LAND CONSOLIDATION, PRODUCTIVTY AND TECHNICAL EFFICIENCY: [1] EVIDENCE FROM A CROSS SECTION OF FARM HOUSEHOLDS IN CHINA

Authors:

Shen CHENG (Presenter)
Ph.D. Student, College of Economics and Management, China Agricultural University, No.17 Tsinghua East Road, Haidian District, Beijing, China, 100083;
Visiting Scholar, Department of Agricultural and Resource Economics, University of Connecticut, 1376 Storrs Road, Unit 4021, Storrs, CT, 06269-1182.
Email Address: shen.cheng@uconn.edu

Boris E. Bravo-Ureta
Professor, Department of Agricultural and Resource Economics, University of Connecticut, 1376 Storrs Road, Unit 4021, Storrs, CT, 06269-1182.
Adjunct Professor of Agricultural Economics, Universidad de Talca, Chile.
Email Address: boris.bravoureta@uconn.edu

Zhihao Zheng
Professor, College of Economics and Management, China Agricultural University, No.17 Tsinghua East Road, Haidian District, Beijing, China, 100083.
Email Address: zhihao.zheng@cau.edu.cn

Hao Sun
Research Assistant, Research Center for Rural Economy, No. 56 Xisi Zhuanta Hutong, Xicheng District, Beijing, China, 100810.
Email Address: holt_s@163.com

Selected Paper prepared for presentation at the 2017 Agricultural & Applied Economics Association Annual Meeting, Chicago, Illinois, July 30-August 1

[1] This study was funded by the Planning Fund on Humanities and Social Sciences of the Ministry of Education, China. No. 13YJA790162.

Abstract:

This article aims to examine whether increasing farm size will improve land productivity for wheat, rice, maize and soybeans under conditions of rapid agrarian transformation in China. We apply panel data methods, including True Fixed Effects (TFE), True Random Effects (TRE) and True Random Effects with Mundlak adjustment (TRE-Mundlak) models to household-level cross-section data from 30 provinces in China in 2011. These models not only enable us to focus on the traditional inverse relationship (IR) measures while controlling for unobservable village-level heterogeneity, but also make it possible to measure managerial performance, namely technical efficiency, across farm size groups. The results show that after controlling for village-level heterogeneity, there is still a significant IR between land productivity and farm size in all the dominant sub-regions for wheat, rice, maize and soybeans, indicating that farms with smaller land holdings do enjoy a land productivity comparative advantage. Thus, from the perspective of protecting food security, the effort to promote consolidation could come at the expense of grain production and therefore should not be pursued.

Key Words: Inverse Relationship, Village-level Heterogeneity, True Fixed or Random Effects

1. Introduction

China has a long history of policies designed to boost agricultural output and increase productivity. Several decades of strong performance in the farming sector are evidence that these policies have borne fruit. These gains have been achieved on some of the smallest farm sizes in the world. Of the world total of small farms, 87% are in China, where 193 million small farms average less than 15 mu (one hectare) and account for 40% of all small farms worldwide. However, in recent years, policymakers have attempted to boost productivity through the promotion of larger scale and more mechanized farms. According to the survey from the Ministry of Agriculture, by the end of 2015, 29.8 million ha of cultivated land had been rented out, which accounted for 33.3 percent of total cultivated land under the household responsibility system, a number four times greater than in 2008. Meanwhile, nearly 3.41 million rural households were operating more than 3.33 ha of cultivated land. Interestingly, a substantial body of literature has emerged over the past few decades that offers no consistent evidence that expanding farm size increases productivity in developing country agriculture. On the contrary, in such countries an inverse relationship (IR) between farm size and land productivity is a relatively well-established empirical occurrence. What about China? Compared to related studies carried out in some developing countries (like India, Pakistan, Brazil, and so on), fewer studies have addressed the farm size-productivity relationship for China, and those that do use relatively outdated data sets that cannot represent the present situation after a decade of rapid agricultural change in China.

China's agriculture production environment has changed dramatically especially in recent years. During the past decades, China's unskilled wage has been increasing at an accelerating rate, which leads to more and more young, strong, and better educated agricultural laborers moving to off-farm sectors of the economy. As a result, the agricultural sector has exhibited a net loss of productive labor. In 2015, the number of migrant workers in China reached 277 million, which was nearly 20 percent of the population. At the same time, with the large-scale outflow of rural labor, the labor input per household in rural areas declined rapidly. According to De Brauw et al. (2013), the labor input per household in rural areas dropped from 3,500 hours in 1991 to 2,000 hours in 2000. In 2009, the average household labor force in rural areas was only 1,400 hours. In addition, the use of machines, chemical fertilizers, and irrigation has increased 9.9, 6.2 and 2.3 percent respectively every year[2] from 1990 to 2014, indicating that the farm structure is undergoing process of capitalization and mechanization.

Some researchers have argued that an essential precondition for the existence of the inverse relationship phenomenon is technical backwardness, suggesting that with advances in technology, the inverse relationship could vanish (Ghose, 1979; Huffman and Evenson, 2001)). Additionally, because of increasing non-agricultural income and the relatively low economic value of agriculture, rural households have been becoming less interested in agriculture, ignoring their own labor costs and over-supplying inputs. So, it is hard to say whether small is beautiful in this current transitional period, which makes re-examination of the farm size-productivity relationship more significant, as this will enhance policies designed to promote agricultural restructuring and development.

The objective of this paper is to examine whether increasing farm size will improve productivity as China undergoes rapid agrarian transformations. This study makes two principal contributions. First, in recent years, the Chinese Government has been making great efforts to promote land consolidation, including separating the three rights to cultivated land (land property right, land contract right, and land operation right), increasing the number of land transfer service centers, providing policy support to large farms, and so on. If the results in this study show that increasing farm size increases land productivity, those land consolidation policies would be pursued; if it finds otherwise, we should re-consider those policies. Second, we examine the land size-productivity relationship using stochastic frontier methods, which is novel in the IR literature, and cross-sectional data, while controlling for unobservable village level heterogeneity. To accomplish our objective, we rely on panel data methods, namely the True Fixed and True Random Effects (TFE and TRE) models. Moreover, the combination of the available data and the models proposed will enable us to control for different sources of heterogeneity, thus addressing criticisms that have been raised about some of the available studies. In addition, using frontier methods will make it

[2] China Statistical Yearbook, 2014.

possible to focus not only on the traditional IR measures but also on managerial performance across farm size groups. Finally, our conclusions can provide not only useful insights for land policy and land reforms in China but also for other developing countries.

The rest of this paper is arranged as follows: Section 2 is the literature review. In Section 3, we discuss the econometric models. Section 4 presents the data analysis and the empirical model. In Section 5, we discuss the estimation results and compare the estimators in different econometric models and sub-regions. Section 6 provides conclusions and discussions.

2. Literature Review

While the farm size-productivity relationship has been the subject of debate among development economists, an inverse relationship (IR) between farm size and land productivity in developing countries is a relatively well-established empirical observation. An inverse relation between farm size and productivity has three main explanations: (1) imperfect factor markets, (2) omitted variables, in particular, omitted controls for land quality, and (3) statistical issues related to the measurement of plot size.

Imperfect factor markets (labor, land, capital, insurance) are linked to differences in the shadow price of production factors that, in turn, lead to differences in the application of inputs per unit of land in ways that are correlated with farm size. Many of the earlier contributions to the IR debate focused on testing this type of explanation (Sen, 1966; Feder, 1985). Using the data from India, Lamb (2003) examined the impact of labor market imperfection on the IR, showing that after putting the variables of work days and unemployment rate, which represent the movement of labor market, into the function, there is no IR. Besides, Feder (1985) also noted that a single market failure is typically insufficient to generate the inverse relationship. Under constant returns to scale, the explanations for the IR likely depend on market failures that prevent land subdivision and distort the shadow price of some productive factors. Moreover, as noted by Barrett (1996), risk concerns, like incomplete insurance markets could also generate the inverse relationship.

The second type of explanation supposes that the IR arises due to omitted variables. Assunção and Ghatak (2003) demonstrated how theoretically unobserved heterogeneity in farmer quality may explain the observed differences in productivity. Farmer self-selection would generate the inverse relationship. Some other studies attributed the existence of the IR to omitted controls for land quality. Using a farm-level data set from Java, Benjamin (1995) posited that the omitted soil variables explained the inverse relationship. Assunção and Braido (2007) found that the IR in rural India is related to unobserved characteristics of the plot rather than the household, such as the peasant mode of production or increasing supervision costs. To compensate the shortage of omitted plot-specific soils data, Barrett et al. (2010) used more precise variables like soil PH, silt, potassium, and so on to represent the quality of land per plot; however, their results show that no part of the IR can be explained by differences in land quality.

The third explanation supposes that the IR arises due to measurement errors in land data. Lamb (2003) used instrumental variables (dummy variables for sharecropping or renting land and double-cropping) to control the measurement errors of farm size and showed that measurement error in the farm size variable likely plays a role, especially in fixed effects estimates. Barrett et al. (2010) also support this view. Similarly, Chen et al. (2011) applied the number of dependents and a dummy variable indicating presence of a household member with urban *hukou* registration as the basic set of instruments for cultivated land in China, and showed that the inverse relationship disappears after using these instruments. Carletto et al. (2013) revisited the role of land measurement error in IR by making use of data from a nationally representative household survey from Uganda, in which self-reported land size information is complemented by plot measurements collected using Global Position System (GPS) devices; their findings indicate that using an improved measure of land size does not weaken but rather strengthens the evidence supporting the existence of the IR.

Compared to studies carried out in some developing countries (like India, Pakistan, Brazil, and so on), fewer studies have addressed the farm size-productivity relationship for China. Benjamin and Brandt (2002) attributed the IR in Chinese agriculture to the local administrative (instead of market) allocation of land and the extent of unevenly developed non-agricultural opportunities. However, Chen et al. (2011) still insisted that the IR may be explained by the unobserved land quality rather than to something inherent to China's agricultural system. Using a sample of 548 households in 48 Chinese villages from 1987-2002, Gao and

Zhang (2006) showed that the IR still existed by using IV estimation and fixed effect models to control for selection bias and heterogeneity of land quality. Based on the data from Fixed Observation Rural Households System between 2004 and 2006, Xin et al. (2009) divided the land scale of farm households into six levels and then validated the inverse relationship. Their results indicated that the relationship between farm size and productivity is not simply linear: while it is obviously inverse when farm-size is larger than 30 mu, this inverse relationship has not been found among smaller households. By using the farm level panel data collected in Hubei province from 1999-2003, Li et al. (2013) examined the IR from a novel angle by using multiple definitions of farm efficiency indicators: land productivity, labor productivity, profit ratio, total factor productivity (TFP), and technical efficiency (TE), and found that farm size and land productivity have a strong inverse relationship, while farm size and labor productivity have a significant positive relationship. Farm size and TFP and TE demonstrate no significant relationship. Adding household-specific variables, soil quality variables, and plot dummy variables to control for household-specific market imperfections, the soil quality omission problem, and farm size measurement error, Wang et al. (2015) measured the farm size-productivity relationship on plot level seasonal data and plot level yearly data from 2011 for China and India, and showed that a strong positive plot size-productivity relationship exists both seasonally and yearly by both measurements in China, taking multiple cropping into consideration. In India, however, the IR has been confirmed despite recent changes. Rada et al. (2015) assessed the potential impacts of farm scale expansion on both yields and per hectare economic returns at the national and provincial levels by employing a 2003-2007 unbalanced farm-household production dataset, and found that for the whole nation, cropland consolidation would dampen yields or have little effect on net returns. However, the pooled provincial data revealed opportunities for grain farms to become larger without reducing yields: assuming minimal transaction costs, then, land will be likely consolidated in most provinces without government intervention.

Most of the existing articles on China used outdated data that cannot represent the relationship between farm size and productivity under the present situation of rapid agrarian transformation. Besides, the data they used are restricted to just one or a few provinces. Because planting structure, agricultural technology, climate, and even institutions could vary drastically from one region to another in China, the results, conclusions, and policy implications for the whole nation could have great limitations. What is more, the majority of studies investigating the IR rely on grain or farming (including both main grain crops and other cash crops) sector, and quite few studies focus on the IR for distinct grains. We might get totally different conclusions if we look at diverse grains. To overcome these shortcomings, in this paper we want to verify whether the IR holds for wheat, rice, maize and soybeans in respective dominant regions and sub-dominant regions, using 2011 cross-section farm-household data from 30 provinces in China.

We also use stochastic frontier methods to examine the IR, which is quite infrequent in the related literature. And we apply panel data methods, namely the True Fixed and True Random Effects (TFE and TRE) models to cross-section data, which will enable us to control for village level unobserved heterogeneity, like the quality, location, and terrain of land; climate; management; economic development; and so on. In addition, using frontier methods will make it possible to focus not only on the traditional IR measures but also on managerial performance across farm size groups.

3. Econometric Models

The traditional approach to testing the inverse relationship is to regress farm output per area of operated land on farm size or cultivated land area. A negative coefficient on land indicates an inverse relationship. Such a simple regression, however, does not account for bias from unobserved farmer heterogeneity or other variables. In this section, we plan to use the True Fixed Effects and True Random Effects models, which were introduced by Greene (2005) to measure time-variant technical efficiency in the stochastic frontier model for panel data in order to test the relationship between farm size and productivity. The major advantage of these models is that we can account for unobserved village level heterogeneity on cross-section data and also measure household level TE, which is novel in the IR literature.

Stochastic frontier analysis

Following Schmidt and Sickles (1984), who introduced a panel data specification in which the farm-specific stochastic term is interpreted as inefficiency, this model for production function can be defined as:

$$y_{it} = \alpha + x'_{it}\beta + v_{it} - u_i \tag{1}$$

The model can also be expressed as

$$y_{it} = \alpha_i + x'_{it}\beta + v_{it}, \tag{2}$$

where y_{it} is the logarithm of output, x'_{it} are the regressors, α and β are the coefficients to be estimated, v_{it} is the error term capturing noise, and $\alpha_i = \alpha - u_i$ is the common firm-effect of the fixed-effects model. In the production frontier literature, the inefficiency scores $\hat{u}_i$ are estimated as the distance from the firm specific intercept $\hat{\alpha}_i$ to the maximum intercept in the sample, $\hat{u}_i$=max$_i$ ($\hat{\alpha}_i$) - $\hat{\alpha}_i$. The fixed effects specification is estimated as a within estimator without any additional distribution assumption on α_i, since they are treated as firm constants. Thus, the consistency of the coefficients does not require the assumption that regressors are uncorrelated with the individual effects.

Based on Greene (2005) and Abdulai and Tietje (2007), the limitation of Schmidt and Sickles' model is that by interpreting the farm-specific term as "inefficiency," any unmeasured time-invariant inter-firm heterogeneity must be assumed away. Secondly, the inefficiency is assumed to be time invariant, which could lead to a biased estimation. Battese and Coelli (1992 and 1995) proposed alternative forms of deterministic variation of inefficiency with time. According to Greene (2005), their model can be written as:

$$U_{it} = g(Z_i, t, T) \times |U_i| , \tag{3}$$

in which Z_i is a vector of firm-specific covariables, *t* indicates variation over time, *T* is the number of periods, and *g(·)* is a deterministic, positive function such as *exp(·)*. This model overcomes the one of the shortcomings in Schmidt and Sickles's model, which assumes independence over time of the efficiency terms. However, this model still cannot solve the problem that any time-invariant unobserved heterogeneity is pushed onto the inefficiency component.

To account for the above limitations, Greene (2005) introduced two stochastic frontier models that are time-variant and which distinguish unobserved heterogeneity from inefficiency. These models are the True Fixed Effects (TFE) and the True Random Effects (TRE) models. The True Fixed Effects model is expressed as:

$$y_{it} = \alpha_i + x'_{it}\beta + v_{it} - u_{it} \quad (4)$$

$$u_{it} \sim N^+(0, \sigma_u^2),\ v_{it} \sim N(0, \sigma_v^2), \quad (5)$$

where α_i represents farm-specific fixed effects (FE) measuring heterogeneity, v_{it} captures the measurement error, and u_{it} is the time-varying inefficiency term. Given that we only have farm level cross-sectional data, we need to change the understanding of observations for a different time period for a given firm by that of different subunits within a given time and for a given firm. Thus, in this study such subunits are separate households that produce different quantities and types of grains, with different levels of inputs as well as differences in other observable characteristics and time to village level invariant heterogeneity. Therefore, our estimating strategy not only accounts for unobserved village level heterogeneity, but also allows for the measurement of household level TE. The True Fixed Effects model for cross-section data is expressed as:

$$y_{ih} = \alpha_i + x'_{ih}\beta + v_{ih} - u_{ih} \quad (6)$$

$$u_{ih} \sim N^+(0, \sigma_u^2),\ v_{ih} \sim N(0, \sigma_v^2), \quad (7)$$

where α_i represents village-specific fixed effects measuring heterogeneity, x'_{ih} are the regressors for household h in village i. v_{ih}captures the measurement error, and u_{ih} is the household-varying inefficiency term. This model is estimated by maximum likelihood. In contrast to the usual FE model mentioned above, in which the fixed effects are the interpreted as inefficiency, the fixed effects in Greene's model represent unobserved heterogeneity. The FE specifications have the advantage that they control for correlation between individual effects and the explanatory variables. However, they do not account for special invariant variables, which is a major advantage of the random effects (RE) formulation. The True Random Effects model for cross-sectional data, which combines a conventional random effect model with a household variant term representing inefficiency, can be represented as:

$$y_{ih} = \alpha_0 + \omega_i + x'_{ih}\beta + v_{ih} - u_{ih,} \quad (8)$$

where ω_i is a farm-specific random term assumed to capture village-specific heterogeneity, while other variables are as defined in equation (7). Give that the regression model appears to have three different disturbances, the question of identification could be raised. However, Greene (2005) argued that such an interpretation would be misleading, since the model actually has a two-part composite error term. The model can be specified as:

$$y_{ih} = \alpha_0 + \omega_i + x'_{ih}\beta + e_{ih}, \text{ where } e_{ih} = v_{ih} - u_{ih} \tag{9}$$

Equation (9) is an ordinary RE model, and the error term e_{ih} has the asymmetric distribution in equation (10). Based on Greene (2005), the conditional (on ω_i) density is that of the compound disturbance in the stochastic frontier model,

$$f(e_{ih}) = \frac{\Phi\left(-\frac{e_{ih}\lambda}{\sigma}\right)}{\Phi(0)}\frac{1}{\sigma}\Phi\left(\frac{e_{ih}}{\sigma}\right), \tag{10}$$

where $\lambda = \sigma_u/\sigma_v$, and $\sigma = \sqrt{\sigma_u^2 + \sigma_v^2}$. The error term does not have a normal distribution. Given that the unconditional likelihood function possesses no closed-form solution, Greene (2005) suggested employing Maximum Simulated Likelihood Estimation method, by integrating out ω_i through Monte Carlo methods.

The random effects model can overcome the shortcoming in FE model, which does not account for spatial-invariant variables. It is important to note that because the random effects framework assumes that farm-specific random terms are uncorrelated with explanatory variables, it could lead to biased estimates. A way to circumvent this problem is the TRE-Mundlak model, which employs the True Random Effects model suggested by Greene (2005) and extends it with the specification proposed by Mundlak (1978). This model helps to eliminate the heterogeneity bias problems and to account for unobserved heterogeneity that is correlated with the explanatory variables. Basically, Mundlak's approach involves modelling the correlation of unobserved heterogeneity with regressors in an additional equation, under the assumption that the unobserved environmental condition factors are correlated with the group means of the explanatory variables (Mundlak terms). To account explicitly for this correlation, an auxiliary regression can be introduced (Mundlak, 1978; Abdulai and Tietje, 2007):

$$\omega_i = x'_{ih}\gamma + z_{ih,} \tag{11}$$

where x'_{ih} represents a vector of explanatory variables for household h in village i, and γ is the vector of parameters to be estimated. Now, averaging over household h for a given village i results in:

$$\omega_i = \gamma \overline{x_\iota} + \overline{z_\iota} \tag{12}$$

It is also assumed that $\overline{z_\iota} \sim N((0, \overline{\sigma^2_{\overline{z_\iota}}})$. Equation (12) can be incorporated into (9) as:

$$y_{ih} = \alpha_0 + \gamma \overline{x_\iota} + \overline{z_\iota} + x'_{ih}\beta + e_{ih} \tag{13}$$

This model decomposes the village-specific component into two effects, the first part being explained by the explanatory variables and the remaining component assumed to be orthogonal to the explanatory variables. According to Mundlak (1978), the heterogeneity bias for u_{ih} will be minimal, considering the correlation between the individual effects and the explanatory variables. An additional advantage is that space-invariant variables can easily be included in the model to be estimated.

In order to compare the performance of different models and get robust results, we plan to estimate the True Fixed Effects (TFE), True Random Effects (TRE), and TRE-Mundlak models together.

4. Data Analysis and Empirical Model

The data are taken from a large comprehensive Chinese rural household survey conducted by the Research Center for the Rural Economy (RERC), which is part of China's Ministry of Agriculture. Sampling for the original data set was conducted by provincial officers under the auspices of the Ministry of Agriculture. Each provincial office first selected equal numbers of upper, middle and lower income counties and then chose a representative village in each county. In total, 40-120 households were randomly surveyed within each village. The dataset for this study consists of 19,912 randomly selected households from 371 villages and 30 provinces and administrative regions, in 2011, which covers most of the provinces in China (except Tibet, Hong Kong, Macau, and Taiwan). After selecting the households that plant grains and deleting some samples which contained obvious data recording errors and missing information, we got a total of 3,490 valid wheat-planting households, 4,658 rice-planting households, 5,420 maize-planting households, and 1,037 soybean-planting households, respectively. This survey provides a longitudinal data set on household socio-demographic characteristics, arable land, assets, production, sales of agricultural products, expenditures on production, and total household income and expenses, which provide us more detailed household level characteristics and production information.

The dataset contains disaggregated input-output variables for different kinds of grains (including wheat, rice, maize, soybeans, and others), which makes it possible to examine the IR separately for major grains. Considering grain planting structures and the wide range of agroecological and climatic variability in China, we separate the 30 provinces into six sub-regions: Northeast, Huang-Huai-Hai Watershed, Yangtze Watershed, Southeast, Southwest, and Northwest. For more details, see Fig.1 and Table 1.

In this paper, we test the IR hypothesis on rice, maize, wheat, and soybeans using distinct models for the dominant sub-region which produced the most of that kind of grain in China and sub-dominant sub-regions whose share of wheat, rice, maize, or soybean production is more than 10 percent. According to Table 1, for wheat, the dominant sub-region is Huang-Huai-Hai watershed, which produced 58.14 percent of China's wheat production in 2011; sub-dominant sub-regions are Yangtze Watershed and Northwest, which accounted for 22.32 percent and 11.36 percent of wheat production, respectively. For rice, the dominant sub-region is Yangtze Watershed and sub-dominant sub-regions are Northeast, Southeast, and Southwest. For maize, the dominant sub-region is Northeast, and sub-dominant sub-regions are Huang-Huai-Hai watershed and Southwest; for soybeans, the dominant sub-region is Northeast, and sub-dominant sub-regions are Huang-Huai-Hai watershed, Yangtze Watershed, and Southwest.

Table 2 shows the definitions of all the variables used in this paper. Grain output in our study refers to the wheat, rice, maize, and soybeans produced in 2011. Considering multiple cropping, we define farm size as total actual planted area (measured in mu[3])over the previous year, which corresponds to our best measure of land input in production. This differs from many previous studies that used cultivated land to indicate farm size. According the Benjamin (1995), using cultivated land rather than total actual planted area could induce measurement error and itself cause the inverse relationship. The inputs include labor (family and hired labor days), capital (animals and machinery costs) and other input costs (seed, organic fertilizer, inorganic fertilizer, plastic mulch, pesticide, electrification and irrigation, fixed asset depreciation and maintenance, tools, and other indirect expenditures).

[3] 1 hectare = 15 mu

Besides farmland, labor, capital, and other input costs, some farm endowment variables are included in the function to control for heterogeneity at the household level. These variables include household size (number of residents for each household), land fragmentation (the number of plots), household head's age (proxy for farming experience, e.g., Chen et. al 2011), household head's gender and education (proxy for managerial ability, e.g., Chen et. al (2011); Huffman (1974); Yang (1997)), and whether there are village officers in the household (1 = there are village officers in household; 0 = none).

Table 3 summarizes the variables used in our econometric models. Farm size in our analysis is defined as planted area, specified in mu. Wheat, rice, maize, and soybean yields are defined as the ratio of kilograms (kg) produced to planted area. Pooling households that planted a grain crop in 2011, the sample's average wheat producer, planting only 4.23 mu, is smaller than a rice (5.28 mu), maize (7.61 mu), or soybean (17.20 mu) producer. In dominant and sub-dominant sub-regions, the average farm size is 3.99 mu and 4.76 mu, respectively, for wheat; 6.00 mu and 5.03 mu for rice; 14.75 mu and 4.05 mu for maize; and 36.86 mu and 2.88 mu for soybeans. These sizes are in line with the 3.45 mu for wheat, 4.35 mu for rice and 5.85 mu[4] for maize that Rada et. al (2015) report for China for 2003-2007. The sample's average crop yields are higher for maize producers than for wheat, rice or soybean producers. Moreover, the rural households, on average, had 4.56 plots, 6.74 plots, 5.14 plots and 6.18 plots planted in wheat, rice, maize, and soybean, respectively, which suggests that land fragmentation in China is evident.

Figures 2-5 present the nonparametric estimation results showing the relationship between the yield of wheat, rice, maize, and soybeans and their respective planted areas in dominant sub-region and sub-dominant sub-regions. For wheat, there is an obvious declining trend as planted area increases in dominant sub-regions. In sub-dominant sub-regions, the yield goes down slightly when the planted area is less than 10 mu. When the planted area is greater than 10 mu but less than 20 mu, wheat yields increase; when the planted area is more than 20 mu, yield declines. The figures for rice tell us that there is an IR in the dominant sub-region; while in sub-dominant sub-regions, the yield of rice declines at first and then increases as the

[4] Rada et. al (2015) reported the data in hectares. All the data have been converted from hectares to mu (1 hectare = 15 mu) in order to draw a comparison.

planted area surpasses 10 mu. Considering maize, there is no obvious IR in either dominant or sub-dominant sub-regions, while for soybeans, we know from both the dominant sub-region and sub-dominant sub-regions that there is declining trend as planted area increases.

Moreover, we also find that the vast majority of rural households plant less than 10 mu of wheat both in dominant sub-regions and sub-dominant sub-regions. The rice-planted area for most of the observations is less than 20 mu in the dominant sub-region and 10 mu in sub-dominant sub-regions. As for maize, the sample is centered within 20 mu in dominant sub-regions and 10 mu in sub-dominant sub-regions. Most of the observations for soybean planting are less than 20 mu in the dominant sub-region and three mu in sub-dominant sub-regions. The data distribution suggests again that China's grain planting is uniquely characterized by small scale farms.

Empirical Model

We estimate the following model, which takes the Cobb-Douglas form, to test the relationship between farm size and productivity.

$$\ln\left(\frac{Y_{ih}}{T_{ih}}\right) = \alpha_i + \beta_1 \ln(T_{ih}) + \beta_2 \ln\left(\frac{L_{ih}}{T_{ih}}\right) + \beta_3 \ln\left(\frac{K_{ih}}{T_{ih}}\right) + \beta_4 \ln\left(\frac{C_{ih}}{T_{ih}}\right) + \beta_5(\hbar ousesize_{ih})$$
$$+\beta_6(plot_{ih}) + \beta_7(age_{ih}) + \beta_8(gender_{ih}) + \beta_9(edu_{ih}) + \beta_{10}(officer_{ih})$$
$$+ V_{ih} - U_{ih} \tag{14}$$

The left-hand variable is the log of annual production for each grain per mu of planted land. The right-hand variables include farm size, T_{ih}, farm labor per mu, $\frac{L_{ih}}{T_{ih}}$, capital per mu, $\frac{K_{ih}}{T_{ih}}$, and other input costs. $\frac{C_{ih}}{T_{ih}}$, α_i denotes village fixed effects in FE models; in TRE or TRE-Mundlak models, $\alpha_i = \alpha_0 + \omega_i$. The control variables include household size, the number of plots, the age, gender and education of the head of household, and whether there are village officers in household. In a constant-return-to-scale economy with perfect factor markets, there should be no observed differences in productivity across farm sizes; that is, $\beta_1 = 0$. Soil quality should also be consistent among households. Egalitarian motives on the part of the benefactor during the local village council's land allocation process would result in higher quality parcels being divided more often than low quality parcels. The negative correlation between farm size and soil quality and the positive correlation between soil quality and yields can, in theory, produce downward bias in the relationship between farm size and yields. Fortunately, Barrett et al. (2010) dismiss such concerns using a unique plot-level production data set. The tests and results of the estimations are shown in Table 4 and Table 5.

5. Results

In order to choose which model is best for the samples in dominant sub-regions and sub-dominant sub-regions for wheat, rice, maize and soybean, we do the Hausman test and Likelihood-Ratio test separately. The results are shown on Table 4. A Hausman test of the null hypothesis that the village-specific effects are uncorrelated with the explanatory variables is conducted in the model, which is used to examine the TFE Model and TRE Model. The test result in wheat dominant sub-region rejects the null hypothesis, suggesting that specifications that do not account for these correlations may produce biased and inconsistent results. We get the same results in rice sub-dominant sub-regions, maize sub-dominant sub-regions and soybean sub-dominant sub-regions. Thus, the TRE model, which assumes lack of correlation between the farm-specific effects and the included variables, may be too restrictive and provide inferior estimates compared with TFE Model in these areas (Abdulai and Tietje, 2007). For wheat sub-dominant sub-regions and rice dominant sub-regions, the null hypothesis of the Hausman test is that the village-specific effects are correlated with the explanatory variables, because when we use the original Hausman test, the chi^2 is negative, suggesting the Hausman test failed. After changing the null hypothesis, the results in both of two places shows that we can’t reject the null hypothesis, indicating the TFE Model is better. However in maize and soybean dominant sub-regions, the null hypothesis which prefers the TRE Model can’t be rejected, suggesting TRE is superior to TFE in these two areas.

The Likelihood-Ratio test (LR) whose null hypothesis is that the Mundlak terms are jointly equal to zero, is carried out the test the TRE Model with Mundlak adjustment versus no Mundlak adjustment. All of the tests in 8 sub-regions show that the null hypothesis should be rejected, indicate not all the auxiliary coefficients in the TRE-Mundlak model are zero. Thus, for both models, Mundlak adjustment is significant in ensuring consistent results. When compared the TFE and TRE, not all the samples prefer TFE; however when the TRE and TRE-Mundlak are taken into consideration, TRE-Mundlak always perform better. Thus, TRE with Mundlak adjustment is the superior model among the three models, which not only accounts for the correlation between the explanatory variables and firm-specific heterogeneity and decrease the heterogeneity bias efficiently, but also allowing space invariant variables into the model.

Estimates of wheat, rice, maize, and soybean samples on farm size's effects on yields in dominant and sub-dominant sub-regions are provided, respectively, in Table 5 with TRE-Mundlak Model. The estimated coefficients represent the percentage changes in the dependent variable associated with a 1 percent increase in each of the explanatory variables. The estimators of farm size for wheat are negative and statistically significant, confirming an IR between farm size and wheat yield. Hence, our results suggest that even under the transformation of agriculture in China, farms with smaller land holdings do enjoy a land productivity comparative advantage for planting wheat.

In the wheat dominant sub-region, the coefficient of farm size is -0.053: increasing wheat planting area by 1 percent results, on average, in a 0.053 percent decrease in wheat output per mu. In addition, except capital (animal and machinery cost), labor and other inputs have the expected significant positive effect on yield. In wheat sub-dominant sub-regions, the absolute estimator of farm size is smaller than that in dominant sub-region, which means that the IR in wheat sub-dominant sub-regions is weaker. Moreover, the estimators of household size and village officer are significantly positive, indicating that the wheat yield grows as there are more residents or there are village officers in a farm household. Besides, compared to female household holder, the male household holder does good to the yield.

Column 3-4 of Table 5 show the regression results for rice in dominant sub-region and sub-dominant sub-regions. Even controlling for with village level heterogeneity, rice yield and planted area still showed a significant negative relationship. And this negative effect is not only applicable to the dominant producing areas of rice, but also to the sub-dominant sub-regions. The results indicate the characteristics of small-scale traditional agriculture for rice planting. For the dominant rice producing areas, the yield will be reduced by 0.029 percent with a 1 percent increase in acreage, and this estimator in sub-dominant producing areas is -0.056 percent. Besides, in both of the dominant sub-region and sub-dominant sub-regions, the increasing of household head age is not favorable to the rice yield; and the village officers in household benefit the rice yield.

The regression results for maize are shown on column 5-6 of Table 8. There is also a significant IR both in dominant sub-region and sub-dominant sub-regions. The estimated elasticity of land and output tells us that in dominant sub-region of China, if the planted acreage of maize is doubled, the yield per acre will decrease by about 3.4 percent. The increase in labor force, animal power, machinery and other inputs, however, contributed significantly to maize yield. In sub-dominant sub-regions, when the planted acreage is doubled, the yield will decrease 2.3 percent, which is a little bit smaller than that in dominant sub-regions. And as the age and education of household head grows, the maize yield will also increase. Moreover, compared to household holder, the male household holder does good to the yield.

Column 7-8 show the regression results for soybeans in the dominant sub-region and sub-dominant sub-regions. In the dominant sub-region(Northeast), the output-size elasticities are -0.042 at the 10 percent significance level, showing a significant IR in dominant planting areas for soybeans. However, there is no significant IR in the sub-dominant sub-regions.

Table 6 lists the estimators related to land productivity and farm size in China in the existing literature, and shows that the coefficients are quite different among different studies. Gao and Zhang (2006) and Li et al. (2012) have a slight overlap in the time span of the sample data, and the coefficients are similar, with both showing a significant IR. But the dependent variables they used are different: Gao and Zhang (2006) used physical quantities per area and Li et al. (2012) used the value per area. Based on the data from 1995 to 1999, Chen et al. (2011) used total annual output of grain as the output indicator, and the coefficient of land was almost equal to 1, which proved that there was no IR. Wang et al. (2015) also indicated that there was no significant IR between rice yield and planted area by using 2007-2010 plot-level data for rice. Fan and Zhou (2014) used 2010 data and showed that there is a significant positive correlation between the yield per mu of rice and the planted area. In this paper, we use household data for 2011 and show that there is an IR in dominant sub-regions for wheat, rice, maize, and soybeans. The estimated output-size elasticities for each grain are much like results in Rada et al. (2015), but a littler smaller, suggesting that the negative relationship is weak. We argue that the coefficient gap among different studies is due to diverse sample selection and the differing time spans, which result in some differences in the results. In addition, measures of output vary widely among researchers, some of whom measured by output value and others by quantities. Third, farm size measurements were also quite different, with some based on cultivated area and some on the planted area. Benjamin (1995) points out that the IR with cultivated area is stronger than for planted area considered for multiple cropping. However, while the early data showed a trend toward a stronger IR, recent data suggested the IR is weaker.

In addition to the parameter and output elasticity estimates, technical efficiency (TE) scores are also estimated for the individual models to describe managerial performance across farm size groups. The average TE scores for wheat, rice, maize, and soybeans in the three models are shown in Table 7. Specifically, the wheat TE score in dominant planting areas is about 0.86, and the results of the three models are very close. In contrast, the TRE-Mundlak achieves the greatest TE score. The TE scores in three models are also very similar in wheat sub-dominant regions, although a little less than in the dominant sub-region. And we can get the highest TE score and lowest dispersion in the TRE-Mundlak model. For rice in dominant planting areas, the TE score in TFE is the highest, 0.841 exactly, and the differences between TE across farms in TFE are also the least. The rice planting farms in sub-dominant regions on average show a significantly lower TE score than those in dominant planting areas. Among the three models, we also get the highest TE score and lowest dispersion in TFE model. The TE scores obtained from the three models for maize in dominant planting areas are also quite close, but the TRE-Mundlak TE score is highest and least volatile. Similarly, for maize in sub-dominant sub-regions, we find that the mean TE scores in the TFE and TRE-Mundlak models are very similar, and higher than that in the TRE. We also find that for soybeans in both dominant and sub-dominant planting areas, the TFE and TRE-Mundlak TE scores always are higher than those in TRE models, and less volatile.

Therefore, the results above suggest that farms in dominant sub-regions show higher TE scores than those in sub-dominant sub-regions for each crop. Among the three models, the TFE and TRE-Mundlak models generally estimates the similar TE score, and has the higher scores and lowest standard deviation when compared with TRE Model. This shows that when the unobserved heterogeneity is taken into consideration in the TFE and TRE-Mundlak Models, the differences in TE across farms fall substantially.

6. Discussion and Conclusions

Using farm level data from 2011, for 30 provinces in China, we investigate the relationship between land productivity and farm size for wheat, rice, maize and soybeans under conditions of rapid agrarian transformation. We use stochastic frontier methods and cross-sectional data while controlling for unobservable village-level heterogeneity. To accomplish our objective, we rely on panel data methods, namely the True Fixed Effects (TFE), True Random Effects (TRE), and True Random Effect with Mundlak adjustment (TRE-Mundlak) models. The combination of the available data and the models enables us to control for different sources of heterogeneity, thus addressing criticisms that have been leveled at some of the available studies. In addition, using frontier methods, we focus not only on the traditional IR measures but also on managerial performance across farm-size groups. We focus on whether IR, which is a relatively well-established empirical occurrence, applies to the transition period in China. Our conclusions are not only applicable to China but also have great significance for other developing countries. As such, this research enriches the empirical field on the IR hypothesis with a case study of China.

Our basic conclusions can be summarized as follows. First, for most of the areas, the regression results in TFE and TRE-Mundlak models are superior to the TRE model. Thus, the TRE model, which assumes lack of correlation between the farm-specific effects and the included variables, may be too restrictive and provide inferior estimates. Second, there is a significant IR between land productivity and farm size in all the dominant sub-regions of China for wheat, rice, maize and soybeans. The results show that even when the village level unobserved heterogeneities and farm-level characteristics are controlled, small households still perform better than large households. Besides, we find the IR for wheat and rice and maize, for soybeans there is neither a significant nor a positive relationship between land productivity and farm size in sub-dominant sub-regions. Therefore, from the perspective of land productivity, small farms still enjoy a comparative advantage over larger farms, and crop cultivation still tends to be dominated by traditional agricultural producing characteristics. However, although the dominant sub-regions producing the four major grains have shown significant IR, the absolute elasticities are quite small. We think one of the reasons for this is that the vast majority of farms in our dataset was small (under 15 mu); it might also be that, because China's traditional agricultural pattern is experiencing transformation, smaller farms' comparative advantage is gradually weakening compared with larger farms. Third, farms in dominant sub-regions, on average, show higher TE scores than those in sub-dominant sub-regions for each crop. Among wheat, rice, maize and soybeans in dominant sub-regions, planting maize is the most efficient, while planting soybeans is the least efficient. Comparing the three models, the TFE and TRE-Mundlak models generally estimates similar TE scores, which are the higher and less deviated than those in TRE Model. This shows that when the unobserved heterogeneity is taken into consideration, the differences in TE across farms fall substantially.

Our findings have significant policy implications, in particular in terms of the Chinese government's current land consolidation efforts. From the perspective of land productivity, small farms indeed still enjoy a comparative advantage over larger farms, and crop cultivation still tends to be dominated by traditional agricultural producing characteristics even during the agricultural transition period. Although more and more rural laborers are moving to off-farm sectors, China's agricultural resource endowment of a vast reserve of farm labor and declining supply of farmland still exists, so smaller farms support the goal of food security in terms of production. In this sense, the household contract responsibility system (HRS), which produced smallholder farming in China, is efficient and remains an effective institutional arrangement. So, from the perspective of protecting food security, the effort to promote consolidation should not be pursued at least at the present and the government should also consider more about how to stabilize or improve the HRS, and how to safeguard rural households' land contract rights (Li et. al, 2013). Moreover, the results show that the IR for grains is not quite strong when controlling the village-level unobserved heterogeneity. A bold conjecture is as the Chinese agriculture under rapid transformation develops, the IR could become weaker and weaker, then vanish in the future. At that time, there is no need to discourage large farms, and the fragmented land parcels might be consolidated into larger farms.

References:

Abdulai, A. and Tietje, H. 2007. "Estimating Technical Efficiency under Unobserved Heterogeneity with Stochastic Frontier Models: Application to Northern German Dairy Farms." *European Review of Agricultural Economics*, 34(3), 393-416.

Assunção, J. J. and Braido, L. H. 2007. "Testing Household-Specific Explanations for the Inverse Productivity Relationship." *American Journal of Agricultural Economics*, 89(4), 980-90.

Assunção, J. J. and Ghatak, M. 2003. "Can Unobserved Heterogeneity in Farmer Ability Explain the Inverse Relationship between Farm Size and Productivity." *Economics Letters*, 80(2), 189-94.

Barrett, C. B. 1996. "On Price Riskand the Inverse Farm Size-Productivity Relationship." *Journal of Development Economics*, 51(2), 193-215.

Barrett, C. B., Bellemare, M. F. and Hou, J. Y. 2010. "Reconsidering Conventional Explanations of the Inverse Productivity–Size Relationship." *World Development*, 38(1), 88-97.

Battese, G. E. and Coelli, T. J. 1992. "Frontier Production Functions, Technical Efficiency and Panel Data: With Application to Paddy Farmers in India," *International Applications of Productivity and Efficiency Analysis.* Springer, 149-65.

Battese, G. E. and Coelli, T. J. 1995. "A Model for Technical Inefficiency Effects in a Stochastic Frontier Production Function for Panel Data." *Empirical Economics*, 20(2), 325-32.

Belotti, F., Daidone, S., Ilardi, G. and Atella, V. 2012. "Stochastic Frontier Analysis Using Stata."

Benjamin, D. 1995. "Can Unobserved Land Quality Explain the Inverse Productivity Relationship?" *Journal of Development Economics*, 46(1), 51-84.

Benjamin, D. and Brandt, L. 2002. "Property Rights, Labour Markets, and Efficiency in a Transition Economy: The Case of Rural China." *Canadian Journal of Economics/Revue canadienne d'économique*, 35(4), 689-716.

Carletto, C., Savastano, S. and Zezza, A. 2013. "Fact or Artifact: The Impact of Measurement Errors on the Farm Size–Productivity Relationship." *Journal of Development Economics*, 103, 254-61.

China Statistical Yearbook (in Chinese). 2012, 2014. Beijing, China Statistics Press.**Chen, Z., Huffman, W. E. and Rozelle, S.** 2011. "Inverse Relationship between Productivity and Farm Size: The Case of China." *Contemporary Economic Policy*, 29(4), 580-92.

De Brauw, A., Huang, J., Zhang, L. and Rozelle, S. 2013. "The Feminisation of Agriculture with Chinese Characteristics." *The Journal of Development Studies*, 49(5), 689-704.

Fan, H. and Zhou, Q. 2014. "A study of the Relationship Between Household Land Acreage and Land Productivity Based on the Survey of Central and Western Seven Counties' Farmers." *China Population, Resource and Environment (Chinese)*, 24(12), 38-45.

Feder, G. 1985. "The Relation between Farm Size and Farm Productivity: The Role of Family Labor, Supervision and Credit Constraints." *Journal of Development Economics*, 18(2), 297-313.

Gao, M. and Zhang Y. 2006. "Are small farmers more effective?-evidence from household data in 8 provinces." *Statistical Research (Chinese)*, 8, 21-26.

Ghose, A. K. 1979. "Farm Size and Land Productivity in Indian Agriculture: A Reappraisal." *The Journal of Development Studies*, 16(1), 27-49.

Greene, W. 2005. "Reconsidering Heterogeneity in Panel Data Estimators of the Stochastic Frontier Model." *Journal of Econometrics*, 126(2), 269-303.

Huang, C. J. and Liu, J.-T. 1994. "Estimation of a Non-Neutral Stochastic Frontier Production Function." *journal of Productivity Analysis*, 5(2), 171-80.

Huffman, W. E. 1974. "Decision Making: The Role of Education." *American Journal of Agricultural Economics*, 56(1), 85-97.

Huffman, W. E. and Evenson, R. E. 2001. "Structural and Productivity Change in Us Agriculture, 1950–1982." *Agricultural Economics*, 24(2), 127-47.

Lamb, R. L. 2003. "Inverse Productivity: Land Quality, Labor Markets, and Measurement Error." *Journal of Development Economics*, 71(1), 71-95.

Li, G., Feng, Z., You, L. and Fan, L. 2013. "Re-Examining the Inverse Relationship between Farm Size and Efficiency: The Empirical Evidence in China." *China Agricultural Economic Review*, 5(4), 473-88.

Mundlak, Y. 1978. "On the Pooling of Time Series and Cross Section Data." *Econometrica: journal of the Econometric Society*, 69-85.

Rada, N., Wang, C. and Qin, L. 2015. "Subsidy or Market Reform? Rethinking China’s Farm Consolidation Strategy." *Food Policy*, 57, 93-103.

Schmidt, P. and Sickles, R. C. 1984. "Production Frontiers and Panel Data." *Journal of Business & Economic Statistics*, 2(4), 367-74.

Sen, A. K. 1966. "Peasants and Dualism with or without Surplus Labor." *The Journal of Political Economy*, 425-50.

Wang, J., Chen, K. Z., Das Gupta, S. and Huang, Z. 2015. "Is Small Still Beautiful? A Comparative Study of Rice Farm Size and Productivity in China and India." *China Agricultural Economic Review*, 7(3), 484-509.

Yang, D. T. 1997. "Education in Production: Measuring Labor Quality and Management." *American Journal of Agricultural Economics*, 79(3), 764-72.

Xin, L., Li, X., Zhu, H. and Liu, X. 2009. "Validation of the inverse farm size-productivity relationship and its explanations: a case study of Jilin provicen." *Geographical Research (Chinese)*, 28(5), 1276-1284.

Table 1. Production and share for all grains in sub-regions and aggregate for 2011

	grain	wheat	rice	maize	soybean
			Production (ten thousand ton)		
Northeast	13164.6	279.7	3268.6	8007.2	887.4
H-H-H	14618.0	6825.9	650.1	6354.1	201.5
Yangtze	13946.0	2620.2	9482.6	1066.8	308.6
Southeast	4433.3	28.3	3489.2	365.1	100.9
Southwest	6969.0	627.7	2993.2	1800.5	287.4
Northwest	3896.4	1333.4	215.9	1681.6	120.3
Nation	57120.8	11740.1	20100.1	19278.1	1908.4
			Percentage (%)		
Northeast	23.05	2.38	16.26	41.54	46.50
H-H-H	25.59	58.14	3.23	32.96	10.56
Yangtze	24.41	22.32	47.18	5.53	16.17
Southeast	7.76	0.24	17.36	1.89	5.29
Southwest	12.20	5.35	14.89	9.34	15.06
Northwest	6.82	11.36	1.07	8.72	6.30

Note: Data is from China's National Bureau of Statistics (NBSC.2012).

Table 2 Definition of the variables included in the econometric models

Variables	Unit	Definition
Yield	kg/mu[5]	Production per mu for wheat, rice, maize or soybean
Land	mu	Total actual planted area for wheat, rice, maize or soybean
Labor	Days/mu	Family and hired labor working days (8 working hours for one day) per mu
Capital	Yuan/mu	Animals and machinery costs per mu
Other input	Yuan/mu	Other input costs per mu
Household size		The number of residents for each household
Plots		The number of plots
Age	Years	The age of household head
Gender	1=male, 2=female	The gender of household head
Education	Years	The education of household head
Village officer	1=yes, 0=no	Whether there are village officers in the household

[5] 1 Mu = 1 hectare / 15

Table 3 Summary statistics for wheat, rice, maize and soybean

Variable	Whole	Dominant	Sub-dominant	Whole	Dominant	Sub-dominant
		Wheat			Rice	
Yield	363.05	419.37	347.64	490.95	522.61	464.31
Farm size	4.23	3.99	4.76	5.28	6.00	5.03
Labor	12.32	11.29	12.98	20.72	16.18	23.84
Capital	93.96	100.10	96.92	119.62	128.86	112.57
Other input	250.39	291.68	240.41	312.58	323.50	307.64
Households	4.07	3.88	4.17	4.03	4.03	4.05
Plots	4.57	3.27	4.76	6.74	6.09	7.23
Age	54.55	55.36	54.50	53.90	55.49	52.80
Gender	1.04	1.04	1.04	1.04	1.03	1.05
Education	6.96	6.89	7.08	6.80	6.69	6.82
Village officer	0.05	0.04	0.05	0.04	0.04	0.04
		Maize			Soybean	
Yield	501.91	617.26	444.59	136.13	144.49	124.78
Farm size	7.61	14.75	4.05	17.20	36.86	2.88
Labor	12.99	8.29	14.06	8.97	4.35	11.28
Capital	66.73	73.39	60.31	45.20	45.99	43.28
Other input	250.21	267.88	238.10	122.20	145.78	103.54
Households	3.75	3.39	3.80	3.82	3.42	3.97
Plots	5.14	4.84	4.83	6.18	5.08	6.54
Age	53.32	51.80	53.97	53.47	51.06	55.79
Gender	1.04	1.02	1.05	1.03	1.02	1.02
Education	6.99	7.28	6.72	6.97	7.30	6.76
Village officer	0.04	0.03	0.04	0.04	0.04	0.05

Table 4 Hausman test and Likelihood-Ratio test for parameters

	Region	Model	chi^2	P	Decision
Hausman Test					
Wheat	Dominant	TFE vs TRE	19.13	0.039	TFE
	Sub-dominant	TRE vs TFE [a]	5.40	0.863	TFE
Rice	Dominant	TRE vs TFE [a]	5.96	0.818	TFE
	Sub-dominant	TFE vs TRE	224.15	0.000	TFE
Maize	Dominant	TFE vs TRE	5.60	0.847	TRE
	Sub-dominant	TFE vs TRE	405.33	0.000	TFE
Soybean	Dominant	TFE vs TRE	1.99	0.996	TRE
	Sub-dominant	TFE vs TRE	28.04	0.002	TFE
Likelihood-Ratio Test [b]					
Wheat	Dominant	TRE vs TRE-Mundlak	315.61	0.000	TRE-Mundlak
	Sub-dominant	TRE vs TRE-Mundlak	295.49	0.000	TRE-Mundlak
Rice	Dominant	TRE vs TRE-Mundlak	783.51	0.000	TRE-Mundlak
	Sub-dominant	TRE vs TRE-Mundlak	104.73	0.000	TRE-Mundlak
Maize	Dominant	TRE vs TRE-Mundlak	590.00	0.000	TRE-Mundlak
	Sub-dominant	TRE vs TRE-Mundlak	71.22	0.000	TRE-Mundlak
Soybean	Dominant	TRE vs TRE-Mundlak	316.80	0.000	TRE-Mundlak
	Sub-dominant	TRE vs TRE-Mundlak	33.46	0.000	TRE-Mundlak

Note: [a] When we do the Hausman test, whose null hypothesis is that village-specific effects are uncorrelated with the explanatory variables (TRE) for wheat sub-dominant sub-regions, the chi^2 is negative, suggesting the Hausman test failed. After we reverse the null and alternative hypothesis, the chi^2 is positive, which means we should accept the null hypothesis and choose TFE. Based on Lian et al. (2014), the reason why chi^2 is negative in the Hausman test is the condition that the covariance of the variable and the error term be zero in the random effect model cannot be satisfied, so we should choose the Fixed Effect Model.

[b] The Likelihood-ration test is carried out to test for the Mundlak adjustment versus no Mundlak adjustment.

Table 5 TRE-Mundlak Estimated Results in Dominant Sub-region and Sub-Dominant Sub-regions in 2011

	Wheat		Rice		Maize		Soybean	
	Dominant	Sub	Dominant	Sub	Dominant	Sub	Dominant	Sub
Land	-0.053***	-0.018*	-0.029***	-0.056***	-0.034***	-0.023**	-0.042*	-0.018
	(0.012)	*(0.010)*	*(0.008)*	*(0.011)*	*(0.009)*	*(0.011)*	*(0.024)*	*(0.036)*
Labor	0.022**	0.0154	0.027***	0.005	0.031***	-0.006	-0.023	0.118***
	(0.010)	*(0.012)*	*(0.009)*	*(0.013)*	*(0.010)*	*(0.012)*	*(0.027)*	*(0.045)*
Capital	0.016	0.025**	0.038***	0.038***	0.024***	0.042***	-0.016	0.105**
	(0.015)	*(0.013)*	*(0.008)*	*(0.011)*	*(0.010)*	*(0.011)*	*(0.029)*	*(0.048)*
Other input	0.074***	0.127***	0.152***	0.130***	0.120***	0.219***	0.068**	0.140***
	(0.019)	*(0.017)*	*(0.012)*	*(0.016)*	*(0.014)*	*(0.018)*	*(0.031)*	*(0.038)*
Household size	-0.001	0.013***	0.005**	0.003	-0.0006	-0.002	0.001	-0.027**
	(0.003)	*(0.003)*	*(0.003)*	*(0.004)*	*(0.003)*	*(0.003)*	*(0.011)*	*(0.011)*
Plots	0.016***	-0.003	0.0007	0.001	-0.0006	0.002	0.001	-0.014***
	(0.004)	*(0.002)*	*(0.001)*	*(0.001)*	*(0.002)*	*(0.002)*	*(0.006)*	*(0.004)*
Age	0.001	-0.0002	-0.001**	-0.001*	0.0002	0.001**	0.001	0.003
	(0.0004)	*(0.0004)*	*(0.0004)*	*(0.0006)*	*(0.0004)*	*(0.0005)*	*(0.001)*	*(0.002)*
Gender	-0.050**	-0.049**	0.002	0.009	0.022	-0.067***	0.012	-0.014
	(0.022)	*(0.023)*	*(0.018)*	*(0.025)*	*(0.028)*	*(0.023)*	*(0.078)*	*(0.110)*
Edu	0.004**	-0.0007	-0.002	0.0008	0.001	0.007***	0.005	0.003
	(0.002)	*(0.002)*	*(0.002)*	*(0.002)*	*(0.002)*	*(0.002)*	*(0.007)*	*(0.007)*
Village officer	-0.031	0.038*	0.044**	0.060**	-0.007	0.041	-0.020	0.004
	(0.021)	*(0.020)*	*(0.019)*	*(0.027)*	*(0.022)*	*(0.027)*	*(0.060)*	*(0.079)*
Mundlak Terms								
Land	0.087	-0.014	0.136***	0.101***	0.091*	0.123***	0.081	-0.304***
	(0.060)	*(0.041)*	*(0.037)*	*(0.028)*	*(0.051)*	*(0.035)*	*(0.064)*	*(0.095)*
Labor	-0.016	0.040	-0.029	-0.035	-0.016	-0.009	0.200**	-0.148
	(0.035)	*(0.057)*	*(0.067)*	*(0.038)*	*(0.023)*	*(0.045)*	*(0.094)*	*(0.141)*
Capital	-0.004	0.082**	0.050	-0.042	-0.040	-0.040	0.204**	0.155*
	(0.058)	*(0.035)*	*(0.050)*	*(0.036)*	*(0.029)*	*(0.040)*	*(0.081)*	*(0.091)*
Other input	0.476***	0.296***	-0.043	-0.255***	0.443***	0.103***	-0.097	-0.313***
	(0.073)	*(0.047)*	*(0.087)*	*(0.055)*	*(0.051)*	*(0.037)*	*(0.087)*	*(0.103)*
Household size	0.006	-0.031	-0.032	0.004	0.069	-0.159***	0.0807	0.295***
	(0.035)	*(0.023)*	*(0.033)*	*(0.030)*	*(0.072)*	*(0.032)*	*(0.064)*	*(0.077)*
Plots	-0.086***	-0.017**	-0.014***	-0.019***	-0.018**	0.006	-0.088***	-0.020
	(0.013)	*(0.008)*	*(0.004)*	*(0.004)*	*(0.007)*	*(0.009)*	*(0.028)*	*(0.023)*
Age	0.015**	-0.003	0.001	-0.003	-0.006**	0.001	0.025***	0.039**
	(0.006)	*(0.008)*	*(0.004)*	*(0.005)*	*(0.003)*	*(0.008)*	*(0.009)*	*(0.018)*
Gender	0.228	0.101	-0.224	0.857***	0.817	0.831*	5.767***	-2.547*
	(0.354)	*(0.400)*	*(0.653)*	*(0.322)*	*(1.621)*	*(0.446)*	*(0.932)*	*(1.349)*
Edu	0.087***	0.012	0.034*	0.029	0.075**	0.059**	-0.441***	-0.158**
	(0.030)	*(0.017)*	*(0.018)*	*(0.022)*	*(0.032)*	*(0.023)*	*(0.029)*	*(0.076)*
Village officer	0.668	-0.059	-0.548	0.756	-1.396	0.609	1.625	-1.800
	(0.619)	*(0.729)*	*(0.600)*	*(0.532)*	*(0.921)*	*(0.581)*	*(1.826)*	*(1.571)*
Constant	1.559***	3.267	5.432***	6.196***	2.096	3.659***	-1.747	5.704***
	(0.533)	*(4.698)*	*(0.326)*	*(0.427)*	*(1.730)*	*(0.663)*	*(1.122)*	*(2.126)*
Log Likelihood	413.928	348.417	-253.249	-342.885	635.713	-148.141	-58.419	-214.479
σ_u	0.258***	0.215***	0.241***	0.332***	0.212***	0.293***	0.502***	0.367***
	(0.008)	*(0.010)*	*(0.008)*	*(0.009)*	*(0.006)*	*(0.010)*	*(0.020)*	*(0.044)*
σ_v	0.081***	0.138***	0.194***	0.175***	0.107***	0.176***	0.077***	0.277***
	(0.005)	*(0.005)*	*(0.004)*	*(0.005)*	*(0.003)*	*(0.005)*	*(0.010)*	*(0.020)*
$\gamma\ (= \sigma_u/\sigma_v)$	3.180***	1.557***	1.242***	1.901***	1.972***	1.667***	6.499***	1.325***
	(0.011)	*(0.014)*	*(0.010)*	*(0.125)*	*(0.008)*	*(0.014)*	*(0.024)*	*(0.060)*
Observations	1,250	1,821	1,848	2,606	1,789	2,371	431	462
No. of village	37	62	53	93	46	74	19	39

Note: Standard errors in parentheses, ***p < 0.01, **p < 0.05, *p < 0.1.

Table 6 The Estimates in Existing Literature for China

Author	Data	Output	Farm size	Elasticity of output/land
Gao and Zhang (2006)	1987-2002; 8 provinces (except 1990,1992,1994)	Grain Yield (Kg/mu)	Grain planted area (mu)	-0.584*** (0.104)
Li et al. (2013)	1999-2003; Hubei Province	Income from crop farming per mu	Cultivated land (mu)	-0.717*** (0.007)
Fan and Zhou (2014)	2012; Hunan Province	Rice Yield (kg/mu)	Rice planted area (mu)	0.056** (0.028)
	2012; Henan Province	Wheat Yield (kg/mu)	Wheat planted area (mu)	0.125* (0.091)
Chen et al. (2011)	1995-1999; 9 provinces	Total Grain production (1000 kg)	Cultivated land (mu)	0.968*** (0.099)
Wang et al. (2015)	2007, 2010; Jiangxi Province	Rice Yield (kg/mu)	Rice planted area (mu)	0.008 (0.017)
Rada et al. (2015)	2003-2007; 11 provinces	Wheat Yield (kg / ha)	Wheat planted area (ha)	-0.068** (0.029)
		Rice Yield (kg / ha)	Rice planted area (ha)	-0.123** (0.061)
		Maize Yield (kg / ha)	Maize planted area (ha)	-0.080*** (0.016)

Note: Standard errors in parentheses, ***p < 0.01, **p < 0.05, *p < 0.1.

Table 7 Summary Statistics of Technical Efficiency Scores

	Place	Model	Mean	SD	Min.	Max.
Wheat	Dominant	TFE	0.855	0.069	0.162	0.986
		TRE	0.859	0.082	0.158	0.982
		TRE-Mundlak	0.863	0.079	0.158	0.982
	Sub-Dominant	TFE	0.853	0.072	0.250	0.989
		TRE	0.851	0.072	0.278	1.000
		TRE-Mundlak	0.853	0.070	0.275	1.000
Rice	Dominant	TFE	0.841	0.064	0.224	0.984
		TRE	0.825	0.100	0.122	1.000
		TRE-Mundlak	0.827	0.099	0.112	1.093
	Sub-Dominant	TFE	0.793	0.100	0.124	0.986
		TRE	0.787	0.115	0.120	1.000
		TRE-Mundlak	0.787	0.137	0.092	1.000
Maize	Dominant	TFE	0.864	0.073	0.146	0.993
		TRE	0.861	0.075	0.144	0.978
		TRE-Mundlak	0.865	0.073	0.146	0.979
	Sub-Dominant	TFE	0.812	0.087	0.165	0.985
		TRE	0.812	0.096	0.158	0.977
		TRE-Mundlak	0.812	0.086	0.159	1.000
Soybean	Dominant	TFE	0.789	0.123	0.203	0.982
		TRE	0.766	0.129	0.198	0.978
		TRE-Mundlak	0.771	0.139	0.206	0.980
	Sub-Dominant	TFE	0.764	0.094	0.182	0.953
		TRE	0.746	0.098	0.170	0.947
		TRE-Mundlak	0.757	0.092	0.182	0.950

Fig. 1. Chinese provinces and sub-regions represented in the RERC household data in 2011

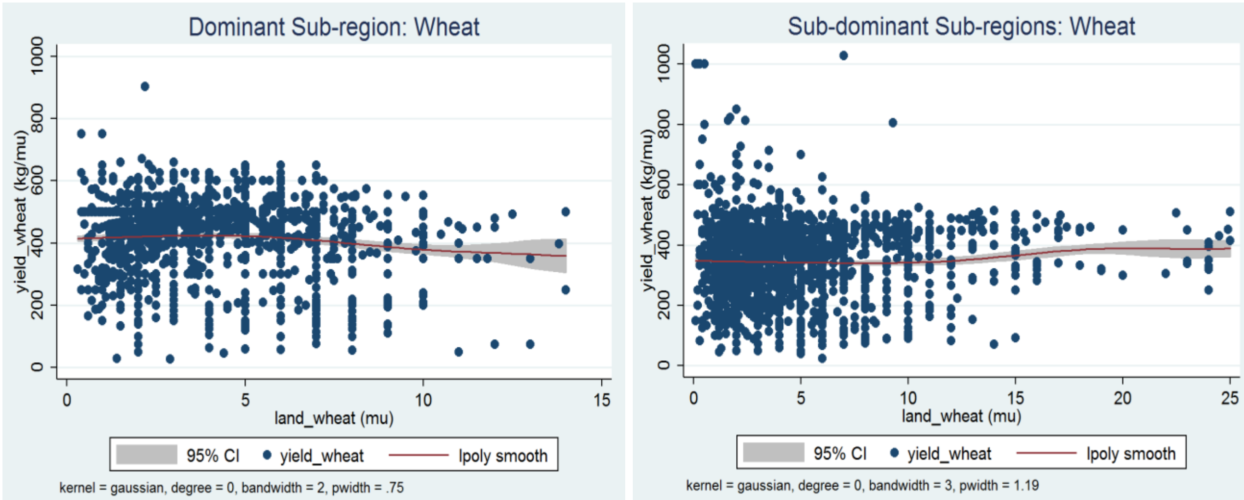

Fig. 2 Wheat yield versus planted area in dominant and sub-dominant sub-regions

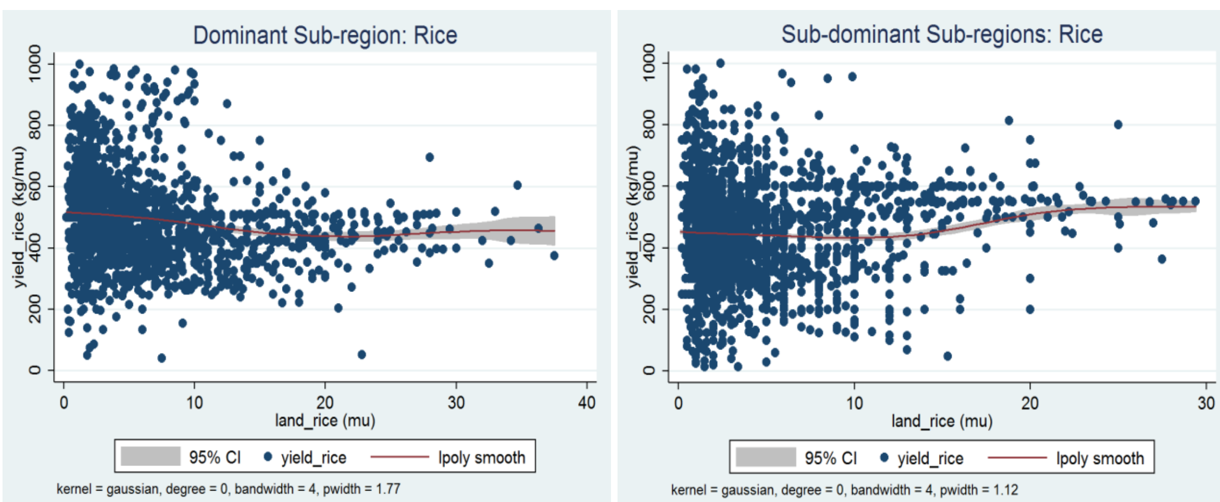

Fig. 3 Rice yield versus planted area in dominant and sub-dominant sub-regions

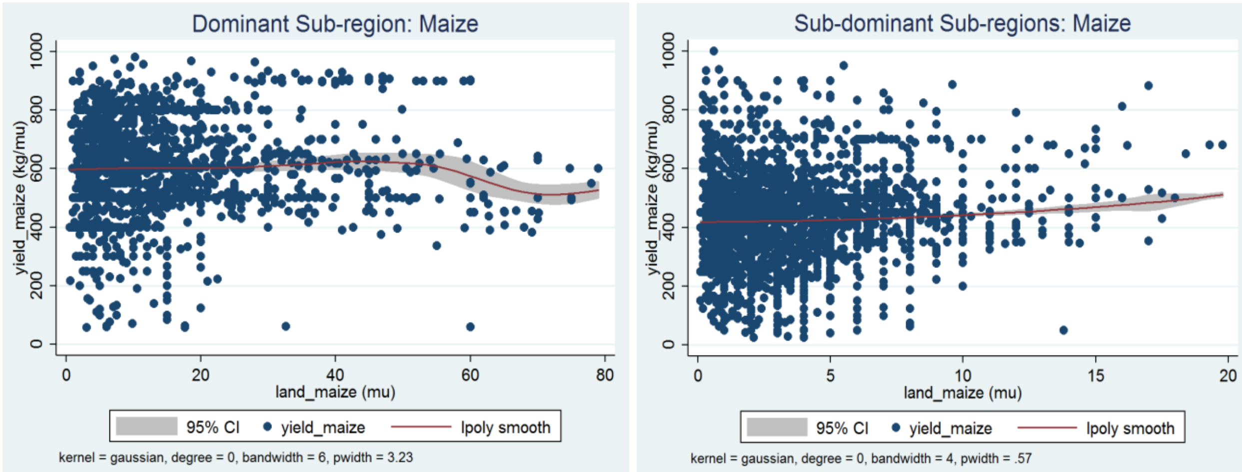

Fig. 4 Maize yield versus planted area in dominant and sub-dominant sub-regions

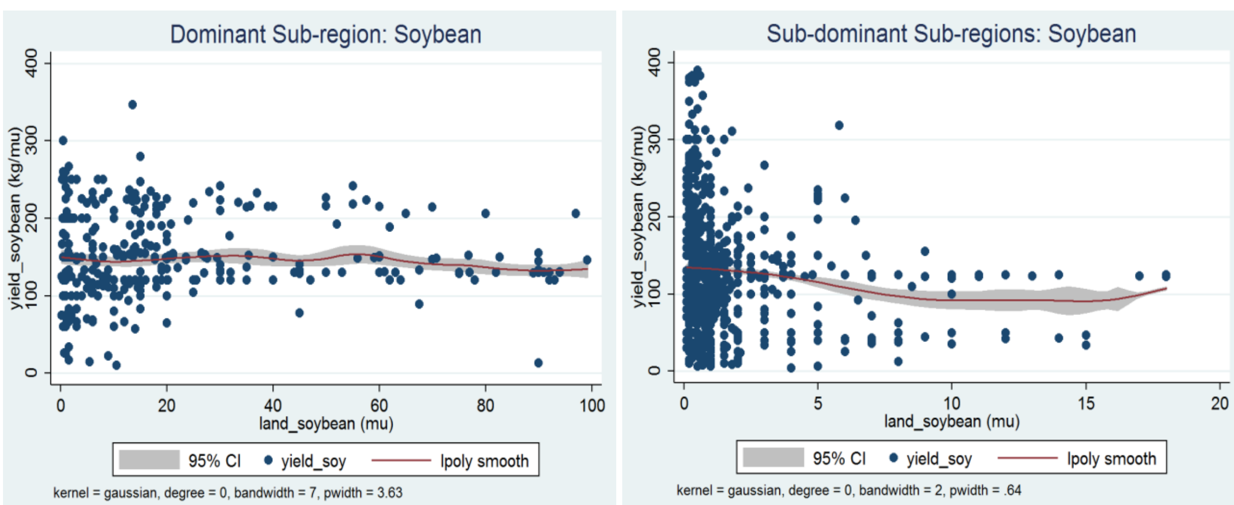

Fig. 5 Soybean yield versus planted area in dominant and sub-dominant sub-regions