efficiency are less likely to be affected by a slight movement of labor [35,47]. In the migration group, the median value and average value of the migrant ratio are close to 0.5. We, therefore, use 0.5 as the threshold. Thus, a less intensive migration group is defined as one where less than half of the family laborers migrate, while a more intensive migration group is where more than half migrated. The sample within common support after matching can be found in Figures S2 and S3. As shown in the 3rd and 4th rows of Table 3, we find no evidence of significant differences in technical efficiency and fertilizer use efficiency between the control group and the less intensive treatment group. In other words, because of labor surplus, technical and fertilizer use efficiency are less likely to be influenced when less than half of the family laborers migrated.

Table 3. The causal effect of migration intensity on technical efficiency and fertilizer use efficiency.

	Treated	Control	Difference [1]	S. E.
Treatment: low intensive migration, $\leq$0.5 migrants				
Technical efficiency	0.9144	0.9169	−0.0025	0.0027
Fertilizer use efficiency	0.2112	0.2173	−0.0061	0.0063
Observations	250	427		
Treatment: high intensive migration, >0.5 migrants				
Technical efficiency	0.9128	0.9195	−0.0067 †	0.0045
Fertilizer use efficiency	0.2076	0.2259	−0.0183 *	0.0114
Observations	62	427		

Note: [1] A *t*-test is used to identify the differences in outcomes between treatment households and their matching partners. * Significant at the 10% level; † Significant at the 15% level.

In contrast, the more intensive migration group produces greater differences in technical and fertilizer use efficiency (see the 7th and 8th rows of Table 3). Specifically, the migration intensity magnifies the negative effect of migration on technical efficiency and fertilizer use efficiency. The technical efficiency of the more intensive migration group is 0.9128 compared to 0.9195 of the control group. The difference is about 0.7%, although it is only significant at the 15% testing level (with a *p*-value of 0.1064). The fertilizer use efficiency of the more intensive migration group is 0.2076, 0.0183 (or 8%) lower than the control group (0.2259). The efficiency reduction effect of migration is enhanced when more laborers participate in migration. The results, therefore, confirm the existence of a "labor reduction effect".

4.3. Robustness Check

We have discussed our empirical results for technical and fertilizer use efficiency and the impact of migration on these two efficiency scores. In particular, we have also compared our studies with the existing studies on rice production in China and other agricultural products in China and other countries. Although the comparison shows consistent results in general, the magnitude of the impact of migration on the two efficiency scores is different for different crops. Therefore, it is worthwhile to further conduct robustness checks of our analysis. To check the robustness of the translog production function, we present the results using the Cobb–Douglas production function in Table S9 and the calculated efficiency scores in Table S10. The results of the production function are generally consistent with our primary results.

The estimated technical efficiency is the same as the estimation from the translog production function, with a mean level of 0.92. However, the estimated mean fertilizer use efficiency is 0.14, which is lower than that estimated from the translog production function. This may be because the Cobb–Douglas production function underestimates the output elasticity of fertilizer. A likelihood ratio test is conducted to test the null hypothesis, "the reduced model (the Cobb–Douglas production function) fits the data as well as the full model (translog production function)". The χ^2 statistic is 34.05 (*p*-value is 0.0033). Therefore, we present the results from the translog production function as the main results.

The robustness of PSM is checked by using another matching method. We use radius matching to check the robustness of the nearest neighbor matching. As shown in Table S11 in the Supplementary Materials, the results are quite consistent with Tables 2 and 3. Migration has a negative impact on technical efficiency and fertilizer use efficiency. After we divide the treatment group into less intensive and more intensive treatment groups, the negative effects of migration are more significant for the less intensive treatment group but are larger for, the more intensive migration group.

We further checked the robustness of the main result by using land productivity (i.e., yield per hectare) and fertilizer use intensity (i.e., fertilizer applied per hectare) as outcome variables. The results are presented in Table S12. Households with migrants also have a lower level of output, i.e., 7266 kg/ha on average. This is 340.85 kg/ha (or about 4.5%), lower than households without migrants (7606 kg/ha). However, there is no difference in fertilizer use intensity between migration and non-migration households. Hence, with a similar intensity of fertilizer application, migration households have relatively lower land productivity levels than non-migration households. This can be explained by the "labor reduction effect". Because migration households can be less flexible in terms of labor use compared to non-migration households, they are more likely to adopt one-time fertilization instead of the practice of spreading fertilizer out several times according to the growth of plants. Therefore, compared to non-migration households, migration households have a lower level of output when the amount of fertilizer applied per unit of the land area is similar.

5. Conclusions

We elaborated on the mechanism of how migration affects farms' economic and environmental performance. We applied the stochastic frontier analysis (SFA) and propensity score matching (PSM) method to the survey data collected in the four regions of Jiangsu, Jiangxi, Liaoning and Chongqing. We estimated the technical efficiency and fertilizer use efficiency of rice-producing households and examined the impact of migration on technical efficiency and fertilizer use efficiency.

The average technical efficiency of sample households is 0.92, which implies that an improvement of 8% of output could be achieved in rice production given the present input level. The average fertilizer use efficiency is 0.22, which indicates that only 22% of applied fertilizer is utilized. A reduction in fertilizer application is possible, given the current technology and output levels. About 78% of applied fertilizer is lost to air, soil and aquatic ecosystems. Therefore, we recommend drawing up policies for improving fertilizer use efficiency.

The results of PSM suggest a negative impact of migration on both the economic and environmental performance of farms; the impact on environmental performance is larger than on economic performance, and the impact is amplified for households that have participated in migration more intensively. Although migration provides another source of income for rural households, it also generates economic and environmental losses for on-farm production. In particular, we identified a labor reduction effect of migration on technical efficiency and fertilizer use efficiency. The results are robust according to our robustness check.

These conclusions might have important implications for policies on migration as well. For example, to avoid the efficiency loss caused by migration, policies encouraging rural households to specialize in either migration or on-farm work might be recommended. Especially for those rural households who participate in migration intensively, specializing in off-farm work and renting out all their farmland to specialized farmers would probably generate higher income and better environmental performance for both migrated households and their lessees.

However, we must point out that the impact of migration on economic and environmental performance is marginal in magnitude, although it is highly significant and robust. There are a number of possible reasons. First, the sustained effects of migration might only be likely to accumulate over time, which cannot be illustrated by the cross-sectional data. Further research is needed to capture the continuing development of rural-urban migration. Second, the labor-reduction effect of migration has been partially offset by mechanization services. Third, non-migration households might also intensively engage in local off-farm jobs and hardly take care of on-farm production in the meantime. However, all these issues need further research, particularly using a panel dataset.

Other limitations should be noted. First, pesticide use efficiency is not included as a measurement of environmental performance because we do not have specific data on pesticide type, contents and concentration levels. Future studies might estimate pesticide use efficiency with more accurate data on pesticides. Second, we examined the "labor reduction effect" of migration by differentiating the treatment group into more intensive and less intensive groups. It might be of interest for future studies with a larger sample size to divide the treatment group into more categories.

Supplementary Materials: The following supporting information can be downloaded at: https://www.mdpi.com/article/10.3390/agriculture13030708/s1, Figure S1: Distribution of pair-wise propensity score (treatment: migration); Figure S2: Distribution of pair-wise propensity score (treatment: less intensive migration); Figure S3: Distribution of pair-wise propensity score (treatment: more intensive migration); Table S1: Definition of variables in estimating propensity score title; Table S2: Descriptive statistics of variables in the production function; Table S3: Descriptive statistics and comparison of variables for estimating participation in migration; Table S4: Estimated results of the production function; Table S5: Output elasticities with respect to each input at sample means; Table S6: Influencing factors of migration; Table S7: Descriptive statistics of treated and control groups after matching; Table S8: Number of treated and untreated households on/off support; Table S9: Stochastic frontier analysis using the Cobb-Douglas production function; Table S10: Technical efficiency using the Cobb-Douglas production function; Table S11: The causal effect of migration and its intensity on technical efficiency and fertilizer use efficiency using radius matching; Table S12: The effect of migration on output and fertilizer use intensity (kg/ha).

Author Contributions: G.R.: conceptualization, methodology, data analysis, writing the original draft and funding acquisition; X.Z.: conceptualization, supervision, editing the manuscript and funding acquisition; S.F.: conceptualization, supervision, editing the manuscript and funding acquisition. All authors have read and agreed to the published version of the manuscript.

Funding: National Natural Science Foundation of China [grant numbers 71673144, 71773046 and 72061137072], National Social Science Fund of China [grant number 18VSJ060], National Key R&D Program of China [grant number 2016YFE0103100], Dutch Research Council (NWO) [grant number 482.19.607], Humanity and Social Science Project of Ministry of Education, China [grant number 21YJC790095], Fundamental Research Funds for the Central Universities [grant number SKYC2021008], Jiangsu Department of Education [grant number 2021SJA0061], the Programme Strategic Scientific Alliances (PSA) of the Royal Netherlands Academy of Sciences (KNAW) and Ministry of Science and Technology, China [grant number PSA-SA-E-01].

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Informed consent was obtained from all subjects involved in the study.

Data Availability Statement: The datasets used during the current study are available from the corresponding author upon reasonable request.

Acknowledgments: The manuscript is a part of the PhD work of the first author. It has been previously circulated under the title "How migration influences the economic and environmental performance of rice farms in China?" for international conferences. The first author would like to thank Nico Heerink for very helpful suggestions and supervision. The first author is thankful to the ALFABET project under European Commission's Erasmus Mundus Programme [2014-0857/001-001] for providing the scholarship. We would also like to thank the reviewers and the academic editor for their valuable comments and suggestions for improving our paper.

Conflicts of Interest: The authors confirm that we do not have any conflict of interest.

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