Property Rights and Land Misallocation:
Evidence from New Land Certified Program in China

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Property Rights and Land Misallocation: Evidence from New Land Certified Program in China

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Abstract: This article investigates the impact of land institution improvements on the land resources misallocation and on agricultural productivity. Based on China's new round of land certification program (LCP), we find that land certification significantly enhances land allocation efficiency and agricultural total factor productivity. In addition, this article distinguishes between the LCP's implementation effects and the certification effects of farmers' participation in the LCP. We use a quantitative macroeconomic model to measure the total misallocation during our sample period. By combaining the empricial estimatation of certification effect and quantitative work, we show that the LCP accounts for about 23.2% of the overall productivity gains by removing all misallocation up until 2019 and suggest that another 15.5% of potential gains could be realized in the future if the LCP is fully implemented. Using village-level and household-level data, we further explore channels through which the LCP increases agricultural productivity, including the activation of land rental markets, land transfer from inefficient farmers to efficient ones, the exit of inefficient farmers from agriculture, and the relaxation of capital constraints for efficient farmers.

JEL Classification: Q15, O12, P26

Keywords: Property Rights, Land Misallocation, New Land Certified Program, Agricultural Productivity, China

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1 Introduction

Agricultural productivity is argued to have significant explanatory power on the income gap across countries (Ranis and Fei, 1961; Gollin et al., 2002). This is because agriculture is the primary sector of labor employment in many developing countries, and the increase in agricultural productivity is closely related to structural transformation and economic growth (Caselli, 2005; Duarte and Restuccia, 2010; Deininger et al., 2021). In recent years, studies using data from different developing countries have consistently shown that resource misallocation is the leading cause of low agricultural productivity in developing countries (Lagakos and Waugh, 2013; Adamopoulos and Restuccia, 2014; Ayerst et al., 2020; Chen et al., 2022). A large amount of literature has been devoted to quantifying the magnitude of misallocation in agriculture and the potential efficiency gain from the reallocation of resources (Hsieh and Klenow, 2009; Brandt et al., 2011; Adamopoulos et al., 2022). However, much less attention has been paid to the underlying causes of misallocation in agriculture (Restuccia and Rogerson, 2017).

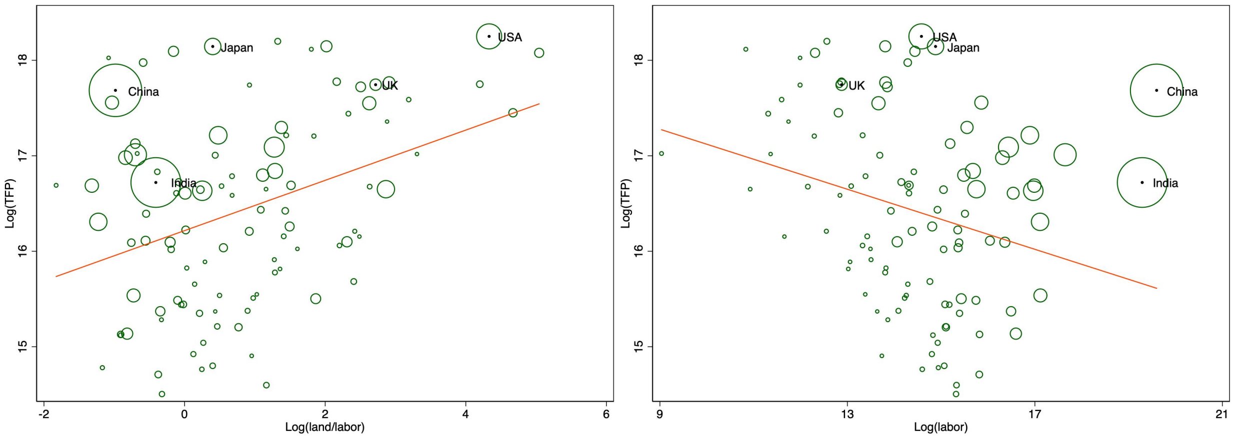
As one of the most critical production factors, the allocation of land among farmers is significant to agricultural production efficiency (Chen, 2019; Adamopoulos et al., 2022). An efficient allocation of land resources implies that more productive farmers operate relatively more land resources in a given community. In practice, land allocation in developing countries is far from efficient. A lack of land transfer rights, barriers to rural-urban mobility, and insecure land property rights are the leading causes of land misallocation in rural areas of developing countries (Gottlieb and

Grobovšek, 2018; Rachel et al., 2019; Zhao, 2020; Wang et al., 2021; Chari et al., 2021; Chen et al., 2022). These restrictive land rights make land transfer difficult among farmers, causing stagnation in reallocation and leading to inefficient and small-scale farming issues in developing countries (Adamopoulos and Restuccia, 2014).

Since the implementation of the household responsibility system (HRS) in the early 1980s, the Chinese government has adopted a series of regulatory and legal reforms to strengthen the land security and transferability of agricultural land and to enhance the mobility of rural laborers. The major land policy in 21st cenruty, Rural Land Contract Law (RLCL), has dramatically reduced the risk of land loss for farmers by increasing the stability of land rights (Deininger and Jin, 2009; Zhao, 2020) and granting farmers the right to transfer land, both of which have contributed to the improvement of land allocation in rural China (Chari et al., 2021). However, without an accompanying systematic land titling effort, legal rights were weakly implemented, which limits the extent of land rental markets (Brandt et al., 2017). It is not surprising that the overall gain in land allocation of RLCL is limited (Chari et al., 2021). We use the mean data range from 2003 to 2010, which is the average of seven years after RLCL, to reflect the agriculture resource allocation situation in China. Figure 1A shows that among main countries with similar TFP, China has the least land per farmer, even compared with Japan, who shares similar geographical conditions. Figure 1B reveals that the reason for China's lower land per farmer is the huge number of farmers (i.e., the denominator in Panel 1A). This reveals the difficulity of achieving reasonable labor adjustment and concentrating of land for China's agricultural sector during this period, suggesting that serious resource misallocation still exists, despite after the RLCL[1].

Figure 1：Agriculture TFP Versus Several Input For Main Countries

. A, TFP versus Land per Labor   B,   TFP versus Labor



Note: Data from the World Bank. TFP is calculated through Cobb-Douglas production function, which can be expressed in logs as follows: $\text{output}_{c,t} = \alpha + \beta_1 \text{labor}_{c,t} + \beta_2 \text{Fertilizer}_{c,t} + \beta_3 \text{land}_{c,t} + \lambda_c + \delta_t + \epsilon_{c,t}$, where output is measure by the agriculture total value constant in 2015 dollors, and labor, fertilizer and land are labor number worked in agriculture sector, fertilizer input and agriculture land input, respectively. Each scatters are the mean values between 2003 to 2010.

To address this problem, the Chinese government implemented the LCP in 2009, which significantly reduced the transaction costs because of the clearly defined boundaries and the issuance of land certificates. Many scholars have studied this policy, especially the effect of the LCP on renting behaviors between different farmers (Ren et al., 2018; Zhang et al., 2019; Cheng et al., 2019) and household welfare (Xu and Du, 2021). Compared with early articles using the Probit model or Tobit model (Ren et al., 2018; Cheng et al., 2019), the latest literature treated the implementation

[1] We need to admit that our TFP calculation is not very accurate due to data limitations, but this has little effect on the conclusion. We also used yield per mu as a proxy for production efficiency, which is shown in Appendix A1, and the conclusions are consistent.

of the LCP as a quasi-natural experiment and employed the difference-in-differences (DID) method to estimate the impact of its implementation (Xu and Du, 2021; Gao et al., 2021). There are four noticeable gaps in the existing literature: (1) earlier studies on misallocation tend to focus on the RLCL (e.g., Chari et al. 2021), whereas the LCP is still understudied; (2) existing studies about the LCP focus primarily on rental activities and other issues, but much less on misallocation; (3) the effect of the implementation of the land titling program and the effect of farmers' actual participation in certification were rarely separated in the previous studies; and (4) none of these articles evaluate the overall policy effect on resource misallocation.

To fill these literature gaps, we use 2015-2019 China Rural Household Panel Survey (CRHPS) data to investigate the impact of the LCP on land allocation efficiency and total factor productivity. We further distinguish the implementation effect from the certification effect of the LCP.[2] We use the difference-indifference method to identify the implementation effects and employ the insturmental variable approach to estimate the certified effect, which had adopted in Field (2007) and Lei and Lin (2009). Separating the certified effects from implementation can help us obtain the complete effect of the LCP on efficiency. Then, we follow the methodology of Adamopoulos et al. (2022) to quantify the gain in allocation efficiency due to the reduction of misallocation in the Chinese agriculture sector. Finally, we combaine cerifited effect estimated by IV approach and the quantitative result using

2 The distinction between the implementation effect and the certification effect is created by the fact that a significant portion of rural households failed to receive land certificates, despite the LCP being implemented in their villages.

Adamopoulos et al. (2022)'s method to fill the forth research gap and measure the whole effect of LCP on resource misallocation.

We find that implementing the LCP increases land allocation efficiency (covariance between TFP and land share) at the village level by 0.043, while the certification effect is 0.141, which implies that land is allocated more effective. Meanwhile, the impact of the implementation of the LCP and the impact of the certification of the LCP on total factor productivity are 10.9% and 36%, respectively. This results of implemnetation effects reveals that the policy impact of LCP is bigger than the RLCL, which is estimated by Chari et al., (2021)[3], and the estimation results of certifited effects show the overall impact of LCP on OP and TFP can reach 0.131 and 39.4%, respectively, if the low household compliance issue can be solved. The quantification of misallocation using the approach of Adamopoulos et al. (2022) shows that the TFP improvement when resources are properly allocated is 93% in our sample period. Through the results of certifited effects and quantitative result, we find that, up to 2019, the introduction of the LCP has alleviated roughly 23.2% of factor misallocation, and the full implementation of the LCP (i.e., 100% of households receiving certificates) in the future could alleviate additional 15.5% of resource reallocation. The above results indicate that the full implementation of LCP policy can eliminate about 39% of the efficiency loss due to resource misallocation. These results are consistent with previous literature (Deininger and Jin, 2009. Rachel et al., 2019)

3 In Chari et al., (2021), the estimated effect of RLCL on TFP is 7.55% - 8.88%. We adopt the same TFP measurement method and find the effect of LCP on TFP is 11.9% and 39.4% for implementation effect and certification effect, respectively. It is worth noting that even the LCP's implementation effect, calculated by DID method (same as in Chari et al., 2021) in our article, is already greater than the impact of RLCL estimated in Chari et al., (2021).

that a decrease in land transaction costs can lead to an increase in allocation efficiency.

In the mechanism analysis section, we propose four main mechanisms through which the LCP improves the factor allocation situation and total factor productivity. More specifically, the LCP led to (1) more active participation in land rental markets, (2) more efficient land rental markets, (3) more efficient labor allocation (e.g., exit of farm by less efficient farmers), and (4) an improved access to credit and long-time investment especially for the more efficient farmers.

This study makes three main contributions. First, this study is directly related to the large existing literature about the importance of secure property rights on economic growth (Besley 1995; Jacoby et al, 2002, Holden et al. 2010). While the tradition debate in this literature tends to emphasize the role of well-defined property rights on investment and productivity, this study adds to the limited number of studies that explore the linkage between land reforms and allocation efficiency (e.g., Field, 2007; de Janvry et al., 2015; Chari et al., 2021, Chen et al., 2022). Second, This study makes the key distinctions of the effect of LCP on productivity enhancement, namely, the implementation effect and the certification effect. Through an assessment of the certified effect, our article obtains the overall impact of LCP. Diverging from previous studies (Xu and Du, 2021, Gao et al., 2021), our work incorporates low household compliance issues into the estimation framework, thereby extending current understanding of the policy effect of LCP. Furthermore, we also identify the channels through which LCP contributes to the mitigation of resource misallocation (Gollin and Udry, 2021).. Third, to the best of our knowledge, it is the earliest study that combaining the empricial effects and quantitative result and evaluating the contribution of the LCP on overall efficiency improvement due to resource reallocation, which has strong policy implications for China and other developing countries.

The article proceeds as follows. Section 2 provides a detailed land institution background of China. Section 3 describes the empirical methodology and data. Section 4 presents the main results. Section 5 further discusses the result. Section 6 shows the potential mechanisms of the LCP's impact, and Section 7 concludes.

2 Background

2.1 Two majot Land Policies in China in 21st century

At the beggining of 21st century in China, there was serious land tenure insecurity problem because of the frequect land reallocation[4]. In this period, land is usually adjusted in response to population change within the community (Zhao, 2020)[5]. Frequent land adjustment significantly undermined the development of rural land rental markets. Benjamin and Brandt (2002) found that less than 3% of rural households rented out their land and most of these leasing activities took place among relatives instead of between differenct efficiency farmers, creating serious efficiency loss due to resource misallocation.

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[4] This situation is mainly caused by the Household Responsibility System (HRS) which is implemented in the late 1970s and early 1980s across rural China (Lin, 1988). HRS allocated land use rights from village collectives to individual farmers based on number of household members. During 1980 - 2000, the change of family member numbers induced the land adjustment within village.

[5] For example, Benjamin and Brandt (2002) found that over two-thirds of villages experienced reallocations at least once and, on average, more than twice during 1983-1995. Li et al. (1998) pointed out that 38% of the surveyed villages experienced land adjustment at least three times since the 1980s.

To strengthen tenure security and promote effective land transfers, China implemented the Rural Land Contracting Law (RLCL) in 2003, which carried out the first round of land certification and provided farmers with legal rights to lease their land. This law made rules for land leasing and the process of resolving and redressing land leasing disputes (Deininger and Jin, 2009). A recent study found that the RLCL stimulated land transfers and alleviated misallocation to some extent (Chari et al., 2021). However, the positive impact of RLCL is smaller than expected. There are only 5% of China's arable land was transferred in 2005[6], three years after the implementation of RLCL[7].

To further penetrate the land market, China implemented a new round of land tenure confirmation program. In 2009, the central government's No. 1 Document announced a pilot project entitled the Land Certified Program (LCP); eight villages were chosen as the pilot villages. In 2011, 50 counties joined the LCP (Cheng et al., 2019; Xu and Du, 2021). In 2013, this project was promoted nationwide. The content of LCP can be summarized in four aspects. First, the LCP uses a geographic information system (GIS) to record the contracted land's spatial geographic information, including the plot's size, scope, and boundary. Second, these information and other contents such as owner's name are recored in a certification and assign to farmers when certain demand is satisfied. This certification is like the ID card of land can can be used as medium when land is transfered. Third, the LCP makes a more

[6] Data from the Ministry of Agricultural and Rural Affairs of China,

[7] There are two main reasons for the limited effects on land transfers and the ensuing efficiency gain. First, this round of land certification was relatively superficial; farmers' land certificates did not record the size and boundary of their land, which led to many land disputes. Second, farmers did not receive a tradable title certificate, which caused high transaction costs for arable land.

detailed division of ownership, contract rights, and management rights (called "the separation of three rights"), which means in legal aspects, farmer can rent their land out to other residents[8]. Last, the LCP allows the lessor and lessee to determine the duration of the land transfer contract through free negotiation.

Compared with the RLCL, the LCP sets more precise farmland boundaries and issues more detailed land certificates, which has reduced the number of land disputes. In addition, the land certificate issued by the LCP has legal rights, which means that the land has a tradable medium, and the formal system protects this medium. Therefore, the LCP not only clarifies the scope of property rights, but also endows property rights with more convenient transaction attributes, which reduces the transaction costs of land transfers and encourages the activities of the land market. In fact, the agricultural land which is transfered in the land rental market rose from 7% in 2008 to over one-third in 2016.

2.2. The low household compliance issues of the LCP

The major issue related to LCP is the low household compliance problem, which means the number of farmers participating in the LCP is far lower than desired. The central government aimed to provide land certificates to all farmers in all regions by the end of 2018. However, according to China Health and Retirement Longitudinal Study (CHARLS) and China Rural Household Panel Survey (CRHPS), two of the

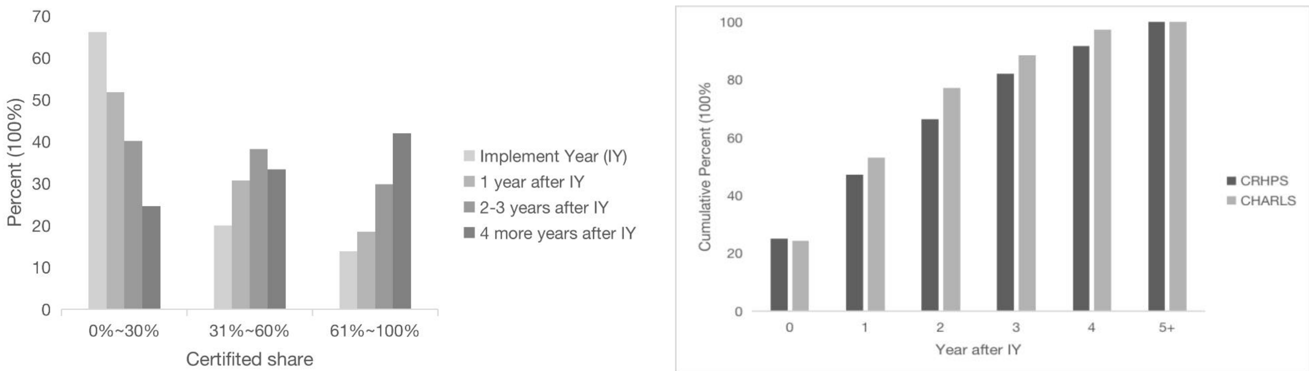
[8] From a legal point of view, the land is owned collectively in villages, and village members obtain land contracting rights according to membership eligibility and contracting agreements, while agricultural producers are granted land management rights for the land they lease from village contractors.

widely used nationally representative datasets in China, the portion of farmers who obtained land certificates was 58.52% in 2018 and 60.71% in 2019, respectively. As shown in Figure A2 in Appendix, the whole certification process involves many steps and in every step, there is a possibility of conflicts/disputes and the consequential mediation processes. Therefore, there is a long time gap between the propaganda of LCP implementation and the acquisition of the land certificate.

There are two kinds of low compliance issues in obtaining land certificates. First, many farmers did not receive land certificates after the LCP was implemented in their villages. Figure 2A presents the share of certified households after the LCP implementation using the CRHPS dataset. Theoretically, all households could receive land certificates and the certifited share should reach 100% at Implement Year (IY). However, the confirmation rate is far below expected. Moreover, even four more years after IY, three are still approximately 40% of the households failed to be certified.

Figure 2：The low household compliance issues reflected by different treatment year groups

A, Confirmation Rates B, Cumulative Percent of Certificated Farmers



Note: Data from the CRHPS and CRHPS and CHARLS in Figure 2A and Figure 2B, respectively. The IY (Implement Year) in figures refers the implementation year of LCP. Analogously, the 1 year after IY means the first year after the implementation of LCP.

Second, for the certified farmers, there is a long lapse between introducing the LCP at the village level and obtaining the land certificates at the household level. Table 2 summarizes how many years it took for farmers to receive certificates after the IY of LCP. Both datasets show that roughly one quarter of the sample farmers got their certificates in the first year of the LCP implementation, and around half got their certificates at least two years after IY.[9]

The low certification rate at the household level points out the importance of separating the program implementation effect from the certification effect in our empirical analysis. However, this distinction was not made clear in the existing literature, with a few exceptions.[10] The low household compliance issue was not unique to the LCP. Earlier studies about the RLCL also found that a significant portion of rural households did not have land documents after the implementation of the RLCL (Deininger and Jin 2009). In any case, this issue was not considered in several recent studies about the LCP..

3 Methodology and Estimation Strategy

3.1 Measuring Agricultural TFP and Land Resources Allocation Efficiency Using

9 There are four main reasons why the process of the LCP was so difficult to implement for all villages and farmers on time. The first reason is the large-scale migration and out-farm work, resulting in the fact that the actual resident population in the village is far smaller than the Hukou registered population. The second reason is related to the change of terrain, such as river widening, resulting in a high degree of mismatch of farmland quantity between this round of land certification and the last round, which caused many disputes among farmers. The third reason is related to land expropriation. This situation frequently occurs in China, especially in the 21st century, and leads to the blurring of land boundaries. The last reason is related to the administrative division adjustment, which resulted in changes in the land character and a delay of confirmation progress.

10 Field (2007) finds that a significant portion of eligible households did not receive land titles in the study of urban land titling in Peru. She estimated both the intention-to-treat effect of the program and the average treatment effect of the households who received land titles.

Micro Panel Data

To investigate the impact of the implementation or the certification of the LCP on land misallocation, we first need to calculate land allocation efficiency and agricultural total factor productivity. Following Hsieh and Klenow (2009), Restuccia and Rogerson (2013), and Bartelsman et al. (2013), we use the Olley-Pakes (OP) covariance method to calculate the efficiency of rural land resource allocation. Olley and Pakes (1996) argue that the productivity of an industry can be broken down into the sum of the average productivity of all firms and the covariance of firm share and productivity. The economic implication is that more productive enterprises should obtain more production factors, so OP covariance is considered as an indicator to measure the efficiency of resource allocation (Asker et al. 2014; Sheng, 2017; Chair et al., 2021).

To obtain the OP covariance, we need to estimate the total factor productivity first. Following Chari et al. (2021), we use the Cobb-Douglas production function in household panel data, which can be expressed in log form as follows:

$$output_{vh,t} = \alpha + \beta_1 labor_{vh,t} + \beta_2 capital_{vh,t} + \beta_3 land_{vh,t} + \lambda_h + \delta_t + \epsilon_{vh,t}, \quad (1)$$

where $\mathrm{output}_{\mathrm{vh,t}}$ is the total agricultural output of household *h* in village *v* in year *t*, $\mathrm{labor}_{\mathrm{vh,t}}$, $\mathrm{capital}_{\mathrm{vh,t}}$, and $\mathrm{land}_{\mathrm{vh,t}}$, stand for labor input, capital input and intermediate input, and land input, respectively. The detail construction process of the input and output indicators of agricultural production founction are shown in Appendix B. λ_h and δ_t represent the household and time fixed effects, respectively, and $\epsilon_{vh,t}$ is the disturbance. The estimation of Eq. (1) allows us to predict household-level agricultural TFP as:

$$\widehat{tfp}_{vh,t} = output_{vh,t} - \widehat{\beta}_1 labor_{vh,t} - \widehat{\beta}_2 capital_{vh,t} - \widehat{\beta}_3 land_{vh,t} \quad , \quad (2)$$

where $\widehat{tfp}_{vh,t}$ is the estimated agricultural TFP in the logarithm for household *h* in village *v* at year *t*. Then, according to Olley and Pakes (1996), the aggregate agricultural TFP and the covariance of land share and productivity (i.e., allocation of land resources) of village *v* at year *t* can be calculated as

$$TFP_{v,t} = \sum_{h=1}^{n} TFP_{vh,t} \, L_{vh,t} = \overline{TFP_{vh,t}} + \sum_{h=1}^{n} (TFP_{vh,t} - \overline{TFP_{vh,t}}) \, (L_{vh,t} - \overline{L_{vh,t}}), \quad (3)$$

$$OP_{v,t} = \sum_{h=1}^{n} (TFP_{vh,t} - \overline{TFP_{vh,t}})(L_{vh,t} - \overline{L_{vh,t}}), \quad (4)$$

where $TFP_{v,t}$ is the aggregate agricultural TFP for village *v* at year *t*, $TFP_{vh,t} = \exp(\widehat{tfp}_{vh,t})$ is the estimated agricultural TFP for household *h* in village *v* at year *t*, and $\overline{TFP_{vh,t}}$ is the arithmetic average of the agricultural TFP for village *v* at year *t*. Moreover, $L_{vh,t}$ is the share of land for household *h* in village *v* at year *t*, and $\overline{L_{vh,t}}$ is the arithmetic average of $L_{vh,t}$ in village *v* at year *t*. Finally, $OP_{v,t}$ is the OP covariance that measures land resource allocation efficiency for village *v* at year *t*. A larger OP covariance indicates that more land is obtained by efficient farmers, which implies greater land resource allocation efficiency. The distribution of OP and TFP by treatment group and control group are shown in Appendix A3, which reveals that the LCP has positive effect on OP and TFP at descriptive level.

3.2 Implementation and Certification Effects of LCP on Allocation Efficiency

We begin to investigate the implementation effect of the LCP on OP and village

TFP. Following Chari et al. (2020) and Gao et al. (2021), our identification strategy relies on the temporal and spatial variation in implementing the LCP at the village level. In particular, we specify a two-way fixed effect model as follows:

$$\mathrm{Y}_{\mathrm{v,t}} = \alpha + \beta_{\mathrm{I}}\mathrm{Implement}_{\mathrm{v,t}} + \gamma\mathrm{control}_{\mathrm{v,t}} + \lambda_{\mathrm{v}} + \delta_{\mathrm{t}} + \epsilon_{\mathrm{v,t}}, \qquad (5)$$

where $Y_{v,t}$ is either *OP* or village-level *TFP* of village *v* in year *t*. $\mathrm{Implement}_{\mathrm{v,t}}$ is a dummy variable to indicate whether village v in year t implemented the LCP or not, and $control_{vt}$ is a vector of control variables. λ_v, and δ_t are village fixed effect and time fixed effect, respectively. β_I is the coefficient we interestd, which measures the implementation effect of the LCP on allocation efficiency and village TFP.

However, the 0-1 dichotomy characterization of the implementation of the LCP in different villages in Eq. (5) can not reflect the overall effect of the LCP. As discussed earlier, there are low household compliance issues during the process of LCP. Therefore, the implementation effects of the LCP (the measure of the extensive margin of the LCP) estimated from Eq. (5) would be different from the certification effects of the LCP (the measurement of the intensive margin of the LCP). It is of policy relevance to estimate both the implementation effects and the certification effects of the LCP.

To estimate the certification effects, we specify an econometrics equation similar to Eq. (5) as follows:

$$Y_{v,t} = \alpha + \beta_c\, Certified_{v,t} + \gamma control_{v,t} + \lambda_v + \delta_t + \epsilon_{v,t}, \qquad (6)$$

where $Certified_{vt}$ is the share of households in village *v* receiving land certificates in year t. All other variables are similarly defined as in Eq. (5). The coefficient of

Certified$_{vt}$, β_c, is the coefficient of interest, measuring the certification effects of the LCP on OP or village TFP.

A potential concern of estimating Eq. (6) using OLS is that the share of certified farmers in each village is endogenous, i.e., $\mathrm{E}(Certified_{v,t}\epsilon_{v,t}|control_{v,t}, \lambda_t, \delta_t) \neq 0$. We adopt an instrumental variable approach to address the endogeneity of *Certified*$_{vt}$.[11] More specifically, we employ a dummy variable indicating whether or not a village implemented the LCP (*Implement*$_{vt}$) to instrument *Certified*$_{vt}$. Based on the premise that certification is the unique central channel through which the implementation of the LCP affects land reallocations and agricultural productivity, *Implement*$_{vt}$ could potentially be a valid IV for *Certified*$_{vt}$[12].

Separating the certified effects from implementation by IV method has two huge benefits. First, we can estimate the complete effect of the LCP on efficiency without endogenous concern. Second, by combaining this IV results and quantitative result through the methodology of Adamopoulos et al. (2022), we can measure the whole effect of LCP on resource misallocation, which has important implications for expanding the boundaries of our understanding of the effects of LCP.

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11 In the policy evaluation, when the baseline covariates are controlled, the implementation of the policy is considered to be random. The intent-to-treat (ITT) effect can be obtained through OLS regression, but because not everyone participates in the policy after the implementation, and whether individuals participate is not random, the ITT is the effect of policy implementation rather than the causal effect. At this time, the treatment on the treated (TOT) effect is the real impact of participating in the policy. Since participation has a strong self-selectivity, we use whether the policy is implemented as an instrumental variable for whether an individual participates to get the TOT effect.

12 A similar IV strategy was also used in Field (2007) and Lei and Lin (2009). For example, Field (2007) evaluates the impact of the Peruvian program (titling program) in Peru on labor outcomes. However, many households located in communities that were affected by the titling program failed to receive land certificates for various reasons, which led to the estimated program effect to bias downward. To address this non-compliance issue, she used the program implementation dummy as an instrument variable to instrument whether households received land certificates or not. The IV estimates measure the certification effect (the average treatment effect on the treated, or TOT), which is different from the program implementation effect (average intent-to-treat effect, ITT).

3.3 Endogeneity Discussion

In this subsection, we discuss the potential sources of bias and the validity of instrument variable.

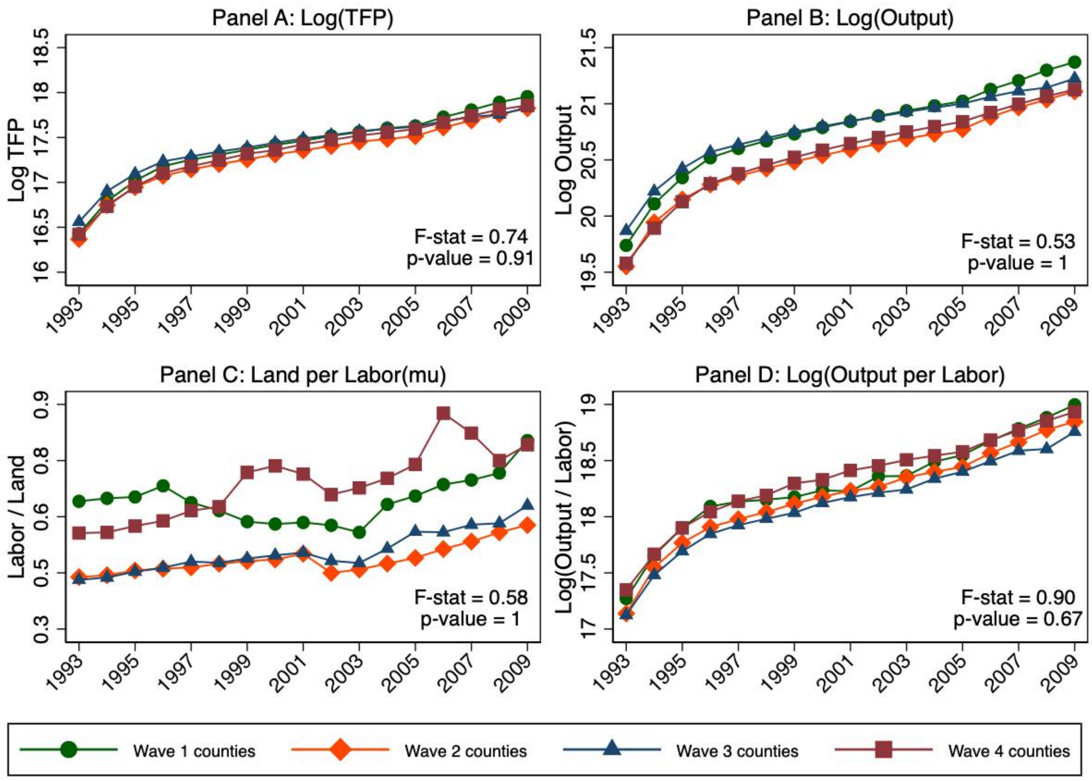
The potential sources of bias: the major concern about our estimate strategy is the households live in villages with earlier LCP implementation are systematically different from those with later LCP implementation. This concern can partly be solved by the village fixed effect λ_v, because it can explain both observed and unobserved time-invariant differences. However, we still concern about the potential bias due to time-variant differences which may correlate with the explained variables because this bias has potential influence for both DID and IV estimation. We provide three pieces of supporting evidence, which is the descriptive evidence from macro data and micro data, respectively, and regression evidence.

Descriptive evidence from macro data: First we match the province-level LCP implementation time data to the county-level data and plot the agriculture sector related indexes over the calendar years by the wave in which the province started the LCP[13]. Figure 3, panel A shows the pattern for the logarithm of TFP.The time trends are fairly parallel across the counties with different LCP starting years. Similar

[13] The province-level LCP implementation data comes from Xu and Du (2021), who purpose that the LCP is implemented by provinces and list the implementation time of 21 provinces. We divide these provinces into 4 waves of implementation, which is between 2009 and 2011(inculding Anhui, Shannxi, Hebei, Henan and Heilongjiang), between 2012 and 2014 (including Gansu, Jilin, Shandong and Sichuan), in 2015 (inculding Jiangsu, Jiangxi, Hubei, Hunan, Ningxia, and Guizhou) and in 2016 (including Shanxi, Liaoning, Zhejiang, Guangdong, Hainan and Yunnan), respectively.

patterns are found for the other outcome variables, including logarithm of output, land per labor and logarithm of output per labor. We also conduct F-tests for parallel trends in the economic indexes.The F-statistic and corresponding p-values are reported in each figure. These tests suggest there are no significant nonparallel trends in macro economy level.

Figure 3：The descriptive evidence from macro data for the parallel trends in agriculture sector



Note: The province-level LCP implementation data comes from Xu and Du (2021) and the agriculture sector related data in county level comes from the China County Social and Economic Statistical Yearbooks. The counties are grouped by the different st arting years of the LCP. Each figure plots the mean from 1993 to 2009. TFP is calculated through Cobb-Douglas production function, which can be expressed in logs as follows: $\mathrm{output}_{c,t} = \alpha + \beta_1 \mathrm{labor}_{c,t} + \beta_2 \mathrm{Fertilizer}_{c,t} + \beta_3 \mathrm{land}_{c,t} + \beta_4 \mathrm{Machine}_{c,t} + \lambda_c + \delta_t + \epsilon_{c,t}$, where output is measure by the agriculture total value constant in 1990 RMB, and labor, fertilizer, land and machine are labor number worked in agriculture sector, fertilizer input, sown area and total power of agricultural machinery, respectively.

Descriptive evidence from micro data: Then, we provide the evidence from micro data..CHARLS conducted a round of survey in 2011 which helps us to do this pre-reform comparison[14]. We divide the data into two groups. The earlier group is composed of those households located in villages where the LCP was implemented before 2014 and the later group is composed of those households in villages where the LCP was implemented between 2015 and 2018. The Appendix Table A1 reports ten variables, including agricultural production variables and rent behaviors variables. The results show that the differences between earlier group and later group are small and insignificant for almost all variables (only the area of rented out is significant at 5%). The observed similarity between two groups reveals there is no systematic contravention to the parallel trend assumption in micro data[15].

Regression evidence: Another supporting evidence is based on the assumption that if the policy is exogenous, the village-level trends in OP covariance and TFP would have been the same in implementation villages and other villages in the absence of the policy. To test this assumption, we conduct an event study using the following model:

$$Y_{v,t,} = \alpha + \sum_{k=-2}^{4} \beta_I Implement_{v,t} + \gamma control_{v,t} + \lambda_v + \delta_t + \epsilon_{v,t}, \qquad (7)$$

where $Y_{v,t,}$, $Implement_{v,t}$, $control_{v,t}$, λ_v, δ_t, and $\epsilon_{\mathrm{v,t}}$ are the same as in Eq. (5) and Eq. (6). Our results are reported in Appendix Table A2, which show that the timing of LCP implementation is not correlated with the key output variables, conditional on certain variables being controlled. It further proves that the policy

14 The reason why we use CHARLS instead of CRHPS to do this pre-reform comparison is the 2011 CRHPS survey is a pilot survey which contains small size of observation and makes hard to merge certificate year variable in 2019 survey to agricultural characteristics variables in 2011 survey.

15 We need to point out that this is a weak evidence, given the fact that the observations in CHARLS is systematically diference with CRHPS because CHARLS only investigate observations older than 45.

timing cannot cause potential source of bias.

The validity of IV: The fundamental assumptions of IV in our article is that the certification is the exclusive channel through which the implementation of the LCP affects explained variables but unfortunately this assumption is usually untestable. However, Hendren and Sprung-Keyser (2020) propose a method that the exogenous policy (LCP) can be considered as an instrumental variable when there is only one mechanism (Certification shares) and the validity of IV can be strengthen by comparing the estimation results from Eq. (5) and the results from the first- and second- stage regressions of Eq. (6) by calculating equation (8).

$$\partial \mathrm{Y}/\partial \mathrm{Z} = (\partial \mathrm{Y}/\partial \mathrm{X})/(\partial \mathrm{Z}/\partial \mathrm{X}), \tag{8}$$

where *Y* is the dependent variable, *X* is the exogenous policy, and *Z* is the mechanism variable. In this article, *Y* is the variable of interest (OP or village TFP), *X* is the implementation of LCP, and *Z* is the village-level certification shares, so Eq (8) can be rewritten as

$$\frac{\partial Y}{\partial Implementation} = \frac{\partial Certification\ share}{\partial Implementation} * \frac{\partial Y}{\partial Certifacation\ share}, \tag{9}$$

where $\frac{\partial Y}{\partial Implementation}$ is the coefficient of $implement_{vt}$ from the estimation of Eq (5), $\frac{\partial Certification\ Share}{\partial Implementation}$ is the coefficient of $implment_{vt}$ from the estimation of the first-stage regression of Eq (6), and $\frac{\partial Y}{\partial Certofocatopm\ Share}$ is the coefficient of $Certified_{vt}$ from the estimation of the second-stage regression of Eq (6). The equality of the left- and right-hand side of Eq (8) would support the argument that the implementation affects the allocation efficiency only through the certification share variable, and therefore confirms the validity of the IV strategy.

4 Data

We employ three rounds of panel data spanning 2015-2019 (every two years) from the China Rural Household Panel Survey (CRHPS) to investigate the impact of the LCP. The survey adopted a stratified, three-stage, and population-scale proportional sampling (PPS) method, covering 29 provinces across the country (excluding Xinjiang and Tibet), with representation at the rural, urban, provincial and national levels. The CRHPS started in 2011 and implemented every two years thereafter, we use the three rounds of data in 2015, 2017 and 2019, due to the larger sample size and fewer issues with missing values. We only include farmers participating in agricultural production in rural areas and remove some outliers with extreme values[16]. Finally, 22,634 household-year samples and 2,654 village-year samples are obtained. Descriptive statistics of the main explained variables and family agriculture production-related variables grouped by policy treatment are shown in Table 1.

Table 1 Summary Statistics for Key Variables

Variable	All sample	Treated	Untreated	T-test
Panel A: Village-level variables				
Main Explained variable				
OP covariance	0.0944 (0.231)	0.118 (0.243)	0.058 (0.206)	0.060***
TFP	3,684 (3,275)	3,756 (3,223)	3,572 (3,833)	184.40**
Rent Behaviors				

16 Extreme values of household-level OP, TFP, land and capital, are winsorized at 1 percent tails. However, the results in the paper are very similar if we do not drop outliers.

Rent in	0.0872 (0.122)	0.111 (0.123)	0.0502 (0.111)	0.061***
Rent out	0.129 (0.174)	0.150 (0.165)	0.098 (0.182)	0.051***
Participate in rent	0.209 (0.208)	0.249 (0.197)	0.145 (0.208)	0.104***
Panel B: Household-level variables				
Agricultural production				
Total output (RMB)	13,925 (22,544)	15,170 (23,251)	13,234 (22,113)	1934***
Labor input (days)	176.3 (231.2)	171.6 (222.9)	222.9 (179.0)	-7.370***
Land input (mu)	9.924 (14.40)	10.73 (14.64)	9.479 (14.24)	1.240***
Capital input (RMB)	3,602 (9,033)	4,116 (9,781)	3,317 (8,577)	798.90***

Note: The Data comes from 2015, 2017 and 2019 wave of CRHPS. The treated and untreated group refers to whether LCP is implemented for village-level variables and whether land certificate is received by the household at the end of the sample period for household-level variables.

CRHPS collects data on agricultural output, and input variables. The detailed input and output data at the household level are used to estimate agricultural TFP as an indicator of agricultural productivity at the household level and, subsequently, agricultural TFP and OP covariance at the village level accordingly. The detail construction process of the input and output indicators of agricultural production founction are shown in Appendix B. In terms of the key independent variables, the land certificate condition at the household level, as well as the implementation and certification condition at the village level, are calculated based on the answers to two questions in CRHPS: “Does your farmland have a rural land contractual management right certificate?” and “When did you obtain the contracted management right certificate for farmland?” Compared with other nationally representative databases, CRHPS can accurately identify the time of certification for each household. Regarding the selection of other control variables at the household and village level, we followed Ma et al. (2020) and Gao et al. (2021). These variables include family demographic and economic variables, as well as village economic and social environment variables, such as household size, education, health status, and facilities.[17]

5 Estimation Results

5.1 Base Results

Table 2 presents the impact of the LCP on land resource allocation efficiency measured by OP covariance (Columns 1-4) and village TFP (Columns 5-8). While the implementation effect regression, Eq. (5), is estimated by the TWFE (or DID) method, the certification effect regression, Eq. (6), is estimated by both the TWFE and IV methods.

Table 2 The Effect of LCP on OP Covariance and TFP

Dependent Variable	OP Covariance				Log(TFP)			
Model settings	TWFE	TWFE	IV		TWFE	TWFE	IV	
			1st stage	2nd stage			1st stage	2nd stage
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Implemented	0.043***	--	0.303***	--	0.109**	--	0.303***	--
	(0.014)	--	(0.011)	--	(0.047)	--	(0.011)	--
Certified	--	0.064**	--	0.141***	--	0.173*	--	0.360**
	--	(0.026)	--	(0.045)	--	(0.091)	--	(0.157)
Village FE	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES	YES
Control	YES	YES	YES	YES	YES	YES	YES	YES
R Square	0.533	0.531	0.537	0.023	0.508	0.507	0.482	0.024
F Value	--	--	102.89	--	--	--	102.89	--
Sample Size	2,654	2,654	2,654	2,654	2,654	2,654	2,654	2,654

Note: Standard errors clustered at the province level. This regression uses all village-level data. The time for the village to implement LCP is determined by the issuance of the first land

[17] All of the results in the article are robust to the exclusion of these controls.

certificate in the village. The regression coefficients reported in the table are standardized , and the standard deviation of the estimator is in parentheses. *, ** and *** indicate that the estimated coefficients are significant at the 10%, 5%, and 1% significance levels, respectively.

The estimation results show that both the implementation and certification of the LCP lead to significant improvement in the efficiency of land resource allocation and TFP regardless of whether the extensive margin or intensive margin is measured. Columns (1) and (5) indicate that, for an average village, the introduction of the LCP can increase its OP covariance by 0.04 and its TFP by 10.9%, which is the implementation effect of the LCP. The positive and significant coefficient of OP covariance implies land resource is allocated more effective because of LCP. In addition, we estimate the impact of LCP intensity by replacing the implementation dummy variable ($Implement_{vt}$) by the share of households in a village with land certificates ($Certified_{vt}$). The results in columns (2) and (6) show that a 10 percentage points increase in the share of households receiving land certificates would cause the OP covariance and TFP to increase by 0.0064 and 1.73%, respectively. The IV estimation, which addresses the endogeneity of $Certified_{vt}$, results in much larger certification effects (Columns (4) and (8)). For instance, increasing the share of households with a land certificate by a 10 percentage points would increase the OP covariance and TFP by 0.0141 and 3.6%, respectively[18]. Our IV results reveal that

[18] Generally, economists are concerned with whether the effects of a policy are immediate or delayed. As far as land policy is concerned, it is generally believed that land policy will not have an immediate effect (Chen et al., 2022), but will become more effective as the land market continues to be active (Ostorm, 2010). We also tested this question with this equation: $Y_{v,t} = \alpha + \beta_I \mathrm{Reformyear}_{v,t} + \beta_2 \mathrm{Postreform}_{v,t} + \gamma \mathrm{control}_{v,t} + \lambda_v + \delta_t + \epsilon_{v,t}$,. The certifited effect also be estimated with samilar equation form. The only difference between this equation and the baseline equation is the dividation of policy effect into immediate effect and lagged effect which is the Refromyear item and Postreform item in above equation, respectively. The regression results are shown in Appendix Table A3. We also coduct the regression for every regression in our article and all results are shown in Appendix Table A3 and A4. All these consistent resutls reveals that the LCP effect is lagged.

with the completely implementation of LCP, the overall effect of LCP on OP covariance and TFP is 0.141 and 36%, respectively[19].

The high F-values (much higher than 10) in the first-stage regressions (Columns (3) and (7)) support the relevance of the instrumental variable. We can further confirm the validity of the IV by checking whether the equality condition of Eq. (8) is satisfied, using the estimated results in Table 2. Multiplying the coefficients of the marginal effect of implementation on certification share and the marginal impact of certification shares on efficiency measures yields 0.0427 (0.303 * 0.141) and 0.1091 (0.303 * 0.394) for OP and TFP, respectively. These results are very close to the marginal effects of implementation on OP and TFP, which are 0.043 and 0.109, respectively, which further supports the validity of the IV strategy.

A potential concern about our baseline results is the composition of the observations. In survey datas, the households usually changes with the wave of survey because of villages or households being added to the survey sample or being attributed from the survey. To address this concern, we further restrict the sample to a balanced panel of households and recalcualte the village level OP covariance and TFP. With the estimation, the certifited effect is 0.136 with 0.052 Std for OP covariance and 0.395 with 0.177 Std for TFP, respectively, which reveals this concern should less

[19] It is worth noting that certifited effects of LCP are based on one assumption: each point estimate from 1% to 100% of the confirmation shares is the same as the point estimate obtained by the IV model, which is 29% to 60%. However, this assumption usually does not match the reality. Those who are willing to participate in the land market generally participate in the LCP earlier, which makes the effect of the initial implementation of the policy more remarkable than that of the end. So, compared with early stage of LCP, our point estimate of LCP is underestimated, and for later stage, the point estimate is overestimated. Nevertheless, this bias is not severe. When we use only the data for 2017-2019, the IV result is 32.2%, which is close to 36%. This result also confirms that the certification effect in the early stage is more significant than that of later data.

be worried.

5.2 More Robust Checks of the Base Results

Table 3 provides some robustness checks for the base results. The first robustness check is to check whether the base results are influenced by the starting year of the LCP introduction. In Table 2, the implementation of the LCP started in 2013. However, fifty counties implemented the LCP during 2009-2013 as pilot counties in China. Although these counties only account for 1.7% of all counties in China, the accuracy of the estimation result may still be affected (Xu and Du, 2021). We employed two approaches to check whether our results are affected by this issue. First, we changed the starting year from 2013 to 2009 to calculate the share of households receiving land certificates[20]. Second, we generated a dummy variable for those villages among those fifty counties and add it into the regression to control for heterogeneity. The results, however, are highly consistent with our base results (Columns 1-2, 4-5, Table 3).

Table 3 Robust Checks for the Base Result (IV)

	OP covariance			Log(TFP)		
	Implementation time		Other policies	Implementation time		Other policies
Model settings	(1)	(2)	(3)	(4)	(5)	(6)
Certified Percent	0.108**	0.141***	0.136***	0.428***	0.442***	0.353**
	(0.043)	(0.048)	(0.047)	(0.151)	(0.166)	(0.162)
Change X	YES	--	--	YES	--	--
Plus var	--	YES	--	--	YES	--

[20] This approach has both advantages and disadvantages: the condition of the villages among those fifty counties is better captured, but the misreported year of receiving land certificates in other counties can not be corrected.

NRPS	--	--	YES	--	--	YES
NCMS	--	--	YES	--	--	YES
Village FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES
Control	YES	YES	YES	YES	YES	YES
R Square	0.027	0.026	0.029	0.022	0.022	0.025
F Value	99.35	96.65	84.39	99.35	96.65	84.39
Sample Size	2,654	2,654	2,572	2,654	2,654	2,572

Note: Standard errors clustered at the province level. This regression uses all village-level data. The regression coefficients reported in the table are standardized coefficients, and the standard deviation of the estimator is in parentheses. *, ** and *** indicate that the estimated coefficients are significant at the 10%, 5% and 1% significance levels, respectively.

We are also concerned about the potential biases associated with other reforms and policies that were enacted in the same period. Hence, the second set of robustness checks address these concerns. The first policy we considered is China's New Rural Pension Scheme (NRPS)[21]. Huang and Zhang (2021) pointed out that the NRPS makes older people withdraw from agriculture and causes age-ineligible adults from farm work into non-farm work. The second policy is the New Rural Cooperative Medical Scheme (NCMS), implemented in 2003, substantially increasing its subsidy standards in 2011-2012. This policy enables farmers to receive a subsidy of 240 RMB from the government when seeking medical treatment, which could change the health and working ability of farmers. These two policies not only affect labor allocation, but also have a potential impact on China's rural land resources due to the Hukou institution[22] (Wang et al., 2021). Considering these two policies, columns (3) and (6) in Table 3 control for the implementation of NRPS and NCMS at the village level. The results show that our base regression results are robust.

[21] This policy was introduced in 2009 and allowed all farmers over 60 to receive 55 RMB (about eight dollars) per month, which is a considerable income for old farmers in China.

22 The hukou system is unique to China and creates rural-urban migration barriers. As a result, in rural areas, labor and land are generally closely linked。

5.3 Concern about the Spillover Effect of the LCP

Another concern about our base result is that the LCP may have a spillover effect in a village. If that happens, our results are overestimated because the estimate coefficient is compose with the true effect and the spillover effect and the policy effect we estimated should be assigned to more households, instead of the certificated households. To rule out this concern, we recalculate the village-level OP covariance and TFP using observations that were not certified during this sample period and use the same method to estimate the effect of the LCP on recalculated allocation efficiency and TFP[23]. Columns (1) and (4) in Table 4 show that if we use those uncertified households to recalculate the village allocation efficiency, the OP covariance and TFP are not significantly different between villages that introduced the LCP and others. A similar conclusion can be drawn from columns (3) and (6).

Table 4 Placebo for the Base Result

Dependent Variable	OP Covariance			Log(TFP)		
Model settings	TWFE	TWFE	IV	TWFE	TWFE	IV
	(1)	(2)	(3)	(4)	(5)	(6)
Implemented	0.014	--	--	0.008	--	--
	(0.017)	--	--	(0.061)	--	--
Certified	--	0.054	0.059	--	-0.127	0.034
	--	(0.043)	(0.067)	--	(0.157)	(0.248)
Village FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES
Control	YES	YES	YES	YES	YES	YES
R Square	0.586	0.586	0.025	0.555	0.554	0.027

23 To avoid the miscalculate question caused by small sample, we drop the villages which certification rate higher than 75%.

F Value	--	--	84.52	--	--	84.52
Sample Size	2,026	2,026	2,026	2,026	2,026	2,026

Note: Standard errors clustered at the province level. This regression uses all village-level data. The regression coefficients reported in the table are standardized, and the standard deviation of the estimator is in parentheses. *, ** and *** indicate that the estimated coefficients are significant at the 10%, 5% and 1% significance levels, respectively.

6 The Contribution of the LCP to Agricultural Productivity

We have shown a positive impact of the LCP on land allocation efficiency and agricultural productivity, but what is the contribution of the LCP to the improvement of allocation efficiency and TFP? To quantify the contribution, we first estimated the TFP improvement when all resource misallocations are eliminated, and then calculated the share of TFP improvement due to the LCP. We employed the methodology from Adamopoulos et al. (2022) to estimate the highest attainable agricultural TFP when resource misallocation is fully removed. First, for a community with a given technology and overall endowment of land and capital, the agricultural output can be maximized through the following optimization process:

$$\max \sum_{i=1}^{M} y_i \ , \{k_i,\ l_i\}_{i=1}^{M}$$

subject to the real output:

$$y_i = (\ A_a s_i)^{1-\theta} (\ l_i^a\ k_i^{1-a})^{\theta}, i = 1, 2, \dots, M \qquad (9)$$

and the resource constraints,

$$\sum_{i=1}^{M} l_i \ = \ L\ ;\ \sum_{i=1}^{M} k_i \ = \ K.$$

The first-order conditions and resource constraints would imply that the ideal resource allocation across households within the community should follow,

$$l_i^e = \frac{s_i}{\sum_{j=1}^{M} s_j} L \ ;\ k_i^e = \frac{s_i}{\sum_{j=1}^{M} s_j} K. \qquad (10)$$

In the above equation, y_i, l_i, and k_i are output, land, and capital, respectively. The parameter s_i is the production efficiency, α is the importance of the land factor in production, and θ is used to control the degree of return to scale of agriculture production. Finally, $\mathrm{l_i^e}$ and $\mathrm{k_i^e}$ are the land and capital inputs under the rational allocation of factors, respectively. Eq. (10) means that the distribution of land and capital should be proportionate to the production efficiency of each household.

Using Eqs (9) and (10), we can obtain the theoretical maximum output of an individual household when resources are properly allocated, and then aggregate them to get the overall maximum benefit:

$$Y^e = A^e M^{1-\theta}[\, L^a \, K^{1-a}]^{\theta} \ .$$

This efficiency gain is equal to $\frac{Y^e}{Y} - 1$ when the misallocation is completely eliminated. It is worth noting that given the fixed level of aggregate factors Y, K, and L, the output gains represent TFP gains.

Using the household sample that did not implement LCP during 2015-2019[24], the estimated TFP improvement when resources are properly allocated is 93% across villages[25]. The combination of the model result and the IV results from the base model

24 Based on Section 3.3 and Table 4, it is believed that there is no evident differences of OP and TFP between treatment group and control group if LCP not happens, which means the TFP improvement when resources are properly allocated calculated by the uncertifited observations can represent the whole picture.

25 We need to point out that our estimates are larger than the 53.2% estimated by Adamopoulos (2022) due to the fact that they use data from 1993-2002 while we perform our estimation from 2015-2019. With their sample, the 90/10 percentile ratio in farm TFP is 5.6-fold and the 75/25 percentile ratio is 2.3-fold, but the numbers are 9.6 and 3.2, which is about twice as big as the numbers in Adamopoulos (2022), respectively, in our sample. Some other literature also finds that compared with the past, the difference in TFP between different farmers or regions has enlarged (Gong, 2020; Zhong et al., 2021). However, compared with the past, there was no significant change in the area of arable land per capita, which means that the TFP gain when removing all misallocation should be more significant in 2015-2019, compared with 1993-2002.

can answer three questions. The first question is: How much misallocation can be removed by the LCP up to 2019? Considering the certification effect is 36%, and about 60% of farmers have received the land certificates up to 2019, the LCP has increased TFP by 21.6% (36%*60%), which is 23.2% of the attainable TFP improvement due to resource reallocation. The second question is: How much would the full potential of the LCP reform effect be? Considering that 40% of farmers did not have land certificates by 2019, the full certification of the remaining 40% of farmers would further increase TFP by about 14.4% (36%*40%), which is about 15.5% of the attainable TFP improvement due to resource reallocation. The third question is: How much misallocation can the LCP remove. Combining the answers of Q1 and Q2, the LCP can remove about 38.7% of all the initial misallocation.

There are two valuable messages from this result. First, the positive impact of the LCP has not been fully implemented and accelerating the process of the LCP (to obtain another 15.5% contribution) is a major task. Second, even if all farmers receive land certificates, about 61.3% of the potential TFP improvements are unexplained by the LCP. For example, the long-term problem of land fragmentation and the rural-urban migration barrier cannot be fully solved by the LCP. Therefore, we should take actions, such as transaction risk control and migration policy, to reinforce stable property rights and reduce factor frictions.

7 Potential Mechanisms

The above results show that the LCP improves rural China's land resource allocation efficiency and total factor productivity. This section discusses the possible mechanisms underlying these effects. We explore four main pathways through which the implementation and certification of the LCP can improve resource allocation efficiency and total factor productivity: 1) more active land transfers; 2) more efficient land transfers; 3) improved labor allocation, and 4) improved access to capital and ability to make more long-term investments. The first two pathways are all directly related to the allocation of land, which will be investigated in subsection 7.1. The last two pathways are related to other production factors that could also improve resource allocation efficiency (albeit not directly related to land allocation), which will be investigated in subsection 7.2.

7.1 The Effect of the LCP on Land Allocation

How rural land is allocated and exchanged has far-reaching implications for the allocation efficiency and productivity of agricultural production in developing countries (Deininger, 2003; Otsuka, 2007; Deininger et al., 2008). Generally, a free and more active land market is a precondition for high allocation efficiency and productivity in agricultural production. Therefore, the first pathway through which the LCP improves efficiency and productivity is that the LCP promotes more active land transfers in rural areas (i.e., More active land transfer). However, an active land market is a necessary, but not sufficient condition for improving land allocation efficiency. Only if the land market transfers land from less efficient farmers to more efficient farmers will a the more active land market improve the allocation efficiency and productivity (i.e., More efficient land transfer)[26]. As a result, more efficient farmers farm more land by renting more land from less efficient farmers (Deininger and Jin, 2005; Jin and Deininger, 2009) (i.e., Concentration of land).

More Active Land Transfers? To check whether the LCP have increased farmers' participation in land transfers, we first focus on village-level land transfers. Table 5 presents the impact of the LCP on participation in land transfers at the village level. Similar as baseline resutls, we slao estimate both implementation and certifited effect.

The results in Appendix Table A5 indicate that the policy led to significant increases in farmers' participation in land transfers. On average, implementation of the LCP increased the share of households renting in land by 2.6% (Col. 1), the share of land renting out by 4% (Col. 4), and the share of land renting in or out by 6.1% (Col. 7), respectively. The certifited effect shows that a one percentage point increase in the share of households receiving land certificates would increase the share of households renting in, renting out, and either renting in or out by 0.089%, 0.133%, and 0.201%, respectively (Cols. (3), (6) and (9))[27].

More Efficient Land Transfers? Then we evaluate the effect of LCP on the efficiency of land transfers, we use household-level data to examine how the

[26] A potential concern with our mechanism is that village productivity is also affected by rent behaviors between farmers and other agricultural entities (such as commercial farms), and only considering the farmer's behaviors may introduce some measurement error. We need to admit that we cannot solve this problems through rigorous regression methods, because CRHPS does not have data related to enterprises, and this database also cannot incorporate with other external data. However, we beilive this measurement error is not vary influencial. According to the calculation of Chair (2021), the land rented within farmers is 11 times larger than those farmers rented to companies (0.33mu verse 0.03mu) based on the 2009 and 2010 wave of national fixed survey, which implies that land transactions among farmers can explain most of the changes in efficiency.

[27] We also calculate the relationship between certifited effect and implementation effect based on equation (9), and the consistent results further strength the vadility of our IV estimate strategy.

implementation/certification of LCP affects who rented in and who rented out land. As mentioned above, land transfers would increase land allocation efficiency and total factor productivity only if the land rental market transfers land from less efficient farmers to more efficient farmers. So we need to find an exogeneous variable to represent farmer's efficiency and interact it with the LCP effect. Following Deininger and Jin (2005), we used households' fixed effects generating from the calculation process of TFP as a proxy variable for household agricultural ability[28] (AA in log form) and explore the heterogeneous behaviors in land transfers.

The results in Table 6 indicate that both the implementation and certification of the LCP improve the efficiency of land rental transfers. The positive and significant coefficient of the interaction term in the first three columns imply that the implementation of LCP increased the probability of renting in land for those higher farming ability households. Besides, the negative coefficient for the interaction term in last three colums shows that those observations are less likely to rent out land. All these results help to explain why the LCP leads to greater land allocation efficiency and total factor productivity.

Table 6 The effect of LCP on heterogeneous farmer's rental behavior

	Rent in			Rent out		
Model settings	TWFE	TWFE	IV	TWFE	TWFE	IV
	(1)	(2)	(3)	(4)	(5)	(6)
Implemented	-0.010	--	--	0.010	--	--
	(0.007)	--	--	(0.006)	--	--
Implemented*AA	0.031***	--	--	-0.015**	--	--

[28] This is a measure of farm-specific and time-invariant production efficiency. Compared to TFP, households' fixed effects are less influenced by policy and can adequately reflect farmers' farming abilities. The Appendix Figure A4 shows that the distribution of AA obeys the normal distribution, as expected.

	(0.008)	--	--	(0.007)	--	--
Certified	--	0.015**	-0.091	--	0.011	0.086
	--	(0.007)	(0.058)	--	(0.007)	(0.055)
Certified*AA	--	0.040***	0.124***	--	-0.013*	-0.067**
	--	(0.008)	(0.031)	--	(0.008)	(0.029)
Household FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES
Control	YES	YES	YES	YES	YES	YES
R Square	0.929	0.929	0.019	0.929	0.929	0.010
F Value	--	--	143.97	--	--	143.97
Sample Size	22,634	22,634	22,634	22,634	22,634	22,634

Note: Standard errors clustered at the province level. This regression uses all household-level data. Rent in (Rent out) represents the households rented in (rented out) land in that year. The equation of estimating the implementation effect following this form: $Y_{v,t} = \alpha + \beta_I Implement_{v,t} + \beta_2 Implement * AA_{v,t} + \gamma control_{v,t} + \lambda_v + \delta_t + \epsilon_{v,t}$,. The certifited effect also be estimated with samilar equation form. In column (3) and (6), the household-level certificate variable (certified) is instrumented by the village-level implementation variable (implemented). The validity of this IV strategy is justified similarly to the validity of the IV strategy for equation (6). All the regressions below follwing same equation. The regression coefficients reported in the table are standardized, and the standard deviation of the estimator is in parentheses. *, ** and *** indicate that the estimated coefficients are significant at the 10%, 5%, and 1% significance levels, respectively.

Increased Farming Scale and Reduced Land Fragmentation? We expected that the consequence of previous two subsections will make land concentrated more in efficient farmers which is just the defination of land efficiect allocation. So we further explore the impact of LCP on farm size and plot size in Appendix Table A6. The positive and statistically significant coefficient of implemented*AA suggest that the LCP has led to larger farm size and plot size for more efficient households than for less efficient households[29]..

[29] It is worth noting that there are two possibilities for the rise in plot size. The first one is that farmers rent in other lands adjacent to their own land and combine several pieces of land into one. The second is that farmers rent in other lands away from their original land, but bigger than their original land. Due to the limited data, we cannot clearly distinguish between these two possibilities. However, based on the result that the interaction term coefficient in column (3) is larger than that in column (6), we believe that the second possibility is more likely to occur.

7.2 The effect of LCP on other factors' allocation

Besides land misallocation, over-allocation of labor in the agricultural sector, and farmers' poor access to credit are other important reasons for allocation efficiency and low productivity of agriculture in a large number of developing countries (Besley, 1995; Holden et al., 2010; Banerjee et al., 2015; Deininger et al. 2022). There has also been a large amount of literature linking land titling programs to labor allocation, credit access, and investments (Carter and Olinto, 2000; Jacoby et al., 2002; Smith, 2004; Field, 2007; Galiani and Schargrodsky, 2010; Janvry et al., 2015; Lovo, 2016; Chari et al., 2021), and we expect the LCP could potentially affect these outcomes as well.

Table 8 presents the impact of the LCP on labor allocation, credit, investment.[30] First, column (1) & (2) reports the effect of the LCP on labor reallocation. More specifically, we examine the effect of the LCP on farmers' decisions to exit farming. The significantly negative coefficient on the interaction term of the certification of the LCP and farming ability suggests that the certification of the LCP reduced the possibility for farmers with high farming ability to exit from farming,

Second, we focus on the link between the LCP and credit. One of the key elements of the legislation of the LCP is to allow land users (farmers who contracted land use rights from his/her village collective or subsequent tenants) to use the land use rights as collateral to borrow official loans from banks[31]. The significant and

30 For brevity, we report the results of DID and IV results, which is implementation effect and certification effect

31 According to the Property Law of China, the certificate issued by LCP has usufruct right, that is, the certificate can be used for shareholding, mortgage, and guarantee in business activities.

positive coefficient for the interaction term in column (3) suggests that the LCP increased credit access for high farming ability farmers and the result is similar in Col. 4 (albeit insignificant).

Finally, we expect the more active and efficient land and labor markets and the enhanced credit accessibility would facilitate farmers' decisions to make investments. More specifically, our results reveals that those who are better at farming are likely to invest in agricultural machinery (columns 5 & 6), besides, these results are also consistent when the machinery investment is measured by the density of agricultural machinery investment measured by labor (columns 7 & 8).

Table 8 The effect of LCP on credit, investment, and labor

Model settings	Exit from agriculture		Loan		Log(Machine)		Log(Machine/Labor)	
	TWFE	IV	TWFE	IV	TWFE	IV	TWFE	IV
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Implemented	-0.004	--	0.012*	--	0.149**	--	0.112*	--
	(0.003)	--	(0.007)	--	(0.075)	--	(0.060)	--
Implemented*AA	-0.008**	--	0.014*	--	0.223***	--	0.209***	--
	(0.003)	--	(0.008)	--	(0.084)	--	(0.068)	--
Certified	--	-0.035	--	0.099*	--	1.196*	--	0.890*
	--	(0.026)	--	(0.060)	--	(0.639)	--	(0.517)
Certified*AA	--	-0.024*	--	0.038	--	0.652*	--	0.642**
	--	(0.014)	--	(0.031)	--	(0.337)	--	(0.272)
Household FE	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES	YES
Control	YES	YES	YES	YES	YES	YES	YES	YES
R Square	0.723	0.013	0.823	0.003	0.858	0.010	0.842	0.024
F Value	--	143.97	--	143.97	--	143.97	--	143.97
Sample Size	15,966	15,966	22,634	22,634	22,634	22,634	22,634	22,634

Note: Standard errors clustered at the province level. This regression uses all household-level data. The small number of observations in column (1) & (2) is mainly because the 2015 data should be used as the benchmark to judge whether farmers quit agriculture. Considering the machine variable is missing for many observations, the Log(Machine) and Log(Machine/Labor) items actually is Log(Machine+1) and Log((Machine/Labor)+1) during the estimation process. The regression coefficients reported in the table are standardized, and the standard deviation of the estimator is in parentheses. *, ** and *** indicate that the estimated coefficients are significant at the 10%, 5%, and 1% significance levels, respectively.

To summarize, this section explores the potential pathways through which the implementation and/or certification of the LCP improves allocation efficiency and productivity. We show that the LCP led to more active and more efficient land transfers, less efficient farmers to exit farming, increased credit access for more efficient farmers, enabled more efficient farmers to make long-term investments, such as in agricultural machinery. All these changes in response to the implementation/certification of the LCP are conducive to improving allocation efficiency and productivity. The results in this section provide empirical evidence that the LCP promotes the efficiency of land resource allocation and reduces misallocation in capital and labor, which leads to an improvement in agricultural total factor productivity.

8 Conclusion

This paper examines the impact of a new round of land reform in China on land misallocation and total factor productivity. Farmers were given clear land title boundaries and tradable land certificates after the introduction of the LCP, which reduces transaction costs, increases land transfers, optimizes input factors, and ultimately contributes to an increase in the efficiency of land resource allocation and agricultural TFP in China. This paper also distinguishes the implementation effect and the certification effect of the LCP. This issue was rarely considered in the breadth of literature assessing the impacts of land reforms in developing countries. In this paper, we show that such distinction is important because a noticeable portion of households in program villages failed to receive land certificates. We find that the implementation effect of the LCP, on average, increased OP covariance by 0.04 and increased TFP by 10.9% at the village level. Meanwhile, the certification effect of the LCP is 0.141 for OP covariance and 36% for TFP, respectively.

Then, we measured how large is the impact relative to the overall misallcaotion in China. We firstly use the framework purposed by Adamopoulos et al. (2022) and calcualate the TFP gain when all misallcation is elimated is 93%. Then, by combaining the empricial results and our quantitative result, we found that, despite the friction caused by the imperfections of other markets and the incomplete implementation of the LCP, the benefits of this reform accounted for 23.2% of the TFP gain when all resource misallocations are eliminated up to 2019, besides, with the further implementation of LCP, the potential benefit could reach 38.7%.

Moreover, we confirm several pathways through which the implementation or certification of the LCP led to improved allocation efficiency and productivity. We find that the LCP improved the activities of land transfers and caused more productive farmers to rent in more and rent out less land. The LCP also increased the probability of less effective farmers exiting agriculture and caused more productive farmers to achieve larger farm sizes and plot sizes, which led to improvements in allocation efficiency and productivity. In addition, the LCP increased more productive farmers' access to formal credit and their probability of investing in agricultural machinery.

The findings of our study have substantial policy implications. For China, the LCP is the most important land policy since the RLCL. Assessing the effects of the policy provides essential insights into understanding the changes in land and labor factors in rural China over the past decade. In addition, since farmers' participation in the LCP was 60% by the end of the sample period, identifying the certification effect of the policy is valuable for evaluating the costs and benefits of its future implementation. On the positive side, it implies that the impact of implementing the LCP was underestimated in the literature and that it still has more potential to increase China's agricultural productivity in the future. On the negative side, the promotion of the LCP is behind schedule, and more effort should be made to fully implement the policy to reduce resource misallocation. The measurement of the effects of land titling policies in China could provide an updated case study for many developing countries that have not yet implemented land titling policies.

For future studies, how to identify the rest of the misallocation is a key issue to be tackled to further increase agricultural productivity. This article finds that removing the transaction costs associated with unclear property rights would eliminate up to 38.7% of all misallocations, which is consistent with the fact that considerable misallocation of agricultural factors still exists in many countries after the implementation of land titling reforms (Bartelsman and Scarpetta, 2013; Rada and Fuglie, 2018; Adamopoulos and Restuccia, 2020). On the one hand, optimizing land reform design to rule out all the misallocation related to land is worth studying. On the other hand, future research can investigate the impact of the household registration system and other labor-related policies on resource misallocation. Moreover, it is also interesting to study the potential interaction effect between land-related and labor-related policies that jointly affect resource misallocation.

Reference

[1] Adamopoulos, Tasso, Loren Brandt, Jessica Leight, and Diego Restuccia. 2022. "Misallocation, Selection, and Productivity: A Quantitative Analysis With Panel Data From China." Econometrica 90(3): 1261–82.

[2] Adamopoulos, Tasso, and Diego Restuccia. 2014. "The Size Distribution of Farms and International Productivity Differences." American Economic Review 104(6): 1667–97.

[3] Adamopoulos, Tasso, and Diego Restuccia. 2020. "Land Reform and Productivity: A Quantitative Analysis with Micro Data." American Economic Journal: Macroeconomics 12(3): 1–39.

[4] Asker, John, Allan Collard-Wexler, and Jan De Loecker. 2014. "Dynamic Inputs and Resource (Mis)Allocation." Journal of Political Economy 122(5): 1013–63.

[5] Ayerst, Stephen, Loren Brandt, and Diego Restuccia. 2020. "Market Constraints, Misallocation, and Productivity in Vietnam Agriculture." Food Policy 94: 101840.

[6] Banerjee, Abhijit, Esther Duflo, Rachel Glennerster, and Cynthia Kinnan. 2015. "The Miracle of Microfinance? Evidence from a Randomized Evaluation." American Economic Journal: Applied Economics 7(1): 22–53.

[7] Bartelsman, Eric, John Haltiwanger, and Stefano Scarpetta. 2013. "Cross-Country Differences in Productivity: The Role of Allocation and Selection." American Economic Review 103(1): 305–34.

[8] Benjamin, Dwayne, and Loren Brandt. 2002. "Property Rights, Labour Markets, and Efficiency in a Transition Economy: The Case of Rural China." Canadian Journal of Economics 35(4): 689–716.

[9] Besley, Timothy. 1995. "Property Rights and Investment Incentives: Theory and Evidence from Ghana." Journal of Political Economy 103(5): 903–37.

[10] Brandt, Loren, Johannes Van Biesebroeck, and Yifan Zhang. 2012. "Creative Accounting or Creative Destruction? Firm-Level Productivity Growth in Chinese Manufacturing." Journal of Development Economics 97(2): 339–51.

[11] Brandt, Loren, Susan H. Whiting, Linxiu Zhang, and Tonglong Zhang. 2017.

"Changing Property-Rights Regimes: A Study of Rural Land Tenure in China." The China Quarterly 232: 1026–49.

[12] Carter, M. R., and P. Olinto. 2000. "Getting Institutions 'Right' for Whom? Credit Constraints and the Impact of Property Rights on the Quantity and Composition of Investment." Wisconsin-Madison Agricultural and Applied Economics Staff Papers 85(1): 173–86.

[13] Caselli and Francesco. 2005. "[Handbook of Economic Growth] Volume 1 || Chapter 9 Accounting for Cross-Country Income Differences." Handbook of Economic Growth 1(1): 679–741.

[14] Chari, Amalavoyal, Elaine M Liu, Shing-Yi Wang, and Yongxiang Wang. 2021. "Property Rights, Land Misallocation, and Agricultural Efficiency in China." The Review of Economic Studies 88(4): 1831–62.

[15] Chen, Chaoran. 2017. "Untitled Land, Occupational Choice, and Agricultural Productivity." American Economic Journal: Macroeconomics 9(4): 91–121.

[16] Chen, Chaoran, Diego Restuccia, and Raül Santaeulàlia-Llopis. 2022. "The Effects of Land Markets on Resource Allocation and Agricultural Productivity." Review of Economic Dynamics 45: 41–54.

[17] Cheng, Wenli et al. 2019. "How Did Land Titling Affect China's Rural Land Rental Market? Size, Composition and Efficiency." Land Use Policy 82(2): 609–19.

[18] De Neve, Jan-Walter, and Günther Fink. 2018. "Children's Education and Parental Old Age Survival – Quasi-Experimental Evidence on the Intergenerational Effects of Human Capital Investment." Journal of Health Economics 58: 76–89.

[19] Deininger, K., and S. Jin. 2005. "The Potential of Land Rental Markets in the Process of Economic Development: Evidence from China." Journal of Development Economics 78(1): 241–70.

[20] Deininger, Klaus. 2003. "Land Markets in Developing and Transition Economies: Impact of Liberalization and Implications for Future Reform." American Journal of Agricultural Economics 85(5): 1217–22.

[21] Deininger, Klaus, Daniel Ayalew Ali, and Tekie Alemu. 2008. "Assessing the Functioning of Land Rental Markets in Ethiopia." Economic Development and Cultural Change 57(1): 67–100.

[22] Deininger, Klaus, and Songqing Jin. 2009. "Securing Property Rights in Transition: Lessons from Implementation of China's Rural Land Contracting Law." Journal of Economic Behavior & Organization 70(1): 22–38.

[23] Deininger, Klaus, Songqing Jin, and Meilin Ma. 2022. "Structural Transformation of the Agricultural Sector In Low- and Middle-Income Economies." Annual Review of Resource Economics 14(1): null.

[24] Duarte, Margarida, and Diego Restuccia. 2010. "The Role of the Structural Transformation in Aggregate Productivity*." The Quarterly Journal of Economics 125(1): 129–73.

[25] Field, Erica. 2007. "Entitled to Work: Urban Property Rights and Labor Supply in Peru*." The Quarterly Journal of Economics 122(4): 1561–1602.

[26] Galiani, S., and E. Schargrodsky. 2010. "Property Rights for the Poor: Effects of Land Titling." Journal of Public Economics 94(9–10): 700–729.

[27] Gao, Xuwen, Xinjie Shi, and Shile Fang. 2021. "Property Rights and Misallocation: Evidence from Land Certification in China." World Development 147: 105632.

[28] Gollin, Douglas, and Christopher Udry. 2021. "Heterogeneity, Measurement Error, and Misallocation: Evidence from African Agriculture." Journal of Political Economy 129(1): 1–80.

[29] Gong, B. 2020. "Agricultural Productivity Convergence in China." China Economic Review 60: 101423.

[30] Gonzalez-Navarro, Marco, Kyle Emerick, Elisabeth Sadoulet, and Alain De Janvry. 2015. "Delinking Land Rights from Land Use: Certification and Migration in Mexico." American Economic Review.

[31] Gottlieb, Charles, and Jan Grobovšek. 2019. "Communal Land and Agricultural Productivity." Journal of Development Economics 138: 135–52.

[32] Hendren, Nathaniel, and Ben Sprung-Keyser. 2020. "A Unified Welfare Analysis

of Government Policies.” The Quarterly Journal of Economics 135(3): 1209–1318.

[33] Holden, S. T., K. Deininger, and H. Ghebru. 2010. “Impacts of Low-Cost Land Certification on Investment and Productivity.” American Journal of Agricultural Economics 91(2): 359–73.

[34] Hsieh, Chang-Tai, and Peter J. Klenow. 2009. “Misallocation and Manufacturing TFP in China and India *.” Quarterly Journal of Economics 124(4): 1403–48.

[35] Huang, Wei, and Chuanchuan Zhang. 2021. “The Power of Social Pensions: Evidence from China’s New Rural Pension Scheme.” American Economic Journal: Applied Economics 13(2): 179–205.

[36] Jacoby, H. G. 1993. “Shadow Wages and Peasant Family Labour Supply: An Econometric Application to the Peruvian Sierra.” The Review of Economic Studies 60(4): 903–21.

[37] Jacoby, Hanan G., Guo Li, and Scott Rozelle. 2002. “Hazards of Expropriation: Tenure Insecurity and Investment in Rural China.” American Economic Review 92(5): 1420–47.

[38] de Janvry, Alain, Kyle Emerick, Marco Gonzalez-Navarro, and Elisabeth Sadoulet. 2015. “Delinking Land Rights from Land Use: Certification and Migration in Mexico.” American Economic Review 105(10): 3125–49.

[39] Jin, Songqing, and Klaus Deininger. 2009. “Land Rental Markets in the Process of Rural Structural Transformation: Productivity and Equity Impacts from China.” Journal of Comparative Economics 37(4): 629–46.

[40] Lafave, Daniel, and Duncan Thomas. 2016. “Farms, Families, and Markets: New Evidence on Completeness of Markets in Agricultural Settings.” Econometrica 84(5): 1917–60.

[41] Lagakos, David, and Michael E. Waugh. 2013. “Selection, Agriculture, and Cross-Country Productivity Differences.” American Economic Review 103(2): 948–80.

[42] Li, Guo, Scott Rozelle, and Loren Brandt. 1998. “Tenure, Land Rights, and Farmer Investment Incentives in China.” Agricultural Economics 19(1–2): 63–71.

[43] Lin, Justin. 1988. “The Household Responsibility System in China’s Agricultural Reform: A Theoretical and Empirical Study.” Economic Development and Cultural Change 36: 199–224.
[44] Lin, Justin. 1992. “Rural Reforms and Agricultural Growth in China.” American Economic Review 82: 34–51.
[45] Lovo and Stefania. 2016. “Tenure Insecurity and Investment in Soil Conservation. Evidence from Malawi.” World Development 78: 219–29.
[46] Ma, Xianlei et al. 2020. “Decisions by Chinese Households Regarding Renting in Arable Land—The Impact of Tenure Security Perceptions and Trust.” China Economic Review 60: 101328.
[47] McMillan, John, John Whalley, and Lijing Zhu. 1989. “The Impact of China’s Economic Reforms on Agricultural Productivity Growth.” Journal of Political Economy 97(4): 781–807.
[48] OLLEY, G. S, and A. PAKES. 1996. “The Dynamics of Productivity in the Telecommunications Equipment Industry.” Econometrica 64(6): 1263–97.
[49] Otsuka, K. 2007. “Chapter 51 Efficiency and Equity Effects of Land Markets.” Handbook of Agricultural Economics 3(06): 2671–2703.
[50] Ostrom, Elinor. 2010. “Beyond Markets and States: Polycentric Governance of Complex Economic Systems.” American Economic Review 100(3): 641–72.
[51] Rachel, Ngai L, Christopher A Pissarides, and Wang Jin. 2019. “China’s Mobility Barriers and Employment Allocations.” Journal of the European Economic Association (5): 5.
[52] Rada, Nicholas E., and Keith O. Fuglie. 2019. “New Perspectives on Farm Size and Productivity.” Food Policy 84: 147–52.
[53] Ranis, Gustav, and John C. H. Fei. 1961. “A Theory of Economic Development.” The American Economic Review 51(4): 533–65.
[54] Ren, Guangcheng et al. 2019. “Perceptions of Land Tenure Security in Rural China: The Impact of Land Reallocations and Certification.” Society & Natural Resources: 1–17.
[55] Restuccia, Diego, and Richard Rogerson. 2013. “Misallocation and Productivity.”

Review of Economic Dynamics 16(1): 1–10.

[56] Restuccia. 2017. “The Causes and Costs of Misallocation.” Journal of Economic Perspectives 31(3): 151–74.

[57] Sheng, Y., T. Jackson, and P. Gooday. 2017. “Resource Reallocation and Its Contribution to Productivity Growth in Australian Broadacre Agriculture.” Australian Journal of Agricultural and Resource Economics 61(1): 56–75.

[58] Smith, Robert E. 2004. “Land Tenure, Fixed Investment, and Farm Productivity: Evidence from Zambia’s Southern Province.” World Development 32(10): 1641–61.

[59] Wang, Feicheng, Chris Milner, and Juliane Scheffel. 2021. “Labour Market Reform and Firm-Level Employment Adjustment: Evidence from the Hukou Reform in China.” Journal of Development Economics 149(C): 102584.

[60] Xu, Licheng, and Xiaodong Du. 2022. “Land Certification, Rental Market Participation, and Household Welfare in Rural China.” Agricultural Economics 53(1): 52–71.

[61] Zhang, Linxiu, Yueming Cao, and Yunli Bai. 2022. “The Impact of the Land Certificated Program on the Farmland Rental Market in Rural China.” Journal of Rural Studies 93: 165–75.

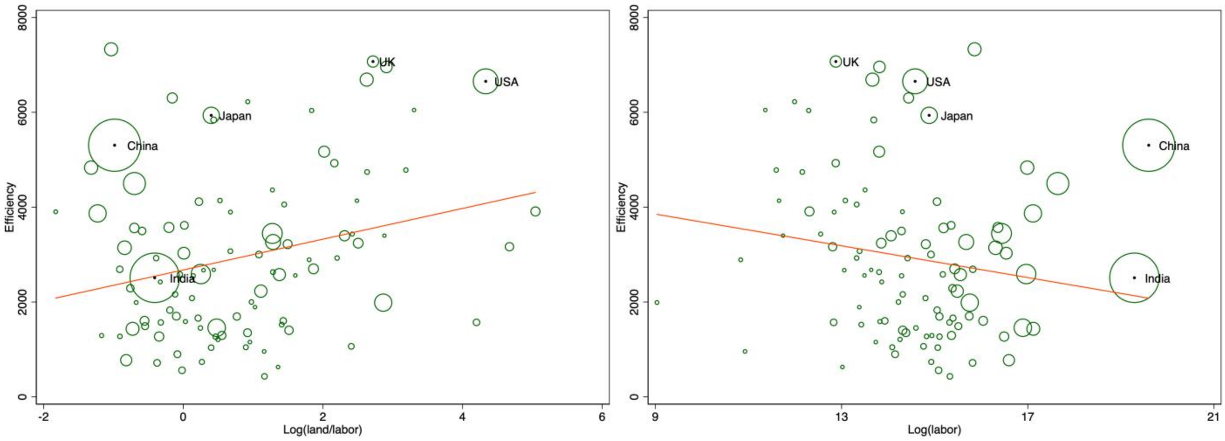
[62] Zhao, Xiaoxue. 2020. “Land and Labor Allocation under Communal Tenure: Theory and Evidence from China.” Journal of Development Economics 147: 102526.

[63] Zhong, Shen, Junwei Li, and Dehua Zhang. 2021. “Measurement of Green Total Factor Productivity on Chinese Pig Breeding: From the Perspective of Regional Differences.” PLoS ONE 16(8): e0255739.

Appendix A：Additional Figures and Tables

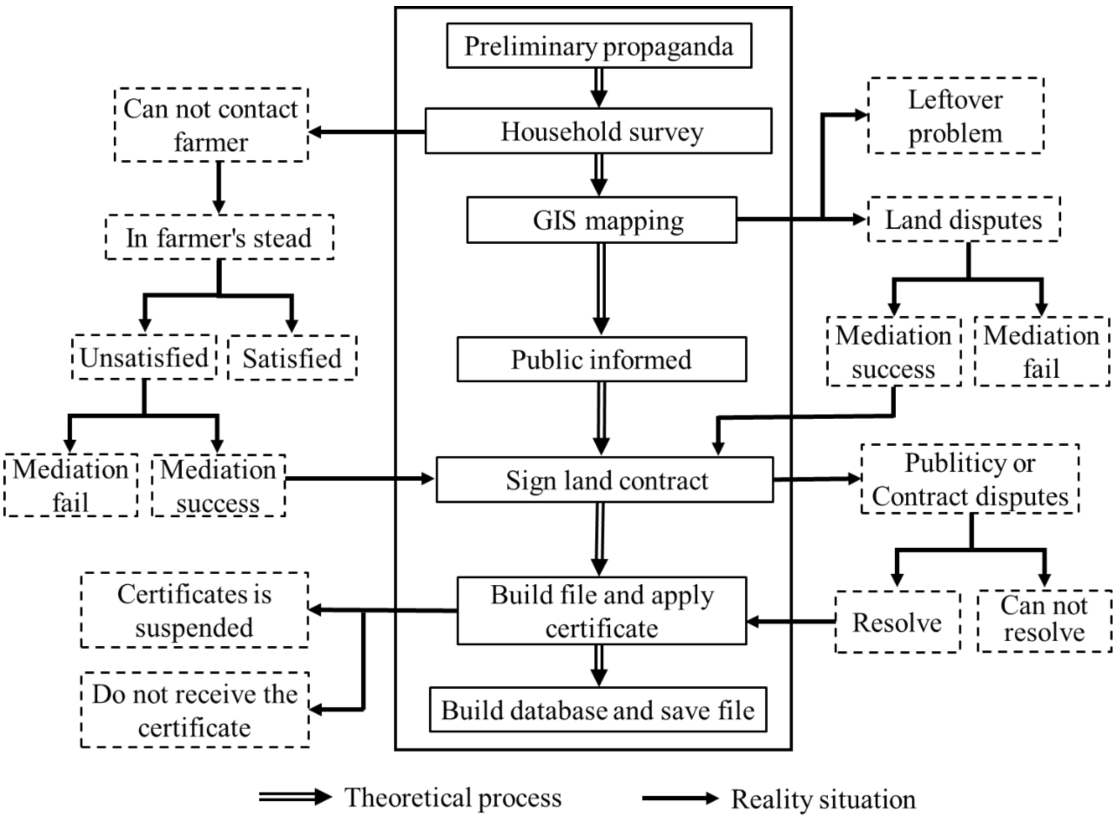
Figure A1：Agriculture Eefficiency Versus Several Input For Main Countries

. A, Effiency versus Land per Labor B, Effiency versus Labor



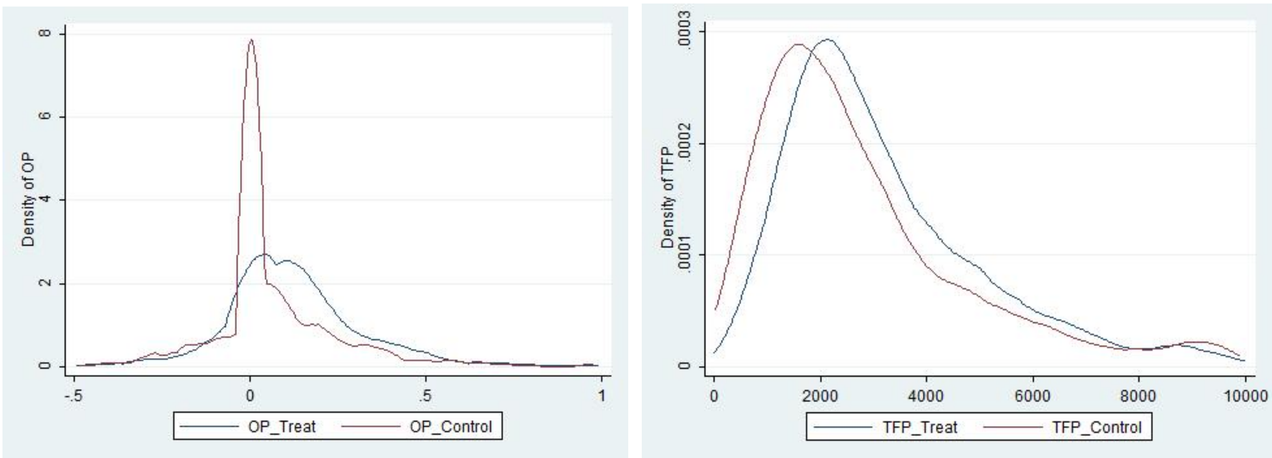
Note: Data from the World Bank. The efficiency is measure by the agriculture output amout per hectare. Labor and land is the same as Figure 1.

Figure A2 Theoretical and Reality Process of LCP



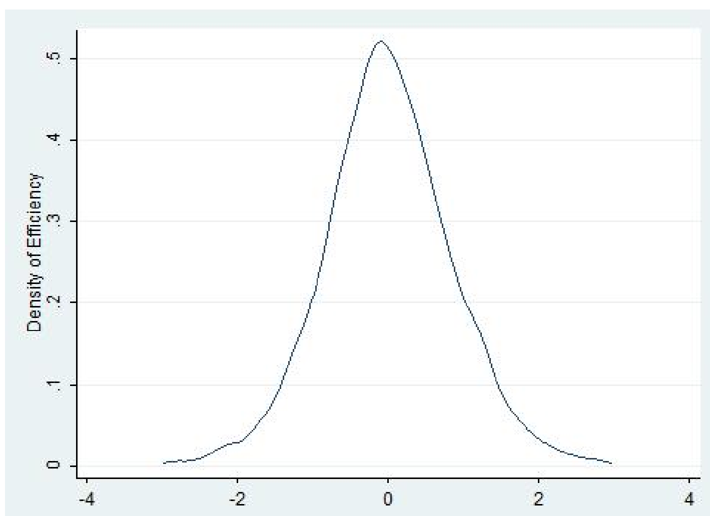
Note: The implementation process of LCP mainly comes from the author's field research

Figure A3 The distribution of OP and TFP between Treatment and Control Groups



Note: The OP and TFP are calculated through equation (3) and (4). The treat and control groups here refers to whether LCP is implemented at village-level. For easy viewing, we drop the observations whose OP covariance are smaller than 0.5 or bigger than 1 and those TFP bigger than 10000. The number of dropped observation less than 3 percent of all observations.

Figure A3 The distribution of Agriculture Ability (AA)



Note: The efficiency is the proxy for the agriculture ability and is generated through household fixed effect during the process of calculating TFP. For easy viewing, we drop the households whose AA smaller than -3 or bigger than 3. The number of dropped observation less than 1 percent of all households.

Table A1 Agricultural Characteristics between Early and Later LCP implemented Villages

Variables	All	Earlier	Later	Diff
Panel A: Agricultural production				
Agricultural value	6,468	6408	6530	-121.9
Contracted land	5.509	5.710	5.450	0.260
Irrigable land	2.649	2.680	2.640	0.0400
Machine value	2,597	2303	2713	-410.3
Capital input	2,833	2810	2856	-46.21
Panel B: Rent Behaviors				
whether rent in	0.116	0.120	0.110	0.0100
rent in area	6.790	6.030	7.140	-1.110
whether rent out	0.114	0.100	0.120	-0.0100
rent out area	4.047	3.200	4.330	-1.13**

Note: Data from 2010 wave of CHARLS. The five variables in Panel A refer to the value of all crop products, the total number of contracted land, the total number of land which is irrigaed, the current value of tractors, threshers, farm implements, water pumps and processing machinery and seeds (including the value of self-retained seeds), chemical fertilizers, farmyard manure, pesticides, plastic films, labor costs etc, respectively.

Table A2 Event Study Test to OP Covariance and TFP

Dependent Variable	OP Covariance	TFP
	(1)	(2)
pre_2	0.080	-0.047
	(0.141)	(0.040)
pre_1	0.050	0.040
	(0.114)	(0.033)
post_0	0.122	0.014
	(0.081)	(0.023)
post_1	0.178**	0.070***
	(0.076)	(0.022)
post_2	0.069	0.035*
	(0.072)	(0.021)
post_3	0.086	0.066**
	(0.090)	(0.026)
post_4	0.147**	0.047**
	(0.071)	(0.020)
Observations	2,654	2,654
R-squared	0.509	0.536

Note: Standard errors clustered at the province level. This regression uses all village-level data. The regression coefficients reported in the table are standardized, and the standard deviation of the estimator is in parentheses. *, ** and *** indicate that the estimated coefficients are significant at the 10%, 5%, and 1% significance levels, respectively.

Table A3 The Lagged Effect of Policy on Efficiency and Rent

	Reform Year		Post Reform Years		Observation
	Coefficient	Std	Coefficient	Std	
Panel A: TWFE Setting					
Log(TFP)	0.104	(0.078)	0.110**	(0.05)	2654
OP	0.013	(0.022)	0.050***	(0.014)	2654
Rent_in	0.005	(0.011)	0.033***	(0.007)	2654
Rent_out	0.018	(0.017)	0.046***	(0.011)	2654
Rent	0.02	(0.019)	0.071***	(0.012)	2654
Panel B: IV Setting					
Log(TFP)	0.521	(0.404)	0.338**	(0.152)	2654
OP	0.056	(0.116)	0.153***	(0.044)	2654
Rent_in	0.021	(0.059)	0.099***	(0.022)	2654
Rent_out	0.082	(0.09)	0.140***	(0.034)	2654
Rent	0.088	(0.101)	0.216***	(0.038)	2654

Note: Standard errors clustered at the province level. This regression uses all village-level data. The estimation following this equation: $Y_{v,t} = \alpha + \beta_I \mathrm{Reformyear}_{v,t} + \beta_2 \mathrm{Postreform}_{v,t} + \gamma \mathrm{control}_{v,t} + \lambda_v + \delta_t + \epsilon_{v,t}$, The coefficient of Reform Year and Post Reform Years refer to the coefficient of β_I and β_2 ,respectively. The regression coefficients reported in the table are standardized, and the standard deviation of the estimator is in parentheses. *, ** and *** indicate that the estimated coefficients are significant at the 10%, 5%, and 1% significance levels, respectively.

Table A4 The Lagged Effect of Policy on Household level variables

	Reform Year * Efficiency		Post Reform Years * Efficiency		Observation
	Coefficient	Std	Coefficient	Std	
Panel A: TWFE Setting					
Rent_in	-0.009	(0.011)	0.020**	(0.008)	22,634
Rent_out	-0.011	(0.011)	-0.005	(0.008)	22,634
Log(Land size)	-0.013	(0.04)	0.182***	(0.03)	22,634
Log(Plot size)	0.027	(0.054)	-0.038	(0.036)	16,016
Exit from agriculture	-0.001	(0.005)	-0.004	(0.004)	15,966
Loan	-0.001	(0.012)	0.016*	(0.009)	22,634
Log(Machine)	0.147	(0.125)	0.286***	(0.093)	22,634
Log(Machine/Labor)	0.016	(0.101)	0.156**	(0.075)	22,634
Panel B: IV Setting					
Rent_in	0.118	(0.186)	0.150**	(0.063)	22,634
Rent_out	-0.149	(0.169)	-0.026	(0.057)	22,634
Log(Land size)	1.088	(0.689)	0.976***	(0.231)	22,634
Log(Plot size)	0.709	(1.329)	0.35	(0.554)	16,016
Exit from agriculture	-0.024	(0.083)	-0.018	(0.028)	15,966
Loan	0.089	(0.185)	0.084	(0.062)	22,634
Log(Machine)	2.677	(2.101)	1.086	(0.706)	22,634
Log(Machine/Labor)	0.646	(1.665)	0.515	(0.559)	22,634

Note: Standard errors clustered at the province level. This regression uses all household-level data. The estimation following this equation: $Y_{h,t} = \alpha + \beta_1 \mathrm{Reformyear}_{h,t} + \beta_2 \mathrm{Reformyear}_{h,t} * AA + \beta_3 \mathrm{Postreform}_{h,t} + \beta_4 \mathrm{Postreform}_{h,t} * AA + \gamma \mathrm{control}_{h,t} + \lambda_h + \delta_t + \epsilon_{h,t}$, The coefficient of Reform Year * Efficiency and Post Reform Years * Efficiency refer to the coefficient of β_2 and β_4 ,respectively. The regression coefficients reported in the table are standardized, and the standard deviation of the estimator is in parentheses. *, ** and *** indicate that the estimated coefficients are significant at the 10%, 5%, and 1% significance levels, respectively.

Table A5 The effect of LCP on village-level rental behavior

	Rent in			Rent out			Rental market participation		
Model settings	TWFE (1)	TWFE (2)	IV (3)	TWFE (4)	TWFE (5)	IV (6)	TWFE (7)	TWFE (8)	IV (9)
Implemented	0.027***	--	--	0.040***	--	--	0.061***	--	--
	(0.007)	--	--	(0.010)	--	--	(0.012)	--	--
Certified	--	0.075***	0.089***	--	0.045**	0.133***	--	0.115***	0.201***
	--	(0.013)	(0.023)	--	(0.020)	(0.035)	--	(0.023)	(0.039)
Village FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
Control	YES	YES	YES	YES	YES	YES	YES	YES	YES
R Square	0.586	0.591	0.138	0.535	0.531	0.053	0.585	0.585	0.131
F Value	--	--	102.89	--	--	102.89	--	--	102.89
Sample Size	2,654	2,654	2,654	2,654	2,654	2,654	2,654	2,654	2,654

Note: Standard errors clustered at the province level. This regression uses all village-level data. Rent in (Rent out) represents the proportion of households who rent in (rent out) land to all households in the village, and Rental market participation represents the proportion of households who rent in or rent out land to all households in the village. The time for the village to implement LCP is determined by the issuance of the first land certificate. The regression coefficients reported in the table are standardized, and the standard deviation of the estimator is in parentheses. *, ** and *** indicate that the estimated coefficients are significant at the 10%, 5%, and 1% significance levels, respectively.

Table A6 The effect of LCP on land size and plot size

Model settings	Log(Land Size)			Log(Plot size)		
	TWFE (1)	TWFE (2)	IV (3)	TWFE (4)	TWFE (5)	IV (6)
Implemented	0.052**	--	--	-0.021	--	--
	(0.024)	--	--	(0.027)	--	--
Implemented*AA	0.216***	--	--	0.055*	--	--
	(0.027)	--	--	(0.031)	--	--
Certified	--	0.020	0.378*	--	-0.046**	-0.102
	--	(0.025)	(0.215)	--	(0.021)	(0.153)
Certified*AA	--	0.095***	0.735***	--	0.010	0.140*
	--	(0.028)	(0.113)	--	(0.023)	(0.077)
Household FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES
Control	YES	YES	YES	YES	YES	YES
R Square	0.922	0.921	0.044	0.95	0.95	0.006
F Value	--	--	143.97	--	--	54.20
Sample Size	22,634	22,634	22,634	16,016	16,016	16,016

Note: Standard errors clustered at the province level. This regression uses all household-level data. The plot size is calculated by dividing the family's total land size by the number of lots. The regression coefficients reported in the table are standardized, and the standard deviation of the estimator is in parentheses. *, ** and *** indicate that the estimated coefficients are significant at the 10%, 5%, and 1% significance levels, respectively.

Appendix B: Measures of Output and Inputs from Panel Data

Output: The output variable we use is farmers' gross agricultural income, which is composed of several parts, namely, farmers' income from food crops, income from cash crops, and other crops. Since we retained farmers who were mainly engaged in planting when we selected samples, because for our sample, food crops and cash crops accounted for 50.1% and 32.1% of farmers' gross income respectively. We also tried using the sum of cash crops and food crops as a proxy for agricultural output, and the results were similar to our baseline results. The biggest problem with our use of gross income to measure output is that we cannot take into account the agricultural products consumed by farmers themselves into the output value. Due to the lack of data on household agricultural product consumption, we cannot make up for it. However, we believe that such absence has little impact on our results, mainly for two reasons. First, the consumption of agricultural products within farmers' households does not account for a large proportion of farmers' agricultural product output, and during our sample period, most farmers chose to sell their professionally produced grain on the market and then use the obtained grain. Income to buy agricultural products needed for daily life. Second, even if all the agricultural products consumed by farmers are produced by their own households, since the proportion of household food consumption decreases as income increases, we expect inefficient households to consume more of their own agricultural products, while high-efficiency households consume more of their own agricultural products, while high-efficiency family is the opposite. This will make the calculated TFP more convergent than the real situation, resulting in an underestimation.

Land, capital and labor: The land input in our analysis is the sum of all plots of land operated by this household, which is composed by four parts (i.e., contracted land, fallen land, rent-in land and rent-out land). The first two kinds are contracted land and fallen land, which is reflected by the operated land in own family. We also include rented-in land plots and exclude rented-out plots for each household to generate the actual farm land. The capital item is the sum of fixed capital and intermediate input. The fixed capital is agriculture machine value, which is composed of the value of tractors, seeders, rice transplanters and threshers etc. Assuming that accumulation began in 2000, we utilize the perpetual inventory method to calculate the value of farm machinery in constant Renminbi (RMB). Because this survey does not capture household ownership of smaller farm tools, and so for just over a third of household-years, the estimated value of their capital stock is zero. To deal with these cases, we also put the intermediate input into capital, These intermediate inputs include fertilizers, pesticides, agricultural machinery rental, mulch, etc. Household labor input is measured by individual's labor time, which includes the time of family members and hired workers.