Migration, Local Off-farm Employment and Agricultural Production Efficiency: Evidence from China

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Selected Paper prepared for presentation at the Agricultural & Applied Economics Association's 2014 AAEA Annual Meeting, Minneapolis, MN, July 27-29, 2014.

Abstract

This paper studies the effect of local off-farm employment and migration on rural households' technical efficiency of crop production using a five-year panel dataset from more than 2,000 households in five Chinese provinces. While there is not much debate about the positive contribution of migration and local off-farm employment to China's economy, there is an increasing concern about the potential negative effects of moving labor away from agriculture on China's future food security. This is a critical issue as maintaining self-sufficiency in grain production will be critical for China to feed its huge population in the future. Several papers have studied the impact of migration on production and yield with mixed results. But the impact of migration on technical efficiency is rarely studied. Methodologically, we incorporate the correlated random-effects approach into the standard stochastic production frontier model to control for unobservable that are correlated with migration and off-farm employment decisions and technical efficiency. The most consistent result that emerged from our econometric analysis is that neither migration nor local off-farm employment has a negative effect on the technical efficiency of grain production, which does not support the widespread notion that vast-scale labor migration could negatively affect China's future food security.

Keywords: migration, local off-farm, agriculture, efficiency, China
JEL Classification: D24, O12, O13

Acknowledgments

The authors would like to acknowledge the support from NSFC-CGIAR Project 71361140370, the CGIAR Research Program on Policies, Institutions and Markets led by IFPRI, and National Social Science Fund of China (Grant No. 13CGL085). The authors are also grateful to Peter Schmidt and Zhengfei Guan for valuable discussions and suggestions on the econometrics method of our paper.

1. Introduction

After Lewis's seminal work on a dualistic economy (Lewis 1954), nearly all development economists agree that a structural transition of the economy is necessary for growth and development (Barrett, Carter, and Timmer 2010). The quintessential feature for that transition is the movement of labor out of agriculture, which is well illustrated by the development path of Japan in the 1950s and 1960sandof South Korea in the 1960s and 1970s (Knight, Deng, and Li 2011).

With its relaxation of the *hukou* (household registration) system and other restrictive regulations, as well as its rapid economic development, China is now experiencing its largest and fastest structural change, which is characterized by the steady flow of labor from rural areas to urban areas and from the agricultural sector to nonagricultural sectors. Official data from the 2011 China Statistical Year Book show that the share of labor employed primarily in agriculture fell from 68.7 percent in 1980 to 36.7 percent in 2010. According to the recent population census, more than 261 million rural residents in China worked in places other than their birth places in 2010 (NBSC[1] 2011), which is more than the total number of international migrants from all countries combined (Sirkeci, Cohen, and Ratha 2012). The flow of migration is expected to increase further as China's economy continues to grow.

The massive labor migration in China has also attracted great research interests among development economists in recent years. The impact of China's internal migration on migration destinations and the overall economy is enormous as migrants accounted for 46.5 percent of China's total urban labor force in 2007 (Cai, Du, and Wang 2009).Migration has also been found to increase migrant households' income (Du, Park, and Wang 2005); smooth consumption and

[1] NBSC: National Bureau of Statistics of the People's Republic of China.

reduce exposure to shocks affecting agricultural production (Giles 2006); encourage investment in agricultural productive assets (Zhao 2002), housing and other consumer durable goods (de Brauw and Rozelle 2008), and children's education (Chen et al. 2009); and contribute to the diversification of rural economy in their source communities (Murphy 2000).

At the same time, there are a number of concerns about the potential negative effects of migration on the destination communities, the source communities, and migrant families. In the related literature about the sending communities and migrant families, two issues stand out. The first issue concerns the well-being of the left-behind family members (de Brauw and Mu 2012; Mu and van de Walle 2011; de Brauw et al. 2013; Chang, Dong, and Macphail 2011; Giles, Wang, and Zhao 2010).As expected, these studies typically find that migration increased additional farm and domestic work time of the left-behind members (women, children, and elderly), especially the female and senior members. The additional work, however, does not necessarily lead to worsened health conditions for the left-behind members (Mu and van de Walle2011). The second issue is related to the potential negative effect of migration on agricultural production (de Brauw et al.2013; Wang, Wang, and Pan 2011; Li et al. 2013; Taylor, Rozelle, and de Brauw2003), with mixed results. A study by the United Nations Development Program argued that the large-scale migration of rural workers and women' staking over farming activities could potentially threaten China's future food security (UNDP, 2003).

The theoretical prediction of the impacts of migration on agricultural production, however, is ambiguous. On one hand, loss of labor to migration can reduce the agricultural production in migrant-sending areas. Furthermore, migration can decrease farmer attention to the appropriate use of technology and change labor quality (from adult male members to female, child, and elderly members) and other inputs, which would ultimately cause a decline in productivity (Yue and Sonoda 2012). But on the other hand, scholars advocating New Economics of Labor Migration argue that migration and remittances might increase agricultural productivity through providing better access to information and more flexible liquidity as well as enabling rural households to overcome credit and risk constraints (Wouterse 2010).

The inclusive theoretical prediction has given birth to a large body of empirical literature. Using the stochastic production frontier method, Mochebelele and Winter-Nelson (2000) and Nonthakot and Villano (2008) found that households with migrants have significantly higher technical efficiency in Lesotho and northern Thailand, respectively, while Chang and Wen (2011) showed negative association between off-farm work and technical efficiency in Taiwan. And Chavas, Petrie, and Roth (2005) did not find any significant impact of off-farm employment on technical efficiency using data from Gambia. In the context of U.S. agriculture, Kumbhakar and Summa (1989) showed that off-farm work is negatively associated with technical efficiency using diary data from Utah. And Fernandez-Cornejo (1996) found similar results using data from a vegetable farm survey in Florida.

There are also studies on the impacts of migration on agricultural production in China. Usingan instrument variable regression approach, Taylor, Rozelle, and de Brauw (2003) show that migration has negative effects on crop income but positive overall effects on yields, which may explain the change in inputs for households with migrants.[2]Using the stochastic frontier production (SFP) function approach, Chen, Huffman, and Rozelle (2009) find a positive association between village migration ratio and technical efficiency. Yue and Sonoda(2012), on the other hand, find that the average technical efficiency is higher for households without a wage worker than for those with a wage worker in all their sample regions. Others find migration has

[2]High yields do not necessarily imply high efficiency, as "high-input" farmers can generate high yields but not efficiently utilize their inputs (Mochebelele and Winter-Nelson 2000).

no effect on yield and production (de Brauw et al. 2013; Wang, Wang, and Pan 2011; Li et al. 2013).

The existing studies about the impact of Chinese internal migration on agricultural production/productivity suffer from several noticeable limitations. First, a large majority of the studies about the impact of migration on agriculture focus on the impact of migration on production, yield, or both, but the impact of migration on technical efficiency is rarely studied. Second, the few that do study the impact on technical efficiency fail to account for the potential endogeneity of technical efficiency (which will be discussed briefly in the next paragraph and more in-depth in the Estimation Method section). And finally, despite the increasing importance of local off-farm activities for rural employment and income (Mohapatra, Rozelle, and Goodhue 2007; Zhang et al. 2006), the impact of local employment on agricultural productivity is largely overlooked in the literature.

In this study, we aim to fill the knowledge gap by studying the impact of migration and local off-farm employment on crop production efficiency using household panel data for 2000 households from five provinces covering the period from 2004 to 2008. While the stochastic production frontier model is a standard approach to study the technical efficiency of crop production, the estimation of the determinants of efficiency for the stochastic production frontier model is a difficult task (Liu and Zhuang 2000). As migration and local off-farm employment are found to be related to some household endowments (Du, Park, and Wang 2005), failure to control for the household unobserved characteristics may lead to biased and inconsistent estimation of migration effects on technical efficiency. In this paper, we adopt a correlated random-effects (CRE) coefficient model (Wooldridge 2002) to control for the unobserved household effects.

We find that after the unobserved household effects are controlled, there is no significant effect of migration on technical efficiency for rural farms. However, the effects are not consistent across different types of migration (for example, long versus short distance, migration versus local off-farm employment), a result similar to that of Chavas, Petrie, and Roth (2005), who used migration data from Gambia. In light of the huge regional difference across provinces (Chen, Huffman, and Rozelle 2009), we also estimated the same regressions using data from each of the sample provinces. And we find that the estimation results based on data from all provinces mask considerable regional differences as well.

The rest of the paper is organized as follows: Section 2 describes the Research Center for Rural Economy (RCRE) data we are going to use. The estimation methodology is presented in Section 3. The results of the stochastic production function estimation and regional comparison are given in Sections4 and 5. We conclude in Section 6.

2. Data and Descriptive Statistics

The data used in this research are panel household data from a National Fixed Point Survey (NFPS), implemented by RCRE, a research unit of China's Ministry of Agriculture. The NFPS started in 1986 in nine provinces. The sample in each province was selected in three stages. First, a set of counties that are stratified by income level was randomly selected. Second, one village was randomly selected from each sample county. Finally, between 40 and 120 households (depending on the size of the village) were randomly selected from each sample village. Benjamin, Brandt, and Giles (2005) provide a detailed description of the survey design and implementation of the NFPS. The initial master sample of the RCRE survey in 1986 contains more than 20,000 rural households. The dataset for our study includes more than 2,000 randomly selected households from five provinces from 2004 to 2008. The households are resampled each year. The five provinces are Heilongjiang, Jiangxi, Shandong, Hunan, and Sichuan. These five provinces cover a wide range of economic and agroecological conditions as well as migration and local employment patterns. Table 2.1 reports the sample distribution for each province for each of the five years. The panel data are unbalanced for two major reasons. First, one or two villages during some years for some provinces were not surveyed. Second, there were a number of missing values for a number of variables of interest.

The reason we use the panel from 2004 to 2008 is that the detailed input and output information was not collected before 2004. One of the key innovations of the RCRE survey since 2004 is that input and output data were collected for each crop rather than for all crops, which enables more accurate information about capital input in agricultural production. In constructing input and output variables, we follow the existing literature (Zhang, Yang, Wang 2011; Chen etal.2009). The output is measured by the total value of grain crops (including wheat, rice, corn, soybean, tuber crops, and others) and cash crops (including cotton, rapeseed, sugar, fiber, tobacco, silkworm cocoon, vegetables, and others) separately. The input variables are the same for grain and cash crops, which include cultivation area (in *Mu*), labor (in person-days) input, cost of fertilizer and pesticide (in yuan), and other input (in yuan).Other input costs include the cost of irrigation, animal power, machine use, and hand-tool purchase as well as the depreciation and repair cost for fixed production assets.

Table 2.2 reports the number of working members and land endowment across provinces. As expected, the number of working members varies only slightly, with an average number of 3,and ranges from 2.76 in Heilongjiang to 3.11 in Jiangxi province. Similarly, the average coefficient of variation is also small for all provinces (0.34–0.38).Unlike the case of working members, there is huge variation in terms of land endowment. While an average household in Heilongjiang owns 44.78 *mu* of arable land, a typical household in other provinces owns less than 6 *mu*of land (ranging from 3.8*mu*in Sichuan to 6.0*mu*in Jiangxi). There is also considerable variation in landholding size within each province as the coefficient of variation ranges from 0.51 in Sichuan to 0.85 in Heilongjiang.

Table 2.3 reports the labor allocation of rural households in our sample across different employment activities (migration, local off-farm employment, and own farm) across provinces over the five-year panel period. *Migration* means "work outside of own county," while local off-farm employment means "work within own county but not on own farm." Overall, agriculture is still the most important source of rural employment as the time spent on own farm still accounted for 51 percent of total time worked in 2008 (slightly down from 56 percent in 2004). Among the off-farm activities, local off-farm employment is more important than migration as the share of time spent on local off-farm employment ranges between 25 percent in 2005 and 29 percent in

2008, compared to between 19 percent (in 2004) and 20 percent (in all other years) for share of time spent on interprovincial migration.[3]

The comparison of labor allocation across different provinces suggests considerable regional variation. The share of time spent on-farm is highest in Heilongjiang (68 percent in 2008 and 79 percent in 2004), compared to between 51 percent (in 2008) and 56 percent (in 2004) for the other provinces. The large share of time spent on farm activities in Heilongjiang is consistent with landholding for an average household in Heilongjiang being almost 10 times bigger than that in the other provinces (Table 2.1). As one of the coastal provinces, Shandong has the most active local off-farm employment as illustrated by the share of time spent on local off-farm employment's reaching 53 percent in 2008, 24 percentage points higher than the national average and Jiangxi Province (the second most active province in local employment in the sample).Hunan, Jiangxi, and Sichuan, on the other hand, are much more active in migration (especially interprovincial migration) than Heilongjiang and Shandong. On average, the share of time spent on migration in these three provinces is between 28 percent and 29 percent in 2008, compared to only 5 percent for Heilongjiang and 11 percent for Shandong in 2008.

Unlike the level of labor allocation, the regional variation is much smaller for the change of labor allocation over time. The share of time spent on own farm and share of time spent on local off-farm employment were dynamic, with Heilongjiang and Shandong Provinces' experiencing relatively bigger changes than did other provinces. For example, the share of time spent on own farm in Heilongjiang (or Shandong) declined from 79 percent (or 48 percent) in 2004 to 68 percent (or 36 percent) in 2008.In the meantime, the share of time spent on local off-

[3]Local off-farm employment's being more important than migration in terms of labor supply points to the need to study local off-farm employment together with migration. Unfortunately, we don't have wage-earning and migration-earning data, so we cannot compare the income from these two types of employment.

farm employment in Heilongjiang (or Shandong) increased from 16 percent (or 42 percent) to 27 percent (or 53 percent).

Table 2.4 reports the total production and yield of crop production over time for all the five provinces. We note that both grain production and grain yield actually increased over the survey years for all the five provinces. This does not support the growing concern that moving labor away from the agricultural sector would reduce crop production and yield. However, production and yield are not equivalent to production efficiency because high yield or production could be achieved in three ways: (1) a higher level of production frontier (that is, better technology), (2) a higher level of input use, and/or (3) high technical efficiency. Table 2.5 reports key inputs of grain production over time. Interestingly, the total sown area for an average household hadslightly increased in all the five provinces. As expected, labor use intensity has indeed declined (from 14.66 working days per *mu* of sown area in 2004 to12.39 working days per *mu*of land in 2008).The decline in labor input is accompanied by a considerable increase in other inputs. While fertilizer continues to be the most important material input, accounting for almost half of nonlabor variable cost, the largest relative increase is the cost of agricultural mechanization (from 23 yuan to 40yuanper *mu*). By 2008, agricultural mechanization accounted for a quarter of non-labor input expenses. Seed intensity and pesticide use intensity also increased to some extent.

The descriptive analysis indicates that while migration and local off-farm employment have absorbed a significant part of agricultural labor away from grain production, the decline in labor intensity has partly been offset by the substantial increase in nonlabor input-use intensity, especially the rapid increase in the level of agricultural mechanization. Meanwhile, the data also indicate an overall increase in grain production and yield despite the loss of labor to off-farm employment. While the descriptive analysis is informative, it does not allow us to establish a causal relationship between migration and local off-farm employment and production efficiency. To identify the causal effects of migration and local off-farm employment on-farmers' technical efficiency, we will rely on a rigorous multivariate econometrics analysis, which is the focus of the rest of the paper.

3. Estimation Method

The SFP function is a standard approach used to analyze technical efficiency. Following the literature (Aigner, Lovell, and Schmidt 1977; Meeusen and van den Broeck 1977), the standard panel data model for SFP can be written as

$$y_{it} = f(x_{it};\beta)\exp(v_{it} - u_{it}), \quad (1)$$

where y_{it} is the grain output produced by household i in year t;x_{it} is a vector of inputs used by household i in year t to produce output y_{it}; v_{it} is assumed to be iid $N(0,\sigma_v^2)$;u_{it} is a nonnegative random variable; and the term $\exp(u_{it})$ is the measure of technical inefficiency of household i in year$t$.

We assume $f(x_{it};\beta)$ to have the general translog functional form. The advantage of the translog functional form over the Cobb-Douglas functional form is that the former is more flexible while the latter restricts the elasticity of substitution between factors of production to be unity. A translog model collapses into a Cobb-Douglas model if all the coefficients of interaction terms and squared terms in the translog function are jointly not significant from zero. A simple F test allows us to choose between the two models. The test results suggest that we should employ the translog functional model.

There are two approaches (two-step approach and one-step approach) in the literature on technical inefficiency analysis using an SFP framework. The earlier studies typically relied on the two-step approach. In the first step, the technical efficiency parameter for each farm is estimated after an SFP model is estimated. In the second step, the estimated technical efficiency parameter is then regressed on variables that could potentially determine the technical efficiency (Pitt and Lee 1981; Kalirajan 1981; Chen, Huffman, and Rozelle 2009). However, this two-step approach was criticized for the inconsistency between the independency assumption of u_{it} in the first step and the dependency assumption in the second step (Wang and Schmidt 2002; Kumbhakar and Lovell 2000). The problem is essentially the same as the omitted variable problem in the linear regression model.

The one-step approach is more popular as it overcomes the above-mentioned concern of the two-step approach. We also adopt this approach in this paper. In the one-step model, the mean of u_{it} is assumed to depend on exogenous variables z_{it}, that is, $u_{it} = (\gamma' \boldsymbol{z}_{it} + \epsilon_{it}) \geq 0$, where $\epsilon_{it} \sim N(0, \sigma_\epsilon^2)$), and the distribution of ϵ_{it} is bounded below by the variable truncation point $-\gamma' \boldsymbol{z}_{it}$. It has been shown that this distribution assumption on ϵ_{it} is consistent with the distributional assumption on u_{it} that $u_{it} \sim N^+(\gamma' \boldsymbol{z}_{it}, \sigma_u^2)$. With the distribution assumption on v_{it} and u_{it}, The method of Maximum Likelihood Estimation can be used to estimate the model.

Another concern arises if one or more of the $\boldsymbol{z}_{it}$ variables are endogenous in the one-step approach. To our knowledge, this has not been well addressed in the literature. In this study, the key variables in $\boldsymbol{z}_{it}$ (share of time spent on migration and on local off-farm employment) are likely to be correlated with household unobservable (c_i) (Greenwood 1971; Lucas 1997; Du, Park, and Wang2005).If we believe c_i is also correlated withthe technical efficiency, that is, $u_{it} = (\gamma' \boldsymbol{z}_{it} + c_i + \epsilon_{it}) \geq 0$, then the one-step estimation without appropriately dealing with the existence of c_i would lead to an inconsistent and biased estimator.

We adopt the CRE model pioneered by Mundlak (1978) and Chamberlain (1980) to address the existence of c_i. Specifically, we assume that $c_i = \bar{\boldsymbol{z}}_i \delta + a_i$ (where $\bar{\boldsymbol{z}}_i$ is the mean of time varying variables during the five sample years) and $a_i \sim N(0, \sigma_a^2)$ .To guarantee the nonnegativity of u_{it}, we need the distribution of ϵ_{it} to be bounded below by the variable truncation point($-\gamma' \boldsymbol{z}_{it} - c_i$). Since both ϵ_{it} and a_i have normal distributions, u_{it} will still have a truncated normal distribution, which can be expressed as $u_{it} \sim N^+(\gamma' \boldsymbol{z}_{it} + \bar{\boldsymbol{z}}_i \delta, \sigma_u^2 + \sigma_a^2)$.

In conclusion, our model can be expressed as follows:

$$lnY_{it} = \beta_0 + \sum_j \beta_j x_{itj} + \sum_k \sum_j \beta_{jk} lnx_{itj} lnx_{itk} + v_{it} - u_{it}$$
$$v_{it} \sim Normal(0, \sigma_v^2) \quad (2)$$
$$u_{it} \sim N^+(\gamma' \boldsymbol{z}_{it} + \overline{\boldsymbol{z}}_i \delta, \sigma_u^2 + \sigma_a^2)$$

Following the existing literature, we include cultivation area, labor input, cost of fertilizer and pesticide, and aggregated capital input inx_{it}. The vector of $\boldsymbol{z}_{it}$ contains household composition, age and education of household head, land size dummy, and our key variables of interest—time spent on intraprovincial migration, time spent on migration to other counties within own province, and time spent on local off-farm employment[4] (Mochebelele and Winter-Nelson 2000; Rao, Brümmer, and Qaim 2012; Chen, Huffman, and Rozelle 2009; Nonthakot and Villano 2008).To control for potential technical changes over time, time dummies were included in all the SFP regressions. We also include provincial dummies and the interaction terms between the time dummies and the provincial dummies.

4. Results and Discussion

We estimated equation 2 for the pooled sample as well as for each province. While equation 2 was estimated using the one-step approach, we present the estimation results in two separate tables. Table 4.1 reports the coefficients for the input variables of the production function (the X_{it} variables in equation 2),and Table 4.2 reports those for the determinants of technical efficiency (the Z_{it} variables in equation 2). The first and second columns are based on the pooled data, and

[4] We will also include time dummies, which capture time-varying efficiency.

the rest of the columns are based on data from individual provinces. The data for Jiangxi, Hunan, and Sichuan are jointly estimated because we were unsuccessful in getting the translog SFP model to converge based on data from each of these provinces. We expect the results from each of these provinces to be similar because these three provinces share a high degree of similarity in agroecological and socioeconomic conditions. And all three provinces are the main migration-sending provinces in China, which is also confirmed by our descriptive evidence reported in Table2.2.

Production Function

The highly significant coefficients for all the interaction terms and square terms of the four types of input (top panel of Table 4.1) tend to suggest that the translog production function is a more appropriate function form than a Cobb-Douglas function form. To help interpret the relative importance of each input, we calculate the elasticity of production for each of the four inputs based on the sample mean (the bottom panel of Table 4.1).The estimated variable input elasticities are all positive as expected. Based on the pooled sample, land is the most important production factor, with an elasticity of 0.48, which means that doubling land size (while holding everything else constant) could cause crop output to increase by 48 percent. The second most important factor is other input (with an elasticity of 0.35), followed by fertilizer and other input (0.26). Labor turns out to be the least important variable input among the four, with an elasticity of 0.1. The estimation results based on data from individual provinces suggest considerable variation in the relative importance of the production factors across provinces. For example, land is the most important factor in Shandong as well as Hunan and Jiangxi, fertilizer and pesticide (or other inputs) are more important than land in Heilongjiang (or Sichuan). Given the large land endowment in Heilongjiang, it is not surprising that the marginal contribution of land is smaller than that of fertilizer and pesticide. The most robust result is the relatively small contribution of labor to grain production across provinces. Except for Heilongjiang, where the labor elasticity is 0.23, the elasticity of labor in all other provinces is less than 0.1, suggesting that labor in general is not likely to be a constrained factor of grain production in China.

Determinants of Technical Efficiency

Turning to the efficiency equation, the results are also quite consistent for a number of variables across provinces. First of all, the mean values of several time-varying variables being significant across provinces indicates that the CRE model is a relevant specification.[5]The results are also consistent for a number of household characteristics. For example, the head's level of education has no effect on technical efficiency, but the head's age has a negative effect on technical efficiency. The family political background has no effect on farming efficiency as neither the coefficient on "having a party member" nor the coefficient on "having a member in village council" is statistically significant.

Second, it is important to note that neither the total number of working members nor the composition of labor (in terms of age or gender) has any significant effect on efficiency. And these results are also highly consistent across provinces. The existing literature on internal migration in China (Zhang, Yang, Wang 2001; Du, Park, and Wang 2005; Zhao 2003) typically shows that migrants are generally younger members. From a technical efficiency point of view, this is not necessarily a concern if more seasoned agricultural labor can be used to replace

[5] In the context of the CRE model, the set of mean values of time varying variables (are added to control for time-invariant heterogeneity. Specifically, we specify the time-invariant unobservable (c_i) as , as discussed in Section 3. The statistical significance of the s is a good indication of the existence of time-invariant c_i but the magnitudes of these variables do not give meaningful interpretation.

younger agricultural labor. Another potential concern is the shift from male agricultural labor to female labor due to migration. Mu and van de Walle (2011) found that the loss of male members to migration causes the remaining female members to work significantly more hours on their own farms. Our results do not find any significant effect of the participation of female members in farming activities on farm efficiency. Putting these two effects together, our results do not support the concern about the potential negative effects of shifting a large number of young and male agricultural laborers away from agricultural activity.

Finally, the coefficients on share of time spent on migration and share of time spent on local off-farm employment allow us to test the effects of engaging in different types of off-farm employment on farming efficiency directly. The insignificant coefficients on both variables in the pooled regressions as well as in all the regressions using data from different provinces suggest that neither migration nor local off-farm employment has any negative effect on farming efficiency. These results are also consistent with the insignificance of household demographic composition variables and the overall small labor elasticity of crop production. To further explore the potential heterogeneous effect of migration and local off-farm employment on the technical efficiency of farmers with different farm sizes, we interact these two variables with a land size dummy variable (=1 if the land size is bigger than village average, and =0 if otherwise).The positive and significant coefficient of the farm size dummy suggests that households with more land are relatively more efficient and the coefficients for the two interaction terms (between land size dummies and the two off-farm employment variables) are statistically insignificant, suggesting that migration and local off-farm employment have no effect on farming efficiency regardless of farm size.

5. Conclusions

No country has experienced the scale of labor movement (from rural to urban and from the agricultural sector to the nonagricultural sector) that China is currently experiencing. According to the recent population census, more than 261 million rural residents in China worked in places other than their birthplaces in 2010 (NBSC 2012), which is greater than the total number of international migrants from all countries combined (Sirkeci, Cohen, and Ratha 2012). Meanwhile, local off-farm employment has also emerged as an important local economic activity in terms of employment and income generation. While there is not much debate on the positive contribution of migration and local off-farm employment to China's economy, there is increasing concern about the potential negative effects of moving labor away from agriculture on China's future food security. This is a critical issue as maintaining self-sufficiency in grain production will be critical for China to feed its huge population in the future. Several papers have studied the impact of migration on production and yield, with mixed results. But the impact of migration on technical efficiency is rarely studied.

This paper studies the impact of migration and local off-farm employment on the technical efficiency of grain production using a large panel dataset from five provinces of China. Using an improved SFP function approach, we find that neither migration nor local off-farm employment has any negative impact on technical efficiency in grain production. This finding is also robust across all provinces, regardless of farm size. There are a number of reasons to support this finding. First, labor is in general abundant relative to land especially for provinces with limited land endowments, which is implicitly supported by the small elasticity of labor. Second, the shift from male labor to female labor or from more young labor to older labor does not affect productivity. Third, the loss of labor to migration is largely offset by the more intensive use of agricultural machinery. In a recent paper, Yang, Zhang, and Reardon (2013) showed that the rapid rise of agricultural mechanization services is among the main reasons agricultural production in China could continue to increase while more and more labor migrates and moves out of agriculture. Finally, migration and local off-farm employment may allow farmers to use higher-quality inputs for grain production.

In addition to its empirical contribution to the ongoing debate about the potential effect of migration and off-farm employment on China's agricultural production, this paper also makes a methodological contribution. A CRE model is incorporated into the traditional SFP function to control for the potential endogeneity of migration and local off-farm employment decisions in the technical efficiency equation. Based on our knowledge, this is the first paper to extend the SFP model to incorporate the CRE model. The same type of extension can be applied to other technical efficiency studies that involve decision variables on the technical efficiency equation.

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Table 2.1—Number of observations for each province, 2004 to 2008

Year	Heilongjiang	Jiangxi	Shandong	Hunan	Sichuan	Total
2004	489	429	329	290	492	2,029
2005	503	377	328	313	488	2,009
2006	542	383	300	266	426	1,917
2007	587	378	226	279	465	1,935
2008	473	297	238	227	370	1,605
Total	2,594	1,864	1,421	1,375	2,241	9,495

Source: Author's own calculations based on Research Center for Rural Economy data

Table 2.2—Number of working members and land endowment of sample households

	Working members (Number)		Land endowment (*Mu*)	
Province	Mean	Coefficient of variation	Mean	Coefficient of variation
Heilongjiang	2.76	0.34	44.78	0.85
Jiangxi	3.11	0.36	6.06	0.68
Shandong	2.91	0.33	4.91	0.51
Hunan	2.95	0.38	4.52	0.67
Sichuan	2.90	0.35	3.77	0.65

Source: Author's own calculations based on Research Center for Rural Economy data.

Table 2.3—Labor allocation across different employment activities

Province	2004	2005	2006	2007	2008
Own farm					
Heilongjiang	0.79	0.80	0.78	0.69	0.68
Jiangxi	0.43	0.46	0.43	0.42	0.43
Shandong	0.48	0.48	0.46	0.40	0.36
Hunan	0.55	0.55	0.54	0.50	0.53
Sichuan	0.56	0.54	0.52	0.50	0.53
Average	0.56	0.57	0.55	0.50	0.51
Local off-farm employment					
Heilongjiang	0.16	0.14	0.16	0.26	0.27
Jiangxi	0.28	0.25	0.29	0.31	0.29
Shandong	0.42	0.42	0.43	0.45	0.53
Hunan	0.19	0.18	0.19	0.21	0.18
Sichuan	0.20	0.21	0.21	0.22	0.18
Average	0.25	0.24	0.26	0.29	0.29
Migration					
Heilongjiang	0.05	0.06	0.06	0.05	0.05
Jiangxi	0.29	0.29	0.29	0.26	0.28
Shandong	0.10	0.11	0.11	0.15	0.11
Hunan	0.26	0.27	0.27	0.29	0.29
Sichuan	0.24	0.25	0.27	0.28	0.29
Average	0.19	0.20	0.20	0.21	0.20

Source: Author's own calculations based on Research Center for Rural Economy data.

Table 2.4—Grain production (kg) and yield (kg/*mu*) by province and year

Province	2004	2005	2006	2007	2008
			Total output (kg)		
Heilongjiang	7714.70	8033.63	7806.13	8671.47	9367.56
Jiangxi	3268.45	3596.79	3268.97	3610.66	3476.70
Shandong	2949.44	2998.49	2839.59	3096.20	3288.15
Hunan	2026.46	2207.19	2308.74	2384.65	2748.69
Sichuan	1366.04	1421.85	1338.47	1413.49	1558.72
Average	3465.01	3651.59	3512.38	3835.29	4087.97
			Yield (kg/mu)		
Heilongjiang	217.14	257.53	316.34	298.55	297.74
Jiangxi	418.84	414.94	408.99	412.90	415.39
Shandong	376.78	377.35	375.90	385.59	407.26
Hunan	418.20	413.86	411.58	419.03	419.45
Sichuan	354.86	350.86	337.42	337.90	363.80
Average	357.16	362.91	370.04	370.79	380.73

Source: Author's own calculations based on Research Center for Rural Economy data.
Note: kg = kilogram.

Table 2.5—Input use for grain production over time

Variable Name	2004	2005	2006	2007	2008
Sown area (*mu*)	15.25	15.59	13.29	16.12	16.83
Labor use (days/mu)	14.66	14.50	13.84	13.04	12.39
Cost of agricultural machinery hiring (yuan/mu)	23.05	26.90	32.62	38.42	40.30
Seed expenditure (yuan/mu)	16.37	18.28	18.82	19.96	22.05
Fertilizer use (yuan/mu)	61.73	70.04	74.59	74.76	91.83
Pesticide use (yuan/mu)	15.94	19.84	20.77	21.53	23.01
Cost of irrigation (yuan/mu)	14.83	14.10	16.14	15.83	15.42

Source: Author's own calculations based on Research Center for Rural Economy data.

Table 4.1—Stochastic frontier production translog production function of crop production

Explanatory variable	Pooled Sample (1)	Pooled Sample (2)	Heilongjiang (3)	Shandong (4)	Jiangxi, Hunan, and Sichuan (5)
Log of sown area	–0.201***	–0.202***	0.033	0.365	–0.634***
	(0.04)	(0.04)	(0.13)	(0.27)	(0.05)
Log of labor	0.502***	0.508***	1.152***	0.547***	0.378***
	(0.05)	(0.05)	(0.16)	(0.18)	(0.07)
Log of fertilizer and pesticide	0.835***	0.833***	1.688***	0.087	0.415***
	(0.05)	(0.05)	(0.20)	(0.20)	(0.06)
Log of other inputs	–0.107*	–0.105*	–1.925***	0.005	0.395***
	(0.06)	(0.06)	(0.14)	(0.26)	(0.06)
Log of Sown Area× Log of Labor	0.119***	0.121***	0.203***	0.110**	0.147***
	(0.01)	(0.01)	(0.04)	(0.05)	(0.02)
Log of Sown Area× Log of Fertilizer and Pesticide	0.206***	0.205***	0.335***	0.052	0.157***
	(0.01)	(0.01)	(0.05)	(0.05)	(0.02)
Log of Sown Area×Log of Other Input	–0.130***	–0.129***	–0.421***	–0.084	0.042**
	(0.01)	(0.01)	(0.03)	(0.07)	(0.02)
Log of Labor×Log of Fertilizer and Pesticide	–0.084***	–0.085***	–0.132***	–0.131**	0.025
	(0.02)	(0.02)	(0.04)	(0.05)	(0.03)
Log of Labor×Log of Other Inputs	0.095***	0.095***	0.079*	0.126**	–0.042*
	(0.02)	(0.02)	(0.04)	(0.06)	(0.03)
Log of Fertilizer and Pesticide ×Log of Other Inputs	–0.098***	–0.100***	0.011	–0.120	0.008
	(0.02)	(0.02)	(0.05)	(0.08)	(0.03)
Log of sown area^2	–0.093***	–0.093***	–0.025	–0.037	–0.218***
	(0.01)	(0.01)	(0.02)	(0.04)	(0.01)
Log of labor^2	–0.078***	–0.079***	–0.119***	–0.071**	–0.056***
	(0.01)	(0.01)	(0.03)	(0.03)	(0.02)
Log of fertilizer andpesticide^2	–0.002	–0.001	–0.126***	0.108***	–0.050***
	(0.01)	(0.01)	(0.03)	(0.04)	(0.02)
Log of other inputs^2	0.058***	0.059***	0.199***	0.041	–0.013
	(0.01)	(0.01)	(0.02)	(0.05)	(0.02)
n	9,495	2,594	2,594	1,421	5,480
Chi^2	12,800	12,800	13031.711	8824.089	67946.448
			Elasticity for each input		
Sown area (α_1)	.48	.49	.32	.52	.52
Labor use (α_2)	.09	.09	.24	.08	.03
Fertilizer and pesticide (α_3)	.26	.26	.37	.29	.20
Other inputs (α_4)	.13	.13	.01	.11	.18

Source: Author's own calculations based on Research Center for Rural Economy data.

Note：***、** and * denote significant at 1 percent、5 percent、10 percent, respectively.

Province fixed effect, year fixed effect, and the interaction of province and year fixed effect are all included in the estimation of (1), (2), and (5). Elasticities are computed based on the parameters estimated in the top panel and the sample mean value of the output and input variables.

Table 4.2—Labor allocation and efficiency of crop production

Explanatory variable	Pooled Data		Heilongjiang	Shandong	Jiangxi, Hunan, and Sichuan
	(1)	(2)	(3)	(4)	(5)
Head's age	–0.010***	–0.011***	–0.015***	–0.003	–0.003
	(0.00)	(0.00)	(0.01)	(0.00)	(0.00)
Head's education	0.000	0.000	–0.001	–0.01	0.002
	(0.01)	(0.01)	(0.02)	(0.02)	(0.00)
Party member dummy	0.01	0.013	–0.12	–0.016	–0.015
	(0.05)	(0.05)	(0.09)	(0.05)	(0.04)
Cadre dummy	–0.039	–0.039	0.044	–0.016	–0.023
	(0.03)	(0.03)	(0.04)	(0.03)	(0.03)
Land endowment	–0.032*	–0.042**	0.000	–0.007	–0.135***
	(0.02)	(0.02)	(0.03)	(0.08)	(0.02)
Labor endowment	0.060	0.054	0.011	0.024	–0.005
	(0.07)	(0.07)	(0.09)	(0.07)	(0.06)
Fixed assets	–0.032	–0.033	–0.041	0.016	–0.027
	(0.02)	(0.02)	(0.03)	(0.03)	(0.02)
Share of workers60 or older	0.015	0.043	0.094	0.101	–0.043
	(0.12)	(0.12)	(0.15)	(0.14)	(0.10)
Share of female workers	–0.095	–0.076	0.135	0.043	–0.125
	(0.13)	(0.13)	(0.17)	(0.13)	(0.11)
Share of time spent on local off-farm	–0.079	–0.051	0.023	–0.014	–0.163*
	(0.09)	(0.10)	(0.14)	(0.11)	(0.08)
Share of time spent on migration	0.011	0.111	0.036	–0.136	–0.069
	(0.10)	(0.11)	(0.17)	(0.00)	(0.09)
Land size dummy (=1 if land is bigger than average)		0.051*	0.077**	0.021	–0.01
		(0.03)	(0.03)	(0.08)	(0.04)
Land Size Dummy×Share of Time Spent on Local Off-farm		–0.016	–0.055	–0.046	0.017
		(0.09)	(0.11)	(0.12)	(0.08)
Land Size Dummy×Share of Time Spent on Migration		–0.106	0.147	–0.039	–0.047
		(0.08)	(0.15)	(0.14)	(0.08)
Age(mean for CRE)	0.008*	0.009**	0.024***	0.001	–0.005
	(0.00)	(0.00)	(0.01)	(0.00)	(0.00)
Sch (mean for CRE)	–0.002	–0.002	0.007	0.016	–0.011*
	(0.01)	(0.01)	(0.02)	(0.02)	(0.01)
ln_labor (mean for CRE)	0.002	0.000	–0.238**	0.039	0.192***
	(0.08)	(0.08)	(0.10)	(0.09)	(0.07)
ln_fix (mean for CRE)	0.025	0.025	0.035	–0.001	0.022
	(0.03)	(0.03)	(0.04)	(0.03)	(0.02)
Share of workers older than 60(mean for CRE)	0.067	0.033	–0.087	–0.055	0.132
	(0.13)	(0.13)	(0.16)	(0.00)	(0.11)
Share of female workers(mean for CRE)	0.119	0.100	–0.03	–0.055	0.124
	(0.15)	(0.15)	(0.20)	(0.22)	(0.13)
Share of time spent on local off-farm(mean for CRE)	–0.546***	–0.575***	–0.848***	0.393***	–0.162*
	(0.10)	(0.10)	(0.14)	(0.11)	(0.09)
Share of migration(mean for CRE)	–0.477***	–0.543***	–0.067	0.422***	–0.330***
	(0.12)	(0.12)	(0.18)	(0.12)	(0.09)
n	9,495	9,495	2,594	1,421	5,480
chi^2	128000	128000	13031.711	8824.089	67946.448

Source: Author's own calculations based on Research Center for Rural Economy data. Note: Sch is the head's level of education in household; ***、** and * denote significant at 1 percent、5 percent、10 percent, respectively. Province fixed effect, year fixed effect, and the interaction of province and year fixed effect are all included in the estimation of (1), (2), and (5). CRE =correlated random-effects.