Citation for the published paper:
Ziming Liu, Lan Zhang, Jens Rommel and Shuyi Feng. (2020) Do Land Markets Improve Land Use Efficiency?. *Applied Economics*. Volume: 52, Number: 3, pp 317-330.
https://doi.org/10.1080/00036846.2019.1645286

Do Land Markets Improve Land Use Efficiency?

Evidence from Jiangsu, China

Ziming Liu[a], Lan Zhang[b], Jens Rommel[c] and Shuyi Feng [b,*]

a. School of Social and Public Administration, East China University of Science and Technology, Shanghai, China

b. College of Public Administration, Nanjing Agricultural University, Nanjing, China

c. Department of Economics, Swedish University of Agricultural Sciences, Uppsala, Sweden

**. Corresponding author. Address: Weigang No.1, Nanjing 210095, P.R. China; E-mail: shuyifeng@njau.edu.cn*

Abstract: Inefficient use of scarce and fragmented land challenges the sustainability of agriculture. Land markets may improve land use efficiency. In recent years, China has employed various instruments to promote land markets. This paper investigates whether land markets affect households' land use efficiency, based on data from 1,202 farm households in Jiangsu Province. The measure of land use efficiency was derived from a stochastic frontier production function, and a control function approach was employed to correct for selection bias. The results indicated that many households are using land inefficiently. While renting in land increases land use efficiency, it is not affected by renting out land, implying that households are not giving up land for efficiency gains. We also provide suggestive evidence that the positive effect of renting in land results from abundant agricultural labour due to labour market failure.

Keywords: Land market, technical efficiency, stochastic frontier analysis, control function

JEL codes: Q12, D24

Introduction

Sustainable development requires the provision of sufficient food for a growing world population with a decreasing area of land, yet in many developing and transition economies such as China, rapid urban sprawl often requires large-scale land conversion (Tan et al., 2009; Zhong et al., 2018). Over time, a dramatic decrease in agricultural land has been observed, undermining the capacity to supply food (Long et al., 2016) and thus raising concerns about food security and calling for the efficient use of agricultural land to increase yields per area (Zhou et al., 2018). Instruments to increase land use efficiency represent as a significant challenge for policy makers in developing and transition economies.

Functioning land rental markets are often viewed as a potential instrument for enhancing land use efficiency (Jin and Deininger, 2009). For example, previous studies have demonstrated that imperfect land markets have a negative effect on land productivity (Heltberg, 1998; Holden et al., 2001). In China in particular, scenario analysis suggests that land transfer could lead to a significant increase in productivity if barriers in land rental markets were to be removed (Deininger and Jin, 2005). Similarly, Feng et al. (2010) found that many Chinese farmers who rent in additional land can increase their productivity. These studies have improved our understanding of the importance of land markets in enhancing land use efficiency.

Our study complements this literature by investigating whether participation in land markets affects household land use efficiency, based on data concerning rice producers in Jiangsu, China. Its contributions are twofold. First, we use a new measure of land use efficiency, defined as the ratio of minimum feasible land input to observed land input, conditional on yield level and other inputs. Traditional measures of resource efficiency are often defined as the output per unit of input (Anne et al., 2017), *i.e.* land productivity, ignoring the variation of other inputs. The identified effects of land markets on land productivity could therefore result from a change in other inputs, rather than from land markets. Our measure also differs from the comprehensive efficiency measure of production, *i.e.* technical efficiency, by focusing on a particular type of input efficiency. To our knowledge, there is only one study by Zhang et al. (2018b) that has employed a similar approach to measuring land use efficiency in corn production. However, we are the first to explain the variation of this new measure of land use efficiency. Second, we provide suggestive evidence about the causal mechanisms whereby renting land may affect land use efficiency.

The remainder of the paper is organised as follows. Section two introduces recent developments in land rental markets in Jiangsu and explains causal mechanisms. In section three, we present the data collection and estimation strategies. The main results are presented in section four, followed by a discussion and conclusions in section five.

Background and theory

Land markets in China

In China, agricultural land is governed under the Household Responsibility System (HRS). The HRS allows households to contract with village collectives to gain use rights over some agricultural land. Compared to the collective farming system, the HRS brought about decentralised decision-making over agricultural production, although in its initial stage households were not allowed to transfer land to others due to concerns about landless households and social inequality. It was not until the beginning of 21st century that land markets in rural China started to develop. However, high transaction costs caused by insecure property rights and land fragmentation limited the development of rural land markets for a long time (Feng et al., 2010; Kung, 2002). Estimates suggest that in 2006 no more than 10 %

of agricultural land had ever been traded on the rental market in this study area of Jiangsu Province. At country level, land markets were even less developed (Liu et al., 2017).

Rapid growth in land rental markets started in around 2008 when intermediate agents, such as land cooperatives (*cf.* Liu et al. (2018)), started to get involved in the process. By the end of 2014, 58 % of farmland in the province was engaged in land markets, accounting for about two million hectares of farmland (Zhang et al., 2018a). Forty-four percent of the transferred land was used for food crops (JSMAS, 2015), particularly rice production. An important role in the process is played by intermediate agents, who rent in land from households and rent it out to others after land consolidation and infrastructure establishment. These agents often have a bureaucratic background and are financially supported by local governments with the aim of consolidating fragmented agricultural land and scaling up farming. In 2014, approximately 29.7 % of transferred farmland was handled by such intermediate agents (JSMAS, 2015).

The role of land rental in land use efficiency

There are several channels through which land markets can affect land use efficiency. The first is economies of scale. Farms with little land often attract insufficient labour, and high fixed costs for machinery or irrigation could lead to lower land productivity (Wu et al., 2005). Even with the same level of access to production factors, often farms with little land are unable to use the inputs efficiently. Input losses per unit of land are greater on small farms (Ma et al., 2014). *Ceteris paribus*, land use efficiency is typically higher for large farms. Since renting in land increases a household's farm size, land use efficiency can be expected to increase. In contrast, households that rent out land may experience negative economies of scale.

The second channel is land quality. Farmers tend to cultivate more productive land under land market imperfections (Holden et al., 2001). This implies that if land markets develop, the soils and nutrient contents of traded land may often be of poorer quality. Indeed, Rahman (2010) found that soil quality is negatively correlated with renting out decisions. Consequently, households who rent in land may have a lower land use efficiency and those who rent out land may have a higher land use efficiency due to quality differences (Rahman and Rahman, 2009).

The third channel is tenure security (Kumari and Nakano, 2015). Compared to owned land, rented land has less tenure security, especially for short-term contracts. Households that rent in land would have overlapping land rights with both secure and insecure property rights (Deininger and Ali, 2008). Tenure insecurity may restrain investment and reduce land productivity (Deininger et al., 2011), but it may also create an incentive for tenants to increase output (Menale and Stein, 2007), *e.g.* by maximising yield with myopic planning (*e.g.* more mineral fertiliser to increase short-term yields at the expense of long-term soil fertility) in the case of short-term contracts. Since households that do not participate in land markets or that rent out land only have land with secure property rights, they are likely to be affected by this.

The fourth channel is limited access to labour markets. If farmers cannot find non-agricultural employment, they may continue farming due to low opportunity costs of labour (Deininger et al., 2018; Lamb, 2003). Consequently, households would have more labour relative to land, which may result in inefficiencies. If there is such a market failure, land markets could partly help to address it and improve efficiency (Lamb, 2003). Households that rent in (out) land would use their labour inputs more (less) efficiently, and consequently their land use efficiency would increase (decrease).

Data and estimation

Data collection

We used data from a household survey of rice producers in Jiangsu Province. The survey took place between 2013 and the beginning of 2014, and covered counties in which arable land accounts for more than 10 % of the total land. From these counties, we randomly selected 64 towns. In each town, we then randomly selected two villages and interviewed approximately ten randomly selected households in each village. Information in the survey refers to the end of 2012. A structured questionnaire was employed to collect information on the households' land market participation, demographic characteristics, land endowments and village characteristics. The final sample consisted of 1,202 households (Table 1), of which more than 65 % reported having rice production in 2012. For the efficiency analysis, we excluded households with zero yield or zero inputs in land or seeds for rice production.

Table 1. Sample distribution across Jiangsu Province

City	Number of observations	Percentage
Suzhou	55	4.58
Wuxi	57	4.74
Nanjing	66	5.49
Taizhou	74	6.16
Huaian	83	6.91
Changzhou	97	8.07
Xuzhou	98	8.15
Yancheng	111	9.23
Suqian	138	11.48
Yangzhou	210	17.47
Lianyungang	213	17.72
Total	1,202	100

Source: Authors' computation.

Estimation strategy

Deriving land use efficiency

Our study's measure of land use efficiency follows that of Reinhard et al. (1999) which was originally developed to measure fertiliser use or environmental efficiency (Abdulai and Abdulai, 2017; Kouser and Qaim, 2015; Ma et al., 2014). A recent paper has applied it to measure land use efficiency in corn production (Zhang et al., 2018b), although there is concern about its application. For example, in comparison to fertiliser, land inputs are lumpier and less divisible. However, because households can adjust their land input by allocating proportions of land to different crops, by laying off land or by renting additional land we argue that its application to land use efficiency is appropriate.

To derive land use efficiency, we first estimated technical inefficiency. For this purpose, we employed a stochastic frontier production function. The translog model was defined as:

$$lnY_i = \beta_0 + \sum_j \beta_j \, lnX_{ij} + \beta_z lnZ_i + 0.5 \sum_j \sum_k \beta_{jk} lnX_{ij} lnX_{ik} + \sum_j \beta_{jz} lnX_{ij} lnZ_i \\ +0.5\beta_{zz}(lnZ_i)^2 + D_i + v_i - u_i \quad (1)$$

where ln is the natural logarithm, Y_i is the total output of producer i, X_i is a vector of j input quantities, including labour, seed, pesticide, machine and fertilizer, Z_i is the quantity of land input, and D_i captures regional fixed effects using town dummies. Since there is typically not much variation in land prices *within* a Chinese town, the inclusion of town dummies can be seen as a control for land prices. β are parameters to be estimated, v_i is a random term, and u_i is a non-negative error term measuring the technical inefficiency which follows an exponential distribution.

Following Reinhard et al. (1999) and Kouser and Qaim (2015), the logarithm of the output of a producer who uses land efficiently can be obtained by replacing the observed quantity of land input (Z_i) in Eq. (1) with the minimum feasible land input Z_i^M. The u_i is set at zero because a producer who uses land efficiently given the yield level and other inputs implies there is no technical inefficiency. Thus, we get the following equation:

$$lnY_i = \beta_0 + \sum_j \beta_j \, lnX_{ij} + \beta_z lnZ_i^M + 0.5 \sum_j \sum_k \beta_{jk} lnX_{ij} lnX_{ik} + \sum_j \beta_{jz} lnX_{ij} lnZ_i^M$$
$$+0.5\beta_{zz}(lnZ_i^M)^2 + D_i + v_i \tag{2}$$

Setting Eq. (1) and Eq. (2) equal and solving for $ln\frac{Z_i^M}{Z_i}$ yields:

$$ln\frac{Z_i^M}{Z_i} = \left[-\left(\beta_z + \sum_j \beta_{jz} lnX_{ij} + \beta_{zz} lnZ_i\right) \pm \left\{ \left(\beta_z + \sum_j \beta_{jz} lnX_{ij} + \beta_{zz} lnZ_i\right)^2 - 2\beta_{zz} u_i \right\}^{0.5} \right] \Big/ \beta_{zz} \tag{3}$$

where $LUE_i = \frac{Z_i^M}{Z_i}$ is defined as land use efficiency by measuring the ratio of minimum feasible land input to observed land input. Assuming a positive under-root term in Eq. (3), land use efficiency LUE_i can be obtained by taking the exponent:

$$LUE_i = exp\left(ln\frac{Z_i^M}{Z_i}\right) \tag{4}$$

Estimating the effect of land markets

To estimate the effect of participation in land markets on land use efficiency, we defined the following function:

$$LUE_i = \alpha_0 + \alpha_1 RENTIN_i + \alpha_2 RENTOUT_i + \alpha_3 G_i + D_i + \varepsilon_i \tag{5}$$

where $RENTIN_i$ and $RENTOUT_i$ denote a household's binary choices of renting in and out land respectively, G_i is a vector of other variables that affect land use efficiency, α are coefficients to be estimated, and ε_i is an error term. Since the efficiency score is a fractional response variable, the best way of modelling Eq. (5) is a beta regression estimated by maximum likelihood (Ferrari and Cribari-Neto, 2004). In particular, beta regression addresses fractional variables when the unity interval is open, which is the case in our study. We employed a link function of complementary log-logistic form for beta regressions, but results from other link functions (logit, probit *etc*.) were similar and are available from the authors upon request.

Since efficient (inefficient) land users may increase (decrease) farm size *via* participation in the land rental market, there may be reverse causality, which raises the concern of endogeneity. To address this concern, we employed a two-step control function approach (Wooldridge, 2014). Following Liu et al. (2017), Lloyd-Smith et al. (2018) and Tessema et al. (2018), we ran a probit model for $RENTIN_i$ and $RENTOUT_i$ respectively[1]. The probit models were defined as follows:

$$RENTIN_i^* = \gamma_0^{IN} + \gamma_1^{IN} W_i + D_i + \delta_i^{IN}, \text{ with } \quad RENTIN_i = \begin{cases} 1, & if \;\; RENTIN_i^* > 0 \\ 0, & otherwise \end{cases} \tag{6}$$

$$RENTOUT_i^* = \gamma_0^{OUT} + \gamma_1^{OUT} W_i + D_i + \delta_i^{OUT}, \text{ with } RENTOUT_i = \begin{cases} 1, & if \;\; RENTOUT_i^* > 0 \\ 0, & otherwise \end{cases} \tag{7}$$

[1] Some authors have employed a linear probability model in the first step of the control function for dichotomous variables (*e.g.* Brasselle et al. (2002) and Rao et al. (2017)). However, Lewbel et al. (2012) point out that a linear probability model in the first step could lead to biased estimates if the outcome variable in the second step is binary or limited. Brasselle et al. (2002) also point out that key assumptions (*e.g.* homoscedasticity) of control functions would be violated if the first step equation were a linear probability model for non-continuous variables.

where $RENTIN_i^*$ ($RENTOUT_i^*$) is a latent variable, and $RENTIN_i$ ($RENTOUT_i$) is the observed decision of participation in land markets, which equals to one if $RENTIN_i^*$ ($RENTOUT_i^*$) is larger than zero. W_i is a vector of explanatory variables, including G_i and at least one instrumental variable IV_i which affects $RENTIN_i$ and $RENTOUT_i$ but has no effect on LUE_i. A Wald test of the statistical significance of the instrumental variables in Eq. (6) and (7) showed their strength. Then, the predicted generalised residual $Residual_i^{IN}$ from Eq. (6) and $Residual_i^{OUT}$ from Eq. (7) could be obtained as follows:

$$Residual_i^{IN} = RENTIN_i\lambda(\gamma_1^{IN}W_i) - (1 - RENTIN_i)\lambda(-\gamma_1^{IN}W_i) \tag{8}$$

$$Residual_i^{OUT} = RENTOUT_i\lambda(\gamma_1^{OUT}W_i) - (1 - RENTOUT_i)\lambda(-\gamma_1^{OUT}W_i) \tag{9}$$

where $\lambda(\cdot)$ is the inverse Mills ratio. For the probit model, the generalised residual equalled the inverse Mills ratio (Lloyd-Smith et al., 2018). The two generalised residuals were then introduced in Eq. (5):

$$\begin{aligned} LUE_i = \alpha_0 + \alpha_1 RENTIN_i + \alpha_2 RENTOUT_i + \alpha_3 G_i + \alpha_4 Residual_i^{IN} + \alpha_5 Residual_i^{OUT} + D_i \\ + \varepsilon_i \end{aligned} \tag{10}$$

A beta regression of Eq. (10) provided consistent estimates of α_1 and α_2. The statistical significance of α_4 and α_5 based on t-statistics revealed the presence of endogeneity. To test whether the instruments could be excluded, we followed the approach suggested Abdulai et al. (2011), which re-estimated Eq. (10) with instruments:

$$\begin{aligned} LUE_i = \alpha_0' + \alpha_1' RENTIN_i + \alpha_2' RENTOUT_i + \alpha_3' G_i + \alpha_4' Residual_i^{IN} + \alpha_5' Residual_i^{OUT} \\ + \alpha_6' IV_i + D_i + \varepsilon_i' \end{aligned} \tag{11}$$

If α_6' is not statistically different from zero, then the instrumental variable IV_i can be excluded from Eq. (11), implying that the instrument is valid. We clustered standard errors at village level for all models.

Since the estimation of LUE_i involved an error component, the concern arose that the two-step estimation of the determinants of LUE_i, which first predicts the efficiency variable and then regresses efficiency variables on explanatory variables, could be inconsistent. Indeed, Battese and Coelli (1995) argue that for the determinants of technical efficiency, the two-step estimation cannot fulfil the error component being independently and identically distributed. However, because the measure of LUE_i is not calculated with a predetermined distributional assumption, but rather from the parameter estimates describing the structure of production technology (Reinhard et al., 2002), the two-step estimation was appropriate.

Variable description

Definitions and descriptive statistics of inputs and outputs are shown in Table 2. Rice output, land input and seed input were measured in physical units. The average rice output, land input and seed input per household in 2013 in our research area were 3,160 kg, 5.78 mu[2] and 36.34 kg respectively. Labour input was measured in days, with an average of 99.6 days. The inputs of machine, pesticide and fertiliser were measured in monetary terms, with the average levels of 1,072, 107.1 and 1,237 RMB Yuan respectively.[3]

Table 3 shows the main variables of our study. Of the 1,202 households, 24.3 % rented in land, while 23.5% rented out land. To explain land use efficiency, we controlled for other factors according to the literature on land productivity and resource use efficiency in general (Abdulai and Abdulai, 2017; Kouser and Qaim, 2015; Ma et al., 2014). Specifically, we controlled for household heads' age and education. Age is a proxy for the experience of the

---

[2] One hectare is equal to 15 mu.

[3] Due to data limitation, we were unable to measure these inputs in physical units. We followed Ma et al. (2014) in their use of monetary units.

head of the farm household. The older the farmer, the better his or her ability to organise agricultural production and achieve the same yield level with less land. For the same reason, we included the education and agricultural training of the household heads (Abdulai and Abdulai, 2017).

Table 2. Descriptive statistics of inputs and output in rice production

Variable	Unit	Mean	S.D.	Observations
Yield	Kg	3,160	3,707	784
Land	Mu	5.780	6.459	787
Seed	Kg	36.34	52.92	783
Labour	Day	99.60	217.5	784
Machine	Yuan	1,072	1,414	782
Pesticide	Yuan	107.1	60.23	782
Fertilizer	Yuan	1,237	1,441	780

Notes: One US dollar is equal to 6.15 Yuan (average in 2013). One day equals eight working hours.

We introduced household heads' experience with off-farm employment and family size in the model. However, off-farm employment may reduce labour availability for agricultural production and prevent households from farming in a timely manner, leading to lower land use efficiency. Yet off-farm employment, which captures the level of household off-farm income, increases households' income, which could stimulate investments in production and increase yields (Rozelle et al., 1999). Family size indicates household labour availability and large families are expected to increase land use efficiency.

Table 3. Descriptive statistics

Variable	Description	Mean	S.D.	Observations
Rent in	1 = Household rented in land, 0 = otherwise	0.243	0.429	1,202
Rent out	1 = Household rented out land, 0 = otherwise	0.235	0.424	1,202
Age of household head	Age in years	57.98	10.15	1,202
Education of household head	1 = Illiterate, 2 = Primary education, 3 = Secondary education, 4 = High school education, 5 = Undergraduate education and above	2.674	0.973	1,202
Off-farm experience of household head	1 = Household head had off-farm work before survey, 0 = otherwise	0.681	0.466	1,202
Household size	Number of household members	4.443	1.836	1,202
Land endowment	Area of land owned by the household (Mu)	5.653	3.296	1,201
Number of land plots	The number of land plots owned by the household	4.092	2.513	1,190
Agricultural training	1 = Household head received training in agricultural techniques before, 0 = otherwise	0.286	0.452	1,202
Agricultural assets	The total value of assets for agricultural production (10,000 RMB Yuan)	0.475	1.667	1,185
Other durable assets	The total value of other durable assets in the family (10,000 RMB Yuan)	1.377	5.283	1,070
Disaster	1= if agricultural production suffered from flood or drought last year, 0 = otherwise	0.374	0.484	1,070
Share of households in land rental market	Share of households that have participated in land rental market in the village (%)	0.447	0.235	1,202
Administrative intervention	Share of households that report the presence of government intervention on land market in the village (%)	0.113	0.224	1,202

Note: The number of observations is different due to missing values.

We introduced land area distributed from the village as a measure of household land endowment and the number of land plots to indicate the extent of land fragmentation. Small farms may have lower productivity because of negative economies of scale (Wu et al., 2005). The number of land plots may decrease the efficiency of other inputs and reduce land productivity and efficiency (Rahman and Rahman, 2009). The total value of agricultural assets and other durable assets were also controlled for because greater investment in agriculture may increase yields. Lastly, we controlled for land quality imprecisely using a variable of whether a household suffered a natural disaster such as flood or drought in production. Such natural disasters are expected to reduce yield level and land use efficiency.

The instrumental variables we employed were the fraction of households who participated in the land market in the village and the extent of administrative intervention in land markets, measured by the fraction of households reporting the presence of government intervention in land markets in the village. A high fraction of households in the village, either renting in or renting out land, implies an active land market and is expected to be positively correlated with households' probability of participation. Previous studies demonstrate that farmers' decisions, such as technology adoption, are affected by other people (Conley and Udry, 2010; Minten and Barrett, 2008). Administrative intervention is also expected to affect household participation in land markets because the evaluation scheme of bureaucrat performance drives the development of land markets in China (Liu et al., 2016).

Valid instrumental variables should not affect land use efficiency through channels other than land markets. This is called the exclusion restriction. In China, administrative intervention in land markets has nothing to do with farmers' production decisions. Moreover, the differences in the activeness of land markets in our research area are mainly driven by local institutional innovations, which are also unrelated to farmers' production decisions (Ito et al., 2016). Thus, it is fair to assume that the two instrumental variables do not affect land use efficiency through channels other than land markets, which can be tested with Eq. (11).

Results

Estimates of the production frontier and land use efficiency

Table 4 reports the estimates of the stochastic frontier production function. We found that more land input significantly increased the yield level of rice production. Similarly, pesticide inputs also had a positive effect on yield, indicating that the pest control effect of pesticide use reduced yield loss in agricultural production (Zhang et al., 2015). Meanwhile, the interaction term between land and pesticides also showed a significant and positive effect on yield, which further confirmed the findings on land and pesticides. While the combination of machine and pesticide input showed a negative effect on yield, the combination of machine and fertiliser input showed a positive effect. One potential explanation is that our machine input measure covers inputs at the ploughing stage, and frequent ploughing reduces pesticide use efficiency to achieve a lower yield level, but improves fertiliser use efficiency to achieve a higher yield level.

Table 4. Translog estimates of stochastic production frontier for rice production

Variable	Coeff.	Variable	Coeff.	Variable	Coeff.
Land	1.168***	Machine squared	-0.014	Seed × Machine	-0.000
	(0.359)		(0.013)		(0.013)
Seed	0.031	Pesticide squared	-0.006	Seed × Pesticide	-0.000
	(0.110)		(0.011)		(0.007)
Labour	-0.081	Fertilizer squared	-0.011	Seed × Fertilizer	-0.003
	(0.124)		(0.013)		(0.015)
Machine	-0.000	Land × Seed	0.020	Labour × Machine	0.009
	(0.180)		(0.030)		(0.016)
Pesticide	0.340**	Land × Labour	0.001	Labour × Pesticide	0.008
	(0.135)		(0.027)		(0.016)
Fertiliser	-0.085	Land × Machine	-0.025	Labour × Fertilizer	-0.004
	(0.175)		(0.044)		(0.018)
Land squared	0.033	Land × Pesticide	0.065*	Machine × Pesticide	-0.045*
	(0.056)		(0.037)		(0.024)
Seed squared	-0.000	Land × Fertilizer	-0.059	Machine × Fertilizer	0.058**
	(0.009)		(0.044)		(0.024)
Labour squared	0.003	Seed × Labour	-0.008	Pesticide × Fertilizer	-0.015
	(0.007)		(0.009)		(0.020)
Log likelihood	553.48				
Observations	779				

Note: Natural logarithm is employed for inputs and output. Town dummies are controlled. Clustered standard errors at the village level are reported in parentheses.

*** Significant at the 1 % level.

** Significant at the 5 % level.

* Significant at the 10 % level.

Based on the estimates above, for each observation we calculated a land use efficiency score. Figure 1 and Table 5 show the distribution and summary statistics of land use efficiency scores. In general, land use efficiency scores were skewed to the left, with approximately 50 % of households having land use efficiency scores at or below 0.940. The average land use efficiency score was 0.930. Since the measure of the land use efficiency score $\frac{Z_i^M}{Z_i}$ is the ratio of minimum feasible land input to observed land input, on average 7.53 % of land was overused compared to the ideal situation of everybody using land efficiently.[4]

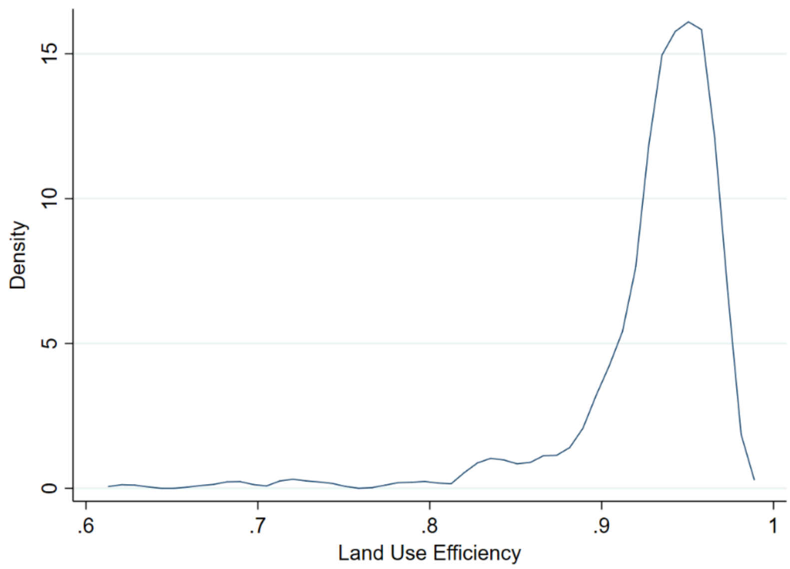

Figure 1. Kernel density estimate of land use efficiency

[4] With the ideal situation as the base, it is calculated as follows: $\frac{Z_i - Z_i^M}{Z_i^M} = \frac{Z_i}{Z_i^M} - 1 = \frac{1}{LUE_i} - 1 = \frac{1}{0.930} - 1 =$ 7.53 %.

Table 5. Summary statistics of land use efficiency scores (observations = 779)

Land use efficiency	Scores
Mean	0.930
Minimum	0.619
25th percentile	0.923
50th percentile	0.940
75th percentile	0.956
Maximum	0.983

Source: Authors' computation.

The effect of land markets on land use efficiency

In this section, we report the determinants of households' land use efficiency scores with an emphasis on the role of land markets.[5] Table 6 reports the main results. The F-statistics from the joint significance test on the strength of the two instrumental variables were 47.75 (P-value = 0.000) and 169.13 (P-value = 0.000) for renting in and renting out respectively, suggesting that there need be no concern about weak instruments. The F-statistics from the joint significance test of the instrumental variables in Eq. (11) was 1.17 (p-value = 0.558), implying that the two instrumentals were valid. While the residual from the first stage estimation on renting out land was insignificant, the residual from the renting in land estimation was significant at the 10 % level, which means that household participation in land markets is endogenous and

[5] Since the determinants of household participation in land markets are beyond the interest of this paper, the first stage estimates of the control function approach are reported only in the appendix in Table A.1.

deems the instrumental variable approach necessary.

Table 6. The effect of land rental on land use efficiency

Variables	Average marginal effect
Rent in	0.039**
	(0.019)
Rent out	0.006
	(0.01)
Age of household head	0.000
	(0.000)
Education of household head	0.001
	(0.002)
Off-farm experience of household head	0.006**
	(0.003)
Household size	0.000
	(0.001)
Land endowment	0.000
	(0.001)
Number of land plots	0.001
	(0.001)
Agricultural training	-0.001
	(0.004)
Agricultural assets	0.001
	(0.001)
Other durable assets	0.001**
	(0.000)
Disaster	-0.008**
	(0.004)
Residual (Rent in)	-0.020*
	(0.011)
Residual (Rent out)	-0.003
	(0.007)
Observations	558

Note: Town dummies are controlled for, but not reported. Clustered standard errors at the village level are reported in parentheses. The F-statistic from the joint significance tests on the strength of instruments for renting in and renting out are 47.75 (p-value = 0.000) and 169.13 (p-value = 0.000) respectively. The F-statistic for the exclusion restriction test from Eq. (11) is 1.17 (p-value = 0.558).

** Significant at the 5 % level.

* Significant at the 10 % level

We found that renting in land had a positive effect on household land use efficiency ($p < 0.05$). The average marginal effect of renting in land was 0.039, which means that renting in land increases land use efficiency by 3.9 %. This is in line with expectations and in general is consistent with the arguments in previous studies finding that land markets lead to an increase in land productivity (Chamberlin and Ricker-Gilbert, 2016; Deininger and Jin, 2005; Feng et al., 2010; Jin and Deininger, 2009). The effect of renting out land, however, was insignificant, suggesting that the overall effect of renting out land on land use efficiency tends to be zero. There could be different causes of this, as outlined in section two. Authorities may also push farmers to transfer land (Liu et al., 2017), and behaviour may not be driven by an attempt to increase efficiency. Indeed, Liu et al. (2016) find that the farmers' decisions to rent out land in rural China are influenced by political interference.

Table 6 also reports the effects of other factors on land use efficiency. We found that household heads' previous off-farm experience had a positive and significant effect on land use efficiency, which supports the argument that off-farm experience can increase productivity through investments (Kousar and Abdulai, 2015; Rozelle et al., 1999). Similarly, Ma et al. (2018) also found that off-farm employment is positively related to yield level in China. The value of other durable assets in the family showed a positive effect on land use efficiency. The statistical significance was at the 5 % level. This suggests that wealthier households may invest other inputs not controlled for in our model to increase their yields. Experience with natural disasters, which, as we have argued, partly captures land quality, showed a negative effect on land use efficiency, which is intuitive because disasters can cause significant yield losses.

Robustness tests

To test the robustness of the effects of land market participation on land use efficiency, we conducted two additional analyses. First, after the estimation of Eq. (6) and (7), we predicted households' probability of renting in and out land. We then estimated Eq. (5) by replacing $RENTIN_i$ and $RENTOUT_i$ with the predicted probability. Standard errors were adjusted with 1,000 bootstraps. This is called a "plug-in" approach which is often used to complement the control function approach in empirical work (*e.g.* Brasselle et al. (2002), Rao et al. (2017) and Liu et al. (2017)). The estimates in Table A. 2 confirmed our previous results.

Second, we re-calculated land use efficiency scores by assuming that the error term of technical inefficiency in the translog production function was half-normally distributed or by using a Cobb-Douglas rather than a translog production function, and then re-estimated the effects of land market participation on the new land use efficiency scores. A likelihood ratio test (LR chi^2 = 19.63, p = 0.545)[6] showed no significant difference between the Cobb-Douglas and the translog production functions, suggesting that the more complex model specification of the translog production function was not preferred. A different model specification would alter the measure of land use efficiency scores ($LUE_i = exp\left(ln\frac{Z_i^M}{Z_i}\right) = exp\left(-\frac{u_i}{\beta_Z}\right)$ for the Cobb-Douglas model), which might lead to different results. However, as shown in Table A. 2, this was not the case.

Third, the skewed land use efficiency scores (Fig. 1) raised the concern that our results could be driven by outliers. Thus, we re-estimated Eq. (10) after dropping observations with land use efficiency scores below the 5 % level. The results showed that the previous inferences still held (Table A. 2).

Identifying causal channels

Given the positive effect of renting in land on land use efficiency, one interesting question may be how this effect emerges. Here we provide some evidence on the potential causal channels introduced earlier. First, we tested whether the positive effect of renting in land resulted from economies of scale. If renting in land improves

---

[6] We performed the test based on the results of the Cobb-Douglas and translog production functions with (non-robust) standard errors.

land use efficiency *via* the change in the area of cultivated land, land input should be a strong predictor of land use efficiency. However, the insignificance of land endowments on land use efficiency in Table 6 suggests that economies of scale may not be important. As households may use more (less) land than land endowment for production, especially when land rental is present, land endowments may capture the exact land input. Thus, we replaced land endowment with land input and estimated its effect on land use efficiency using Eq. (5) after excluding households that either rent in or rent out land. The effect of land input remained insignificant. These results suggest that renting in land does not affect land use efficiency through the change in land input, in line with the argument of Rigg et al. (2016) that economies of scale may be limited in farming.

Second, we tested whether the positive effect of renting in land on land use efficiency was due to better land quality. Note that we introduced a measure of land quality – disaster experience – in our estimation. It is evident that flood and drought significantly increase soil nitrogen losses and reduce the functionality of soil microbes (Nguyen et al., 2018; Yang et al., 2016). The positive effect of renting in land should therefore be independent of land quality. Although disaster experience may not fully capture land quality, it approximates a general tendency of land quality. Thus, we further tested this causal channel by investigating whether traded land was of better quality. Specifically, we ran a probit model of disaster experience on land rental with all other control variables. The results (Table A. 3) showed that disaster experience was significantly and negatively correlated with renting out land, implying that households that rent out land are less likely to have experienced disasters. This provides suggestive evidence that traded land is of poorer quality, which is consistent with the literature (Rahman, 2010) but in contrast to the proposed causal channel.

Third, we tested whether the positive effect of renting in land results from variations in property rights. Without the separation of inputs and outputs from land with different property rights, this cannot be directly tested. However, given the positive effect of renting in, land use efficiency for rented land could be expected to be greater than that for owned land. In this case, land use efficiency should increase with the household's share of rented in land. To test this hypothesis, we interacted the variable of rent-in with households' land endowment and then calculated the average marginal effect of rent-in when households' land endowments are fixed at different values. The results (Table A. 4), however, showed an increasing average marginal effect of rent-in, which again did not support a causal impact of property rights.

Fourth, we tested whether a high labour-land input ratio due to labour market failures could drive the positive effect of renting in. Households with a higher labour-land input ratio could be expected to show a larger effect of rent-in. Thus, we generated a new variable defined as the ratio of actual labour input to land input. We included the new variable and its interaction term with rent-in in Eq. (10) and then calculated the average marginal effects of rent-in for different values of households' labour-land ratio. The results in Table 7 showed an increasing average marginal effect of rent-in, thus supporting our hypothesis. This finding is in line with the argument that land markets will improve land use efficiency if there is labour market failure (Deininger et al., 2018; Lamb, 2003).

Table 7. The interaction effect of renting in land with labour-land input ratio on land use efficiency

Variables	Average marginal effects
Rent in (labour-land input ratio = 1)	0.035**
	(0.017)
Rent in (labour-land input ratio = 5)	0.036**
	(0.016)
Rent in (labour-land input ratio = 10)	0.037**
	(0.016)
Rent in (labour-land input ratio = 15)	0.038**
	(0.016)
Rent in (labour-land input ratio = 20)	0.039**
	(0.016)

Note: This table reports the average marginal effect of renting in land on land use efficiency when household labour-land input ratio is fixed at different representative values. Other variables are controlled.

** Significant at the 5 % level.

Conclusions

On a global scale, population growth and a decrease in agricultural land raises concerns about food security. An efficient use of scarce land has therefore also become a key concern for policy makers. Land market development is a promising policy instrument for enhancing land use efficiency. In this paper, we derived a measure of land use efficiency using a stochastic frontier production function, and estimated the causal effect of farm households' participation in land markets on land use efficiency using a control function approach. We also provide suggestive evidence on the causal channels of land market development on land use efficiency. Our analysis complements the existing literature on the economic consequences of land markets. Our empirical results allow three main conclusions to be drawn.

First, on average about 7.53 % of agricultural land has been overused, which provides room for efficiency improvements in rice production in our study area that could eventually also enhance food security. While many policies focus on the maintenance of agricultural land, *e.g.* by limiting land conversion for cities, improving the land use efficiency of existing farmland may be a viable way of increasing yields without compromising urban development. Second, households that rent in land have a significantly higher land use efficiency. Allowing households to rent in land from others can positively contribute to higher rice yields in China. Although we did not find an effect of renting out land on land use efficiency, it is possible that if the political pressure to rent out land were lower, such effects would have been found. Third, the positive effect of renting in land on land use efficiency appears to be the result of a high labour-land input ratio due to labour market failure. Although in our research area the non-agricultural sector is much more developed than elsewhere in

China, this finding implies that the current opportunity costs of farming are low. Removing labour market constraints could further contribute to a sustainable development of the sector in the future.

Our paper does have some limitations. Despite our efforts to develop a solid identification strategy, we were hampered by the availability of cross-sectional data. Panel data would have allowed us to limit the risk of bias from omitted variables, such as farming ability. The small sample size at village level also makes it difficult to control for village-level effects. Our research area is known for intensive farming and therefore could have greater land use efficiency than other areas in China. Thus, our results may predominately extrapolate to other developed areas, but they should be validated and complemented by other case studies.

Acknowledgements

This work was supported by the National Natural Science Foundation of China (grant numbers 71673144 and 71773046), the Specialized Research Fund for the National Social Science Fund of China (grant number 18VSJ060), Humanity and Social Science Youth Foundation of Ministry of Education of China (grant number 18YJC790110), China Postdoctoral Science Foundation (grant number 2017M620217) and the 111 Project (B17024).

Declaration of interest statement

None

References

Abdulai, A., Owusu, V., Goetz, R., 2011. Land tenure differences and investment in land improvement measures: Theoretical and empirical analyses. Journal of Development Economics 96, 66-78.

Abdulai, A.N., Abdulai, A., 2017. Examining the impact of conservation agriculture on environmental efficiency among maize farmers in Zambia. Environment and Development Economics 22, 177-201.

Anne, B., Edeltraud, G., Sami, K., 2017. Resource efficiency and an integral framework for performance measurement. Sustainable Development 25, 150-165.

Battese, G.E., Coelli, T.J., 1995. A model for technical inefficiency effects in a stochastic frontier production function for panel data. Empirical Economics 20, 325-332.

Brasselle, A.-S., Gaspart, F., Platteau, J.-P., 2002. Land tenure security and investment incentives: puzzling evidence from Burkina Faso. Journal of Development Economics 67, 373-418.

Chamberlin, J., Ricker-Gilbert, J., 2016. Participation in rural land rental markets in Sub-Saharan Africa: Who benefits and by how much? Evidence from Malawi and Zambia. American Journal of Agricultural Economics 98, 1507-1528.

Conley, T.G., Udry, C.R., 2010. Learning about a new technology: Pineapple in Ghana. American Economic Review 100, 35-69.

Deininger, K., Ali, D.A., 2008. Do overlapping land rights reduce agricultural investment? Evidence from Uganda. American Journal of Agricultural Economics 90, 869-882.

Deininger, K., Ali, D.A., Alemu, T., 2011. Impacts of land certification on tenure security, investment, and land market participation: Evidence from Ethiopia. Land Economics 87, 312-334.

Deininger, K., Jin, S., Liu, Y., Singh, S.K., 2018. Can labor-market imperfections explain changes in the inverse farm size-productivity relationship? Longitudinal evidence from rural India. Land Economics 94, 239-258.

Deininger, K., Jin, S.Q., 2005. The potential of land rental markets in the process of economic development: Evidence from China. Journal of Development Economics 78, 241-270.

Feng, S., Heerink, N., Ruben, R., Qu, F., 2010. Land rental market, off-farm employment and agricultural production in Southeast China: A plot-level case study. China Economic Review 21, 598-606.

Ferrari, S., Cribari-Neto, F., 2004. Beta regression for modelling rates and proportions. Journal of Applied Statistics 31, 799-815.

Heltberg, R., 1998. Rural market imperfections and the farm size-productivity relationship: Evidence from Pakistan. World Development 26, 1807-1826.

Holden, S., Shiferaw, B., Pender, J., 2001. Market imperfections and land productivity in the Ethiopian highlands. Journal of Agricultural Economics 52, 53-70.

Ito, J., Bao, Z., Ni, J., 2016. Land rental development via institutional innovation in rural Jiangsu, China. Food Policy 59, 1-11.

Jin, S., Deininger, K., 2009. Land rental markets in the process of rural structural transformation: Productivity and equity impacts from China. Journal of Comparative Economics 37, 629-646.

Kousar, R., Abdulai, A., 2015. Off-farm work, land tenancy contracts and investment in soil conservation measures in rural Pakistan. Australian Journal of Agricultural and Resource Economics 60, 307-325.

Kouser, S., Qaim, M., 2015. Bt cotton, pesticide use and environmental efficiency in Pakistan. Journal of Agricultural Economics 66, 66-86.

Kumari, R., Nakano, Y., 2015. Does land lease tenure insecurity cause decreased productivity and investment in the sugar industry? Evidence from Fiji. Australian Journal of Agricultural and Resource Economics 60, 406-421.

Kung, J.K.S., 2002. Off-farm labor markets and the emergence of land rental markets in rural China. Journal of Comparative Economics 30, 395-414.

Lamb, R.L., 2003. Inverse productivity: land quality, labor markets, and measurement error. Journal of Development Economics 71, 71-95.

Lewbel, A., Dong, Y., Yang, T.T., 2012. Comparing features of convenient estimators for binary choice models with endogenous regressors. Canadian Journal of Economics/revue Canadienne Déconomique 45, 809-829.

Liu, Z., Müller, M., Rommel, J., Feng, S., 2016. Community-based agricultural land consolidation and local elites: Survey evidence from China. Journal of Rural Studies 47, 449-458.

Liu, Z., Rommel, J., Feng, S., 2018. Does it pay to participate in decision-making? Survey evidence on land co-management in Jiangsu Province, China. Ecological Economics 143, 199-209.

Liu, Z., Rommel, J., Feng, S., Hanisch, M., 2017. Can land transfer through land cooperatives foster off-farm employment in China? China Economic Review 45, 35-44.

Lloyd-Smith, P., Schram, C., Adamowicz, W., Dupont, D., 2018. Endogeneity of risk perceptions in averting behavior models. Environmental and Resource Economics 69, 217-246.

Long, H., Tu, S., Ge, D., Li, T., Liu, Y., 2016. The allocation and management of critical resources in rural China under restructuring: Problems and prospects. Journal of Rural Studies 47, 392-412.

Ma, L., Feng, S., Reidsma, P., Qu, F., Heerink, N., 2014. Identifying entry points to improve fertilizer use efficiency in Taihu Basin, China. Land Use Policy 37, 52-59.

Ma, W., Renwick, A., Grafton, Q., 2018. Farm machinery use, off-farm employment and farm performance in China. Australian Journal of Agricultural and Resource Economics 62, 279-298.

Management and Administration Station of Rural Cooperative Economy of Jiangsu (JSMAS), 2015. Tabulation on rural collective financial affairs, assets and annual statistical report of agricultural economy of Jiangsu in 2014. China Statistics Press, Beijing.

Menale, K., Stein, H., 2007. Sharecropping efficiency in Ethiopia: threats of eviction and kinship. Agricultural Economics 37, 179-188.

Minten, B., Barrett, C.B., 2008. Agricultural technology, productivity, and poverty in Madagascar. World Development 36, 797-822.

Nguyen, L.T.T., Osanai, Y., Anderson, I.C., Bange, M.P., Tissue, D.T., Singh, B.K., 2018. Flooding and prolonged drought have differential legacy impacts on soil nitrogen cycling, microbial communities and plant productivity. Plant and Soil 431, 371–387.

Rahman, S., 2010. Determinants of agricultural land rental market transactions in Bangladesh. Land Use Policy 27, 957-964.

Rahman, S., Rahman, M., 2009. Impact of land fragmentation and resource ownership on productivity and efficiency: The case of rice producers in Bangladesh. Land Use Policy 26, 95-103.

Rao, F., Spoor, M., Ma, X., Shi, X., 2017. Perceived land tenure security in rural Xinjiang, China: The role of official land documents and trust. China Economic Review.

Reinhard, S., Lovell, C.A.K., Thijssen, G., 2002. Analysis of environmental efficiency variation. American Journal of Agricultural Economics 84, 1054-1065.

Reinhard, S., Lovell, C.K., Thijssen, G., 1999. Econometric estimation of technical and environmental efficiency: an application to Dutch dairy farms. American Journal of Agricultural Economics 81, 44-60.

Rigg, J., Salamanca, A., Thompson, E.C., 2016. The puzzle of East and Southeast Asia's persistent smallholder. Journal of Rural Studies 43, 118-133.

Rozelle, S., Taylor, J.E., de Brauw, A., 1999. Migration, remittances, and agricultural productivity in China. American Economic Review 89, 287-291.

Tan, R., Beckmann, V., van den Berg, L., Qu, F., 2009. Governing farmland conversion: Comparing China with the Netherlands and Germany. Land Use Policy 26, 961-974.

Tessema, Y.M., Asafu-Adjaye, J., Shiferaw, B., 2018. The impact of conservation tillage on maize yield and input demand: the case of smallholder farmers in north-west Ethiopia. Australian Journal of Agricultural and Resource Economics 62, 636-653.

Wooldridge, J.M., 2014. Quasi-maximum likelihood estimation and testing for nonlinear models with endogenous explanatory variables. Journal of Econometrics 182, 226-234.

Wu, Z., Liu, M., Davis, J., 2005. Land consolidation and productivity in Chinese household crop production. China Economic Review 16, 28-49.

Yang, H., Sheng, R., Zhang, Z., Wang, L., Wang, Q., Wei, W., 2016. Responses of nitrifying and denitrifying bacteria to flooding-drying cycles in flooded rice soil. Applied Soil Ecology 103, 101-109.

Zhang, C., Guanming, S., Shen, J., Hu, R.-f., 2015. Productivity effect and overuse of pesticide in crop production in China. Journal of Integrative Agriculture 14, 1903-1910.

Zhang, L., Feng, S., Heerink, N., Qu, F., Kuyvenhoven, A., 2018a. How do land rental markets affect household income? Evidence from rural Jiangsu, P.R. China. Land Use Policy 74, 151-165.

Zhang, Q., Sun, Z., Huang, W., 2018b. Does land perform well for corn planting? An empirical study on land use efficiency in China. Land Use Policy 74, 273-280.

Zhong, T., Qian, Z., Huang, X., Zhao, Y., Zhou, Y., Zhao, Z., 2018. Impact of the top-down quota-oriented farmland preservation planning on the change of urban land-use intensity in China. Habitat International 77, 71-79.

Zhou, Y., Shi, X., Heerink, N., Ma, X., 2018. The effect of land tenure governance on technical efficiency: evidence from three provinces in eastern China. Applied Economics, 1-18.

Appendices

Table A 1. Determinants of renting in and renting out land

Variables	Rent in	Rent out
Age of household head	-0.017***	0.009
	(0.006)	(0.007)
Education of household head	0.050	0.041
	(0.064)	(0.071)
Off-farm experience of household head	-0.099	0.067
	(0.115)	(0.129)
Household size	-0.012	-0.042
	(0.028)	(0.034)
Land endowment	-0.007	0.073***
	(0.021)	(0.024)
Number of land plots	-0.056*	0.060**
	(0.032)	(0.029)
Agricultural training	0.382***	-0.098
	(0.115)	(0.132)
Agricultural asset	0.083***	-0.013
	(0.029)	(0.033)
Other durable asset	-0.013	-0.004
	(0.011)	(0.011)
Disaster	0.160	-0.261*
	(0.108)	(0.145)
Share of households in land rental market	1.703***	2.651***
	(0.272)	(0.284)
Administrative intervention	-0.930***	1.591***
	(0.216)	(0.293)
Constant	0.256	-3.752***
	(0.559)	(0.575)
Pseudo R^2	0.140	0.272
Log likelihood	-483.782	-350.559
Observations	987	885

Note: The table reports coefficients. Clustered standard errors at the village level are reported in parentheses. The *F*-statistic form the joint significance tests on the strength of instruments for renting in and renting out are 47.75 (p = 0.000) and 169.13 (p = 0.000) respectively.

*** Significant at the 1 % level.

** Significant at the 5 % level.

* Significant at the 10 % level.

Table A 2. Results from robustness tests

Variables	Average marginal effect			
	Robustness test I	Robustness test II	Robustness test III	Robustness test IV
Rent in	0.052**	0.046*	0.038**	0.033**
	(0.021)	(0.024)	(0.019)	(0.016)
Rent out	0.006	0.008	0.004	0.008
	(0.012)	(0.013)	(-0.011)	(0.008)
Residual (rent in)		-0.024*	-0.019*	-0.018*
		(0.014)	(0.011)	(0.009)
Residual (rent out)		-0.003	-0.003	-0.004
		(0.008)	(0.007)	0.033

Note: Robustness test I is from the estimation with the "plug-in" approach. Robustness test II is from the estimation with a half-normal distributed error term in a translog production function. Robustness test III is from the estimation with a Cobb-Douglas production function. Robustness test IV is from the estimation after excluding outliers. All other variables are controlled.

** Significant at the 5 % level.

* Significant at the 10 % level.

Table A 3. Correlation of land markets and disaster

Variables	Correlation coefficients
Rent in	0.101
	(0.106)
Rent out	-0.307**
	(0.147)

Notes: Clustered standard errors at the village level are reported in parentheses. All other variables and town dummies are controlled.

** Significant at the 5 % level.

Table A 4. The interaction effect of renting in land with land endowments on land use efficiency

Variables	Average marginal effects
Rent in (land endowment = 1 mu)	0.034**
	(0.016)
Rent in (land endowment = 5 mu)	0.036**
	(0.016)
Rent in (land endowment = 10 mu)	0.038**
	(0.017)
Rent in (land endowment = 15 mu)	0.041**
	(0.019)
Rent in (land endowment = 20 mu)	0.043**
	(0.022)

Note: This table reports average marginal effects of renting in land on land use efficiency when household land endowment is fixed at different representative values. Other control variables are the same as those in Table 6.

** Significant at the 5 % level.