Journal of Development Economics 165 (2023) 103165

Contents lists available at ScienceDirect

Journal of Development Economics

journal homepage: www.elsevier.com/locate/devec

Regular Article

Land titling, human capital misallocation, and agricultural productivity in China

Shouying Liu[a,1], Sen Ma[b,1], Lijuan Yin[c,1], Jiong Zhu[d,1,*]

[a] School of Economics, Renmin University of China, 59 Zhongguancun Ave, Beijing, 100059, China
[b] Institute for Economic and Social Research, Jinan University, 601 Huangpu W. Ave, Guangzhou, 510632, China
[c] School of Finance and Trade, Liaoning University, 66 Chongshan Middle Road, Shenyang, 110036, China
[d] Center for Macroeconomic Research, School of Economics and Wang Yanan Institute for Studies in Economics, Xiamen University, 422 Siming South Road, Xiamen, 361005, China

ARTICLE INFO

JEL classification:
Q15
O12
O13

Keywords:
Land titles
Human capital
Misallocation
Productivity
China

ABSTRACT

Previous studies quantifying the relationship between land titles and agricultural productivity have not explored the role of human capital reallocation. This paper enhances existing literature by examining the effects of land titling on the reallocation of labor with heterogenous human capital endowments between agricultural and non-agricultural sectors. In reference to China's county-by-county rollout of the land titling program, this paper applies a difference-in-differences (DID) framework and finds that farmers with higher human capital are more likely to migrate out of villages following the completion of the titling program, which in turn causes a "brain drain" from the agricultural sector. There is a subsequent decrease in agricultural productivity and output. This productivity loss has not been thoroughly discussed in previous studies and nor considered in the policy making process. Our results indicate that future land reforms should consider the impact of land titling programs on the reallocation of human capital across sectors.

1. Introduction

The misallocation of resources is an important source of productivity differences across countries (Gollin et al., 2002; Caselli, 2005; Restuccia et al., 2008). The agricultural sector of developing countries mainly suffers from two sources of misallocation: a farm size that is too small and away from optimal scale due to transaction frictions in the land market, indicating a misallocation of land (Adamopoulos and Restuccia, 2014; Chari et al., 2021; Chen et al., 2022); excess labor employed in the agricultural sector due to mobility frictions in the labor market, suggesting a misallocation of labor (Do and Iyer, 2008; Giles and Mu, 2018; Foster and Rosenzweig, 2022). Both types of misallocation are partially rooted in insecure land property rights. While the lack of protection of land *transaction rights* hinders the full functional operation of the land market (Carter and Yao, 2002; Chari et al., 2021), *"use-based" land property rights*, also known as "land rights established through contingent use of the land", bind too much labor to the agricultural sector. Because farmers face a high risk of loss of land if they leave the land idle or let it to others (Liu et al., 1998; de Janvry et al., 2015; Zhao, 2020).

Existing studies on land property rights and agricultural productivity focus on addressing land misallocation within the agricultural sector by investigating policies that attempt to secure *transaction rights*; such studies predict that improvements in the protection of *transaction rights* raise agricultural productivity (Chari et al., 2021). However, relatively less is known about how land property rights reforms that rectified the misallocation across sectors, affect agricultural productivity through the labor market channel. More importantly, if labor and human capital are trapped in the agricultural sector due to *"use-based" land property rights*, any reforms that secure property rights by delinking land property rights from land use, may reallocate labor and human capital away from the agricultural sector. This "brain-drain" effect may cause a reduction in agricultural productivity, which complicates the prediction that secure property rights increase agricultural productivity whenever property rights are viewed merely as *transaction rights*.

This study leverages China's land titling program, notably the largest in the world,[2] to empirically investigate how secure property rights

* Corresponding author.
E-mail addresses: liusy18@126.com (S. Liu), senma2@jnu.edu.cn (S. Ma), ljyin@ucdavis.edu (L. Yin), zhujiong@xmu.edu.cn (J. Zhu).
[1] Authors are listed in alphabetical order and contribute equally to the paper and all could be treated as joint first authors.
[2] The program costs about 60 billion yuan (8.6 billion US dollars) (Zhang et al., 2020).

https://doi.org/10.1016/j.jdeveco.2023.103165
Received 26 January 2023; Received in revised form 3 August 2023; Accepted 5 August 2023
Available online 8 August 2023

through granting farmers formal land titles affect agricultural productivity. The land titling program, which was formally implemented nationwide between 2014 and 2019, provides land certificates that specify the particular plots of contracted land and their respective boundaries and areas. The certification effort provides land rights security that may delink the ownership of land from the contingent use of land, especially for potential migrant workers. We employ the staggered roll-out of the land titling program across Chinese counties using a difference-in-differences (DID) strategy to empirically evaluate the policy effects. Specifically, we use household-level data from the National Fixed-Point Survey (NFPS) to document rural households' agricultural practices and the allocation of labor across sectors.

We find that the land titling program led to a reduction in agricultural productivity. Our empirical estimates use the logarithm function of agricultural revenue per area of land and the logarithm function of conventional agricultural Total Factor Productivity (TFP) estimated following Chari et al. (2021) as the dependent variables. We find that agricultural revenue per area and TFP decrease by a similar magnitude (around 8–9 percent) following completion of the land titling program.

We argue that the decrease in agricultural productivity is driven by the reallocation of human capital away from the agricultural sector, which is resultant of delinking land ownership from the contingent use of land. In a simple theoretical model, we show that whenever land property rights are established through the contingent use of land, households will devote too much labor to the agricultural sector. Subsequently, when the land tenure insecurity constraint is removed by the land titling, households will reallocate more labor to non-agricultural sectors. We assume that human capital has relatively higher returns in the urban sector hence the labor that migrates to the urban sector will have a relatively higher level of human capital than the labor that remains in the agricultural sector. Subsequently, the land titling program will reduce agricultural productivity through allocating human capital away from the agricultural sector.

We test the hypotheses proposed by the model and obtain the following results. First, we find that the land titling program promotes rural-to-urban migration. The program not only increases migration time, but also increases migration income and cost, indicating that migrant workers could explore more migration opportunities by paying a higher cost. Second, we find that households with higher agricultural human capital before the reform, as measured by education, health, and age, allocate more labor to migration by reducing the labor devoted to agricultural production. Third, we find that the average human capital level of agricultural labor decreases after the reform due to the reallocation of human capital away from the agricultural sector. In other words, laborers employed in the agricultural sector become less educated, less healthy, and are less likely to be of working age.[3] As a farmer's ability to farm is positively correlated with their human capital, the reform thus results in a decrease in agricultural productivity. Fourth, the land titling program places the concentration of agricultural land into the hands of households with lower agricultural human capital through land transfers. Such concentration of land further aggravates the decrease in agricultural productivity. Specifically, we observe an increase in the land held by households from the lowest quartile of the agricultural human capital distribution, while there is a decrease in the land held by other households after completion of the land titling program. Finally, we show that if we control for agricultural human capital when estimating TFP, land titling will not significantly reduce this alternative measure of TFP, indicating that the drop in human capital of agricultural labor is the major driving force of the reduction in conventional TFP.

In order to further clarify the mechanisms through which the land titling program affects agricultural productivity, we estimate the heterogeneous effects of the program on agricultural productivity (measured by conventional TFP) by land tenure security and migration opportunity. First, we find that the effects of the land titling program are larger in villages that have lower land tenure security prior to the program, as is proxied by the amount of land related disputes, land expropriation risk, and village-level adjustable land (*jidongdi*). Thus, the land titling program affects agricultural TFP by enhancing tenure security. Second, we find the effects of the land titling program to be greater in villages with more migration opportunities, indicating that the program affects agricultural TFP through promoting rural-to-urban migration.

Our study contributes to several strands of literature. First, existing literature on property rights and agricultural productivity generally argues that land tenure insecurity hampers land transactions (Deininger and Jin, 2005; Deininger et al., 2010; Lunduka et al., 2009; Macours et al., 2010). Consequently, a lack of *transaction rights* reduces productivity in the agricultural sector through creating the misallocation of land. Reforms that attempt to protect *transaction rights* can reverse land misallocation within the agricultural sector and enhance agricultural productivity (de Janvry et al., 1991; Adamopoulos and Restuccia, 2014; Chari et al., 2021; Chen et al., 2022). The second strand of literature emphasizes investment incentives. This line of research argues that secure property rights are conducive to investments and agricultural efficiency (Besley, 1995; Banerjee et al., 2002; Jacoby et al., 2002; Banerjee and Iyer, 2005; Deininger and Jin, 2006; Goldstein and Udry, 2008; Besley et al., 2016; Chankrajang, 2015). Our study complements previous analyses by identifying the distinct effects on agricultural productivity that arise when "insecure property rights" are defined as "*use-based" land property rights*. We find that a land titling program that secures property rights through delinking land property rights from land usage resolves the misallocation of labor across sectors. However, as a side effect, the reform reduces agricultural productivity through reallocating human capital away from the agricultural sector.

Second, our study relates to literature on land property rights and migration decisions. It is well documented that *"use-based" land property rights* often cause households to oversupply labor to the agricultural sector, indicating that a small amount of land is occupied by a large number of farmers (Kung, 2002; Do and Iyer, 2008; de la Rupelle et al., 2009; de Brauw and Mueller, 2012; Giles and Mu, 2018; Gottlieb and Grobovšek, 2019; Foster and Rosenzweig, 2022). Improving land security by delinking land property rights from land use frees up the labor trapped in the agricultural sector, which is equivalent to reducing migration cost (de Janvry et al., 2015; Brandt et al., 2002). Zhao (2020) founds that the elimination of land insecurity increases migration in China. In addition to the quantity of migration, de Janvry et al. (2015) investigate how the decrease in the quantity of agricultural labor force, resultant of migration, affects land use and farmer welfare. We contribute to existing literature by studying not only the allocation of the *quantity of labor*, but also the allocation of *human capital*. We uniquely show that securing property rights may lead to a decrease in both the quantity and quality of the agricultural labor force. The decrease in human capital leads to a novel empirical prediction that securing property rights may reduce agricultural productivity, which is measured by conventional agricultural TFP.[4] The overall effect of securing property rights may be efficiency-enhancing since it resolves the misallocation of human capital across sectors by freeing up the labor that has higher human capital and is inefficiently trapped in the agricultural sector.

Third, our study serves as a policy evaluation of land titling programs. Governments from developing countries spend millions of dollars each year on land titling programs in the hope of enhancing agricultural productivity. Empirical evaluations of these programs, however,

[3] Working age is defined as between the ages of 18 and 65 years.

[4] The decrease in the quantity of agricultural labor will predict the decrease in yields but not the decrease in conventional TFP, which is estimated by controlling for the quantity of labor as inputs.

produce mixed results. In terms of land rentals, a variety of studies find that land titling programs can alleviate misallocation through promoting land rental activities (Beg, 2022), while other studies find that land titling may exert a negative impact on rental market participation such as in Nepal (Aryal and Holden, 2011) and Ethiopia (Holden et al., 2011). In terms of credit access, some studies find that land titles are conducive to credit access (López and Romano, 2000; Carter and Olinto, 2003; Deininger and Goyal, 2012), while other studies think otherwise (Field and Torero, 2006; Do and Iyer, 2008; Galiani and Schargrodsky, 2010).

Land titling has been the center of agricultural policy debates in China since 2000s. Earlier studies have documented that holding land certificates surprisingly has no impact on land rental activities in the land market (Jin and Deininger, 2009). However, later studies that exploit the early stage of the implementation of China's land titling program show mixed results. Wang et al. (2018) and Gao et al. (2021) find that the land titling program promotes agricultural productivity through encouraging land rentals among households, which corresponds with the initial policy objectives. In contrast, Cheng et al. (2019) and Ji et al. (2021) find that the program fails to increase the scale of rural land rental markets. Zhang et al. (2022) find ambiguous results, which show that the program only increases rent-in but not rent-out of the land. In addition to the effects on land market participation, Bu and Liao (2022) find that the program spurs entrepreneurship and business creation in the non-agricultural sector. We use more comprehensive and representative household-level survey data that covers the entire reform period to investigate the policy effects of the land titling program in China. We find that the human capital reallocation channel dominates other channels in determining agricultural productivity.

The remainder of this paper is organized as follows: the second section introduces the institutional background of the land titling program in China. The third section develops a simple theoretical model explaining land titling, human capital, and migration. The fourth section discusses the data source and the measures of agricultural TFP. The fifth section introduces empirical strategy. The sixth section reports empirical results. The final section concludes.

2. Background

2.1. Reforms of land institutions in China

Several major land reforms have been implemented in rural China since 1949. The first reform in the early 1950s was revolutionary in that land was expropriated from landlords and distributed to landless farmers. A further reform then forced individual farmers to join collectives, named as the People's Commune. Under this system, land was owned and collectively operated by the local authorities. Land rights were distributed according to the egalitarian principle.

The third land reform was introduced in the early 1980s and gave farmers the freedom of land use rights by means of a family-based contract system named as the Household Responsibility System (HRS). Under the HRS, land was collectively owned by all villagers and villages had to constantly readjust the distribution of land to cope with a changing population structure. A 15-year period of land use rights was granted to farmers in the early 1980s. To manage the problem of insecure land tenure induced by land readjustments, the Land Management Law (LML) was introduced in the 1990s, which extended the land use rights of households for another 30 years. Land readjustments saw a large decline in the late 1990s and most were completely abandoned by 2003 following the enactment of the Land Contracting Law (LCL) in 2003.

The Land Contracting Law marked a new round of land reforms that aimed to secure the property rights under the HRS. In addition to abandoning land readjustment, the law provided farmers with the legal right to rent out and rent in land, and outlined rules for leasing, transferring leases, and methods to address land leasing disputes. Most significantly, the law reform promoted land transfers and transactions through offering legal security to both parties of a leasing contract (Chari et al., 2021).

2.2. Land titling program

While the Land Contracting Law granted farmers *transaction rights* of land, other aspects of property rights remained ambiguous. For example, the reform left shortsighted farmers with few incentives to improve their agricultural capital and infrastructure (Chari et al., 2021). In order to further enhance efficient land usage, China's central government initiated a new round of reforms nationwide in 2014 that aimed to improve land property rights by providing land titles to farmers. The "No. 1 Document" produced in 2013 added a new section instructing the nationwide roll-out of the land titling program that would start in 2014. The implementation of the program was expected to finish in five years' time.[5] This action was based on the belief that further securing land rights can improve productivity in the agricultural sector.

The central government and Ministry of Agriculture decided to implement the pilot program of the land titling reform in 2009 in a limited number of sites, with the aim of evaluating the program's effectiveness, costs and benefits, and potential social risks. Most of the pilot sites, such as Chengdu city, were located in Sichuan province. During the experimentation stage, the pilot program was supposed to be interpreted as a sequence of trials and errors. It was intended that only the successful practices were promoted to the entire country in the subsequent nationwide roll-out stage. As noted by Li (2012) and Deininger et al. (2020), the central government applied knowledge and experience gathered from the Chengdu land titling experiment to design a national land titling policy.

In this study, we focus on the nationwide roll-out stage of the program and exclude the earlier pilot program province (Sichuan province) from our sample. We argue that the land titling pilot program was not ideal for investigating the effects of institutional changes because it was not implemented in a standard and unified way during the trial-and-error stage. In other words, the contents and procedures of the program may vary across pilot counties. The nationwide roll-out stage serves as a more suitable case for our research because the program followed a standardized guideline provided by the central government, which was based on the knowledge and experience acquired from the pilot program.

The standardized land titling program in the nationwide roll-out stage consists of three major phases: land measurements, land registrations, and land certifications. In phase one, a professional team of survey-cartographers constructs a 1:2000 draft of geo-coded land information system, which contains information on land types, land serial numbers, and land areas for each land parcel in all villages. In phase two, village organizations then identify the land "owner" of each land parcel based on the completed geo-coded land information system. In phase three, the recording and registration of the land "owner-parcel" pairs are confirmed by the county land management office. After a systematic error checking process, the land management office finalizes the program by recording the cases into the land management information system and issuing land certificates accordingly. The above processes usually take about one and a half years.

According to the "No. 1 Document" issued by Chinese Central government in 2013 and 2014, the nationwide roll-out of the program would start in 2014 and was expected to reach universal coverage by the end of 2019 (in five years' time). The provincial governments decided the timing of the policy roll-out at the county level. We obtain data on the timing of a county's completion of the titling program. We gather information from the official websites of local agricultural bureaus county by county. The websites include information about the schedule

[5] It can be found at: http://www.moa.gov.cn/ztzl/yhwj2013/zywj/201302/t20130201_3213465.htm.

of the land titling program, which is recorded and published in the form of work plans, year-end summaries, and public announcements.[6] The completion timing for each county is shown in Fig. 1. We treat the completion timing of villages in the same way as the completion timing of their affiliated counties.

Our measure of policy timing differs from a relevant previous study (Bu and Liao, 2022) in that we use the *completion* timing of the titling program from public announcements while Bu and Liao (2022) use the *start* timing of the program from confidential records from the Chinese Ministry of Agriculture. Whilst the average time taken for a county to complete implementation of the program is one and a half years, the actual time taken can still vary across counties. We argue our usage of the completion timing as the policy timing is more appropriate in our research context for addressing the changes in incentives related to *"use-based" land property rights*. The *"use-based" land property rights* indicate that farmers are incentivized to remain in the agriculture sector in order to maintain their property rights. This incentive remains strong during the implementation stage of the program because farmers are strongly incentivized to stay at home to make sure that their land rights are sufficiently secured during the titling process. For most farmers, the incentive to stay due to *"use-based" land property rights* would not be relaxed until completion of the program. Therefore, we choose to use the completion timing to mark the relaxation of constraints induced by *"use-based" land property rights.*

Another reason for which we use the completion timing rather than the start timing to mark the timing of the titling program is that some local governments unintentionally delayed the process and rushed to complete the program just before the expected completion time. Once the land titling program has been announced, the upper-level government will set an expected time of completion. The incentive for local governments to implement the program only strengthens when the deadline for completion is approaching. For example, according to some official county government websites, local officials make comments such as, "we will be fully committed to complete the land titling program in the last 100 days. We will call it 100-day movement"; "Because we are pressed for time, we have to work hard, effectively, and under pressure, to achieve the goal of getting the land titling program completed on time".[7] Therefore, we believe the completion timing is a more accurate measure of the actually timing of the policy because of potential delays in implementation.

Even though the titling program enhanced land property rights from multiple perspectives, it may only play a limited role in further strengthening *transaction rights*, which had already been granted to farmers in the earlier Land Contracting Law reform back in 2003, and land transfers had already been widely practiced before the issuance of land certificates. In Fig. 2, we plot the ratio of transferred land over total land across time at the national level. We find that even though the ratio of transferred land continues to increase over time, the growth rate decreases after 2014 when the land titling program was implemented on a large scale. Thus, we argue that the land titling program plays a limited role in providing additional incentives for land transfers through enhancing *transaction rights*.

2.3. Land titling program, land property rights, and rural-to-urban migration

This paper argues that the titling program provides more secure property rights through delinking land property rights from the contingent use of land. We firstly provide some stylized facts that identify that before the titling program, China's insecure property rights policies inefficiently bound farmers to their land, and thus hindered migration to urban regions.

2.3.1. Insecure land property rights for migrants

Even though the Land Contracting Law in 2003 enhanced land property rights by reducing village-level land readjustments and granting farmers with *transaction rights*, the early version of the law did not provide a clear legal guidance on the preservation of rural land contracts for potential migrant workers. As more farmers started to migrate to urban regions, village magistrates (cadres or clan heads) were more incentivized to seize migrants' land during their absence (Rozelle and Li, 1998; Ho, 2001; Brandt et al., 2002). First, under the communal land system, land is a quasi-public good that supports the subsistence of the poorest households (Li et al., 1998; Kung, 2000; Zhao, 2020). Since migrants no longer rely on land for subsistence, then taking back the contracted land of migrants becomes somewhat justifiable (Zhao, 2020). Second, the price of land has increased rapidly over the past decades, making land a more valuable asset (Olson, 1990; Ding, 2003; Lichtenberg and Ding, 2008). Subsequently, increasing numbers of migrant workers face a high risk of losing their land contracts.[8] According to a survey of rural households in 17 Chinese provinces, which was conducted in 2010, more than half of them (54.4%) believed they had to return contracted land to the village if any household members migrated to cities (Feng et al., 2013). Thus, the ambiguity surrounding the 2003 version of the Land Contracting Law and the flaws in local implementation, meant farmers perceived that migration plans were linked to a high risk of losing land contracts. This paper argues that land titles can substantially reduce that risk,[9] since they provide more legal protection against potential expropriation. In Appendix A10, we detail a legal case in which migrant workers successfully use their land certificates to defend themselves against the expropriation of their contracted land from the village collectives.

2.3.2. The ambiguity of land tenancy

The ambiguity of land tenancy, otherwise known as the length of the land contracting period between farmers and the village authorities, created uncertainties in the late 2010s. The initial land contracts signed in the early 1980s, which were based on the number of household laborers at the time (Li, 2003), were supposed to last for around 15 years. To provide more secure land tenure, the contract was extended by another 30 years in the early 1990s (Zhu, 1999). Subsequently, most land contracts were due to come to an end in the late 2010s, and it was unclear whether the central government would issue new policies to extend existing land contracts or implement a new round of land readjustments. There was also an increasing call from the bottom for further land readjustments since the rural household labor structure had significantly changed since the 1980s. For example, the survey conducted by Zheng and Gao (2017) shows that more than 30% of farmers advocated for land readjustments as a means to reflect population change. The support for readjustments varied across regions, in some of which it reached more than 50% (e.g., Shandong province). Uncertainty

[6] For example, the public announcement issued by the Huizhou prefectural government indicates that Boluo County completed its land titling program by the end of 2017 on the official website of Huizhou prefectural bureau of agriculture and rural affairs. The announcement can be found at: http://dara.gd.gov.cn/snnyxxlb/content/post_1494556.html.

[7] Those can be found at: http://lqnews.zjol.com.cn/lqnews/system/2018/07/16/031013171.shtml, and https://www.sohu.com/a/154711540_693084.

[8] A report by the Chinese Academy of Social Sciences in 2011 found that about 50 million migrants out of 250 million migrants, were landless farmers due to expropriation. A further 3 million people lost their land every year. The report can be found at: https://www.ft.com/content/33ae0866-3098-11e5-91ac-a5e17d9b4cff.

[9] The Land Contracting Law was revised in 2019; the new Article 27 specifically clarified the protection of migrant land contracts. The insecure land property right for migrants was a significant problem before 2018; the revision addressed the ambiguity in the previous versions with regards to land property rights for migrants. which corresponded to our study period.

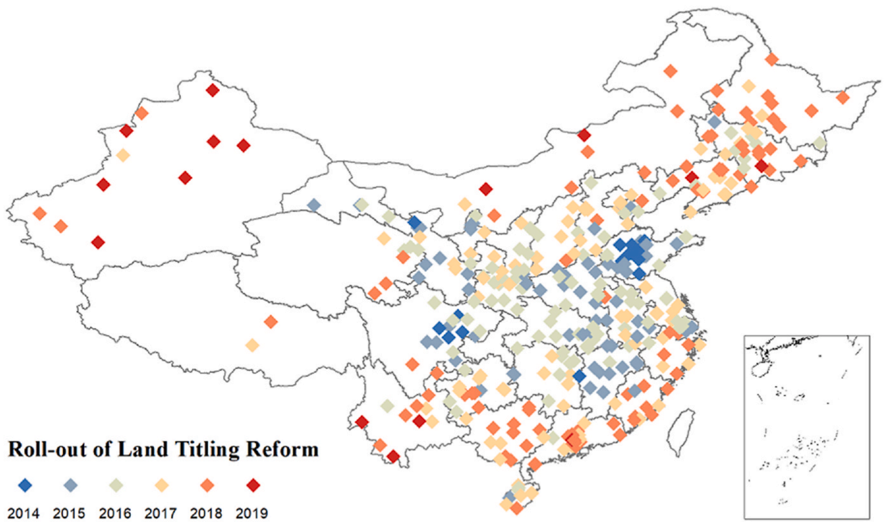

Fig. 1. The Roll-out of the Land Titling Program across China
Notes: In the figure, we show the roll-out of the land titling program across the sampled villages over time. The nationwide roll-out of the program started in 2014 and reached universal coverage by the end of 2019. We treat the completion timing of villages the same as the completion timing of their affiliated counties.

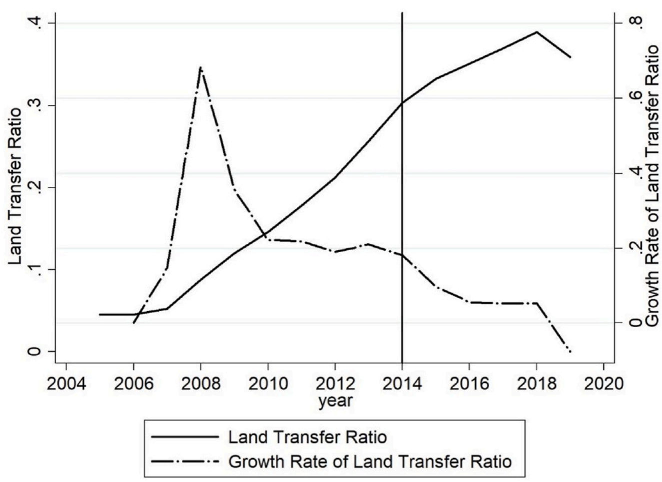

Fig. 2. The Time Trend of Land Transfers at the National Level
Notes: In the figure, we show the time trend of the development of land transfers at the national level. The solid line shows the time trend of land transfer ratio (transferred land over all land). The dashed line shows the time trend of the growth of land transfer ratio. Data source: China Rural Business Management Annual Report.

over future land contracts incentivized farmers to remain cultivating their land in the villages; this was considered the less risky option in terms of losing their land during the forthcoming new round of land contract extension (Liu and Zhang, 2008; Pan et al., 2013; Deng, 2014).[10]

2.3.3. Land disputes and land expropriation

Land disputes and land expropriation risks caused by insecure land property rights also hinder rural-to-urban migration (Ho, 2001; Prosterman et al., 2009; Besley and Ghatak, 2010). Out-migrating farmers become easy targets in land disputes and their land rights are more likely to be infringed by neighboring villagers (Ho, 2001, 2005). The administrative process to settle land related disputes is generally complicated and time consuming[11]. Households are thus needed to allocate a fraction of labor to protecting their land rights and resolving land disputes. The risk of land expropriation is another factor that has kept farmers in villages (Guo, 2001; Song and Pijanowski, 2014). Compensation for land expropriation has become non-negligible with the continuous increase in land value. As the timing of land expropriation is unpredictable (Sha, 2023), potential migrants must remain in the villages to obtain more economic concessions from rural authorities in case their land enters the expropriation process.

3. A simple theoretical model

In this section, we set out a simple model to illustrate how the land titling program's promotion of migration allocates human capital away from the agricultural sector. The model describes the decision-making process of rural households, which comprises individual members with different human capital endowments, when allocating labor between farming and migration. The model can intuitively be described as follows: the household allocates labor between the rural agricultural sector and the urban non-agricultural sector to maximize total household revenue. When land tenure is insecure, some households have to allocate a more than optimal amount of labor into the agricultural sector in order to maintain land property rights. After the land titling program, these extra labor inputs will be freed from the agricultural sector and moved to the urban non-agricultural sector through migration. We assume that human capital has relatively higher returns in the urban sector hence the labor that migrates to the urban sector will have a relatively higher level of human capital than the labor that remains in the agricultural sector. Subsequently, the land titling program will reduce agricultural productivity through allocating human capital away from the agricultural sector.

A representative household in our model is composed of K household members. Each member is denoted by i. Each household member is endowed with labor L_i. The level of human capital of each member is described as H_i. To simplify the model, we assume that each household

[10] In 2018, the land contracting period was formally extended by another 30 years.

[11] In the absence of a well-functioning rural legal system, Chinese farmers rarely initiated a lawsuit in the court system when there was a violation of land rights, unless the potential economic losses were extensive. Farmers always ask the village leader for a decision because only they are capable of deciding the case.

member is endowed with the same amount of labor such that $L_i = L$, and varies only in human capital endowments. Each household is endowed with land N. The household decides the amount of labor that each household member input into the agricultural sector, denoted as l_i^e, and the migration urban sector, denoted as l_i^m.

The agricultural sector is described by a Cobb-Douglas production function at the household level as follows:

$$Y = A\left(\sum_{i=1}^{K} H_i l_i^e\right)^{\alpha} N^{1-\alpha},$$

where Y denotes output and $\sum_{i=1}^{K} H_i l_i^e$ denotes household agricultural labor input weighted by human capital. We assume that human capital H_i measures the heterogenous productivity of labor, and therefore enters the agricultural production function by changing the productivity of each unit of labor input. A refers to factors other than human capital that can influence agricultural productivity. We derive the expression of TFP as follows:

$$Y = A\left(\frac{\sum_{i=1}^{K} H_i l_i^e}{\sum_{i=1}^{K} l_i^e} \times \sum_{i=1}^{K} l_i^e\right)^{\alpha} N^{1-\alpha},$$

$$ln\ Y = lnA + \alpha\ ln\left(\frac{\sum_{i=1}^{K} H_i l_i^e}{\sum_{i=1}^{K} l_i^e}\right) + \alpha\ \ln\left(\sum_{i=1}^{K} l_i^e\right) + (1-\alpha) lnN,$$

where $\left(\frac{\sum_{i=1}^{K} H_i l_i^e}{\sum_{i=1}^{K} l_i^e}\right)$ measures the average of household members' human capital weighted by their agricultural labor input. If we calculate TFP in a conventional way, and only treat quantity of labor as labor input, we will arrive at $lnA + \alpha\ ln\left(\frac{\sum_{i=1}^{K} H_i l_i^e}{\sum_{i=1}^{K} l_i^e}\right)$ as conventional household level agricultural TFP, which is denoted as $TFP_{conventional}$. Obviously, $TFP_{conventional}$ positively correlates with the human capital level of agricultural labor. If we control for the human capital level of agricultural labor when estimating the production function, we will get lnA as TFP net of human capital input, denoted as $TFP_{human\_capital\_control}$.

Migration wage is assumed to be: $w_i = wH_i^r\ (r > 1)$. $r > 1$ models that the return to human capital is higher in the urban industrial sector than in the rural agricultural sector, and the price of agricultural goods is normalized to 1.

We adopt two key assumptions regarding human capital: (1) human capital increases both agricultural and non-agricultural productivity; (2) human capital has a higher marginal return in the urban sector. We use these assumptions to model that household members with higher human capital have absolute advantage in both agricultural and non-agricultural production. In contrast, household members with higher human capital have comparative advantage in non-agricultural production.

We follow Zhao (1999) and model tenure insecurity constraint as the minimum amount of labor ($\underline{L}$) that households must supply to agriculture in order to maintain their land rights (*"use-based" land property rights*). As aforementioned, farmers face various risks of losing land rights if they leave their land idle or let it to others. Since land is a valuable long-term asset, we assume households always want to keep their land rights by supplying at least $\underline{L}$ to the agricultural sector. We assume that the land titling program removes the tenure insecurity constraint by delinking land property rights from land use.

3.1. Equilibrium without tenure insecurity constraint

Without the tenure insecurity constraint, a household's problem can be described as:

$$Max_{l_i^m, l_i^e}\ w\sum_{i=1}^{K} H_i^r l_i^m + A\left(\sum_{i=1}^{K} H_i l_i^e\right)^{\alpha} N^{1-\alpha},$$

$$\text{s.t. } l_i^m + l_i^e \le L_i = L,$$

The household maximizes total revenue from the agricultural sector and migration income.

We denote a household's agricultural labor input weighted by human capital as $\Pi = \sum_{i=1}^{K} H_i l_i^e$. For any given household member, the marginal benefit from migration can be expressed as:

$$MR_{migration} = wH_i^r,$$

The marginal cost of migration (forgone agricultural output) at Π can be expressed as:

$$MC_{migration} = AH_i\alpha(\Pi)^{\alpha-1} N^{1-\alpha},$$

$$\frac{MR_{migration}}{MC_{migration}} = \frac{wH_i^{r-1}}{\alpha A(\Pi)^{\alpha-1} N^{1-\alpha}}$$

According to our model assumptions, the benefit from migration increases with human capital, since $r > 1$. Therefore, the household will always prioritize the migration of labor that has higher human capital.

Thus, the equilibrium condition can be described as follows:

When $Max(H_i)$ (the highest human capital among household members) is sufficiently large, some household members will migrate, and there is a cut-off household member j with human capital level H_j such that:

$$\begin{cases} l_i^e = 0, if\ H_i > H_j \\ l_i^e = L, if\ H_i < H_j \\ l_j^e = l_j^{e*}, such\ that\ \alpha A\left(H_j l_j^{e*} + \sum_{H_k < H_j} H_k L\right)^{\alpha-1} N^{1-\alpha} = wH_j^{r-1} \end{cases}$$

This result indicates that all members with human capital higher than H_j will migrate, and that all members with human capital lower than H_j will remain in agriculture. The member with human capital H_j will distribute labor across migration and agriculture.[12] When $\Pi = H_j l_j^{e*} + \sum_{H_k < H_j} H_k L$, for the member with human capital H_j, $MR_{migration} = MC_{migration}$. For $H_i > H_j$, $MR_{migration} > MC_{migration}$, the labor of these household members will be allocated to migration. For $H_i < H_j$, $MR_{migration} < MC_{migration}$, the labor of these household members will be allocated to agriculture.

3.2. Equilibrium with tenure insecurity constraint

With the tenure insecurity constraint, household i's problem can be described as:

$$Max_{l_i^m, l_i^e}\ w\sum_{i=1}^{K} H_i^r l_i^m + A\left(\sum_{i=1}^{K} H_i l_i^e\right)^{\alpha} N^{1-\alpha}$$

$$\text{s.t. } l_i^m + l_i^e \le L_i = L,$$

[12] When $Max(H_i)$ is low and $\alpha A(\sum_{i=1}^{K} H_i L)^{\alpha-1} N^{1-\alpha} > w(Max(H_j))^{r-1}$, there will be no incentive for the household member with the highest human capital endowment to migrate. Therefore, no member in this household will migrate. These households are not the focus of our study, since their decisions are not affected by land titling.

$$\sum_{i=1}^{K} l_i^e \geq \underline{L}$$

The tenure insecurity constraint is binding when $l_j^{e*} + \sum_{H_i<H_j} L < \underline{L}$, i.e., the optimal total labor supply to the agricultural sector derived from Section 3.1 is smaller than $\underline{L}$. When the condition is binding, the household will supply $\underline{L}$. The equilibrium can be described as a cut-off household member j^* with corresponding human capital level H_{j^*}, such that:

$$\begin{cases} l_i^e = 0, \textit{if } H_i > H_{j^*} \\ l_i^e = L, \textit{if } H_i < H_{j^*} \\ l_{j^*}^e = l_{j^*}^{e**}, \textit{such that } l_{j^*}^{e**} + \sum_{H_k<H_{j^*}} L = \underline{L} \end{cases}$$

Similar to the argument presented in Section 3.1, the household will always prioritize the migration of members with relatively higher human capital. Those with relatively low human capital will stay in the agricultural sector to meet the requirement of land tenure insecurity constraint. When the constraint is binding, a more than optimal amount of labor will be allocated to the agricultural sector.

Total human capital weighted labor input into the agricultural sector can be expressed as:

$$H_{j^*} l_{j^*}^{e**} + \sum_{H_k<H_{j^*}} H_k L$$

When the tenure insecurity constraint is binding, $l_{j^*}^{e**} + \sum_{H_k<H_{j^*}} L = \underline{L} > l_j^{e*} + \sum_{H_k<H_j} L$. Thus, $H_{j^*} \geq H_j$. Since more labor is allocated to the agricultural sector, the household member on the cut-off has a higher human capital level. Therefore, household members with human capital between H_j and H_{j^*} are inefficiently "trapped" in the agricultural sector by the tenure insecurity constraint.

3.3. The effects of the land titling program

We compare the above two results to derive the following four hypotheses regarding the impact of land titling on migration and the allocation of human capital.

First, when the tenure insecurity constraint is removed by land titling, agricultural labor supply decreases by $\underline{L} - \left(l_j^{e*} + \sum_{H_i<H_j} L \right)$ for those households facing binding tenure insecurity constraint. Therefore, we have the first hypothesis:

H1. The land titling program will increase average household migration.

In terms of household heterogeneity, households facing binding tenure insecurity constraint tend to have higher human capital "trapped" in the agricultural sector prior to the land titling reform. Therefore, we have.

H2. The increase in migration is more salient for households with higher agricultural human capital before the land titling program

We now discuss the changes in the average of human capital in the agricultural sector before and after the land titling program.

$$H_{insecure} = \frac{H_{j^*} l_{j^*}^{e**} + \sum_{H_k<H_{j^*}} H_k L}{l_{j^*}^{e**} + \sum_{H_k<H_{j^*}} L},$$

$$H_{secure} = \frac{H_j l_j^{e*} + \sum_{H_k<H_j} H_k L}{l_j^{e*} + \sum_{H_k<H_j} L}$$

Note that $H_{j^*} \geq H_j$ when the tenure insecurity constraint is binding. Household members with human capital between H_j and H_{j^*} are inefficiently "trapped" in the agricultural sector by the tenure insecurity constraint. Since "trapped" labor has higher human capital than H_j, the average human capital is higher when the tenure insecurity constraint is binding.

$$H_{insecure} \geq H_{secure}$$

H3. The land titling program will decrease the average human capital of agricultural labor.

As mentioned in the discussion about the definition of TFP, the conventional agricultural TFP positively correlates with the human capital level of agricultural labor. Thus, we have the following hypothesis.

H4. The land titling program will decrease conventional agricultural TFP.

4. Data

4.1. Description of the data and variables

Our primary data source is the National Fixed-Point Survey (NFPS), which is a panel survey collected by the Research Center for Rural Economy (RCRE) of the Chinese Ministry of Agriculture since 1986. The NFPS survey tracks a nationally representative sample of about 20,000 rural households in approximately 300 villages, covering all 31 of China's mainland provinces. The NFPS villages were selected for representativeness based on region, income, cropping pattern, population, and non-farm activity. Within each village, the NFPS randomly selects around 50 to 100 households to answer an annual household survey.[13] Each selected respondent household must maintain diaries of income, expenditure, and labor activities. A resident enumerator visits each household once a month to collect information from their diaries throughout the survey period. The rigorous procedures in the collection, checking and processing of the NFPS data make reporting and measurement errors very unlikely (Benjamin et al., 2005; Chen and Zhang, 2009).[14] Our analysis covers a 10-year sample period between 2009 and 2018 for the purpose of data comparability because the questionnaire underwent major changes in 2009.

The NFPS survey consists of three sub-surveys: the village survey, the household survey and the household member (individual) survey. The village survey is answered by local officials, while the household and individual surveys are answered by household heads. The village survey contains information on local socio-economic conditions. The household survey contains information on crop-level agricultural inputs and outputs, while the individual-level survey contains information on labor allocation and the characteristics of each household member.

Since our purpose is to analyze the effects of land titling on agricultural productivity and the allocation of agricultural labor, we adopt the following procedures to acquire a sample of farming households from rural China. First, we match the household survey with the individual survey and acquire a total of 202,899 household-year

[13] The number of households sampled in each village is chosen to reflect the population share of the region.

[14] The NFPS data contain detailed information on farm agricultural production, employment, and income. Benjamin et al. (2005) demonstrate that the data are of high quality and provide a detailed overview of the data.

observations from 387 villages. Second, we drop villages from the pilot reform regions (Sichuan Province), which equates to 946 household-year observations from 2 villages. Third, we drop villages located in urban districts to better focus on the analysis of households from rural areas, which reduces the sample size to 142,825 household-year observations from 258 village.[15] Fourth, we drop 29 of the 258 villages, because we could not find open sources to provide information on their land titling completion timing.[16] Finally, we exclude households that do not cultivate any agricultural crops, which leads us to a final analytical sample of 99,630 household-year observations. The sample with TFP as the dependent variable has a slightly smaller sample size (98,386) because calculating TFP requires the control of inputs and multiple fixed effects. There is a small proportion of households that have missing information on inputs or do not have enough data to allow for the control of fixed effects. Due to the focus on agricultural production, households from our analytical sample rely extensively on agriculture. The summary statistics in Table 1 shows that an average household from our sample cultivates 12.67 mu of land and acquire 14,445 yuan of agricultural income per year which consists of 76.7 percent of total household income.

The key advantages of the survey data are the panel structure and the detailed information on agricultural inputs and outputs at the household-crop-year level from the household survey. We acquire information on outputs both in terms of revenue, and in terms of physical number of outputs (as measured in kilograms). The detailed agricultural production information allows us to estimate agricultural TFP and to closely examine how the land titling program impacts farm output and TFP.

The NFPS individual survey provides information on demographic characteristics and a detailed structure of labor supply for each household member. Demographic characteristics include gender, age, educational background, health status, technique certificates, and political background etc. These variables enable us to investigate the changes in labor and human capital after implementation of the land titling program. We use three measures for human capital: **education** (schooling years), **health status** (whether the household member's health status is "Excellent", "Good" or "OK"[17]), and **good working age** (whether each household member is between the ages of 18 and 65).

The labor supply data includes the number of days each household member devotes to different types of work, including the number of local on-farm labor days, local off-farm labor days (non-agriculture), and labor days as migrant workers away from their home county. In addition to the allocation of labor, the data includes migration income and costs. It is noteworthy that the data includes information on those household members who work as temporary migrant workers. Even if they reside outside the household for the majority of the year, their migration time and migration income and costs, will be tracked and reported. The detailed migration information enables us to construct measures of demographic shifts across agricultural and non-agricultural sectors. Panel B of Table 1 presents the descriptive statistics of these aggregated variables. Around 40 percent of households in the sample have at least one migrant worker and the average household spends around 169 days on off-farm migration work. The average household migration income is about 13,000 yuan (about 2000 US dollars).

Table 1
Summary statistics.

	Mean	Std Dev	Observations
Panel A: Agricultural Productivity			
Log of Aggregate Agricultural Revenue per mu	6.998	0.873	99633
Agricultural TFP (Conventional)	1.272	0.811	98398
Agricultural TFP (Human Capital Control)	0.747	0.723	98398
Panel B: Labor Allocation and Characteristics			
Any Migration	0.395	0.489	99633
Aggregate Household Migration Days	169.379	270.461	99633
Aggregate Household Migration Income (yuan)	13471.79	34456.28	99633
Aggregate Household Migration Cost (yuan)	3057.96	11213.41	99633
Aggregate Household Farm Labor Days	214.053	219.588	99633
Aggregate Household Off-Farm Working Days (Non-agriculture)	117.435	212.516	99633
Education Level of Household Agricultural labor (weighted by individual labor days)	5.559	3.109	99309
Health Status of Household Agricultural labor (weighted by individual labor days)	0.797	0.390	99309
Whether Household Agricultural labor is in good Age (weighted by individual labor days)	0.631	0.455	99309
Age of Household Agricultural labor (weighted by individual labor days)	43.139	21.181	99309
Panel C: Agricultural Inputs			
Total Agricultural Capital (yuan)	14981.02	85523.01	99633
Total Agricultural Area (mu)	12.266	15.539	99633
Panel D: Agricultural Income			
Household Aggregate Agricultural Income (yuan)	14444.99	18097.54	99633
Share of Agricultural Income over Total Income	0.767	0.919	99633

Notes: In this table we report the summary statistics of major variables. Individual-level and crop-level variables are aggregated to the household level.

We then explain how to measure the human capital of different types of work at the household level. There are three types of work, notably, local agricultural work, local non-agricultural work, and migration out of the home county. In addition to the time allocation across each type of work, we create a human capital index at the household level to measure the average human capital level of labor in each type of work. There are three types of human capital: education, health status and good working age. The human capital index is written as follows:

$$HCI_h^{S,H} = \sum_{i\in h} HCI_i^H \frac{LaborDays_i^S}{\sum_{i\in h} LaborDays_i^S},$$

where S denotes the three types of work (agricultural, local non-agricultural, or migration), H denotes the three types of human capital (education, health status, or good working age), h denotes household, and i denotes each household member. HCI_i^H denotes human capital H of each household member i. The household level human capital index

[15] We exclude villages from urban districts for the following reasons. First, due to the fast pace of urbanization, many rural areas near cities have been transformed into urban districts and so agriculture is no longer the major income source for those households. Second, converting agricultural land into urban use has become a central concern in regions close to cities. Land titling may affect villages located in urban districts through urbanization rather than agricultural production. Thus, we decide to focus on households from rural areas to address the impact of land titling through the agricultural production channel.

[16] A number of counties, some of which are from ethnic minority regions, do not report their government documents online. Therefore, we are not able to acquire information on the completion timing of land titling for about 10% of the counties in our sample. The missing of information on the completion timing may cause a potential sample selection issue. In Table A9, we conduct a balance test at the village level using information from village surveys, and compare those villages for which we cannot find information on the timing of land titling with other villages. We do not find statistical differences for most key variables including total population, the amount of arable land per capita, share of income from non-agriculture, human capital level of labor, and the pattern of out-migration.

[17] The individual-level data of the National Fixed-Point Survey asks household members to choose one out of the five given choices with regards to his or her health status, which includes "Excellent", "Good", "OK", "Bad", and "Disabled".

Table 2
The effects of land titling on agricultural productivity.

	(1)	(2)	(3)	(4)	(5)	(6)
	Log Revenue per Area	Log Revenue per Area	Log TFP (Conventional)	Log TFP (Conventional)	Log TFP (Control for Human Capital)	Log TFP (Control for Human Capital)
Post*Treated Villages	−0.076**	−0.084**	−0.092**	−0.093**	−0.038	−0.035
	(0.035)	(0.037)	(0.040)	(0.041)	(0.031)	(0.032)
Household Fixed Effects	Yes	No	Yes	No	Yes	No
Province*Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Village Fixed Effects	No	Yes	No	Yes	No	Yes
Cluster of Standard Errors	County	County	County	County	County	County
Observations	99633	99633	98386	98386	98386	98386
Adjusted R-square	0.598	0.463	0.597	0.447	0.597	0.303

Notes: In this table, we show the effects of the land titling program on agricultural productivity estimated using the DID model specified as Equation (6). In Columns (1) and (2), we use revenue per area to measure productivity. In Columns (3) and (4), we use the conventional TFP, which is estimated following Equation (2) without considering variation in labor productivity by human capital, to measure productivity. In Columns (5) and (6), we use the TFP estimated following Equation (5) by controlling for the human capital level of labor input. In Columns (1) (3), and (5), we control for household fixed effects. In Columns (2) (4), and (6), we control for village fixed effects. The sample with TFP as the dependent variable has a slightly smaller sample size (98,386) because calculating TFP requires the control of inputs and multiple fixed effects. There is a small proportion of households that have missing information on inputs or do not have enough data to allow for the control of fixed effects. Robust standard errors clustered at the county level are shown in parentheses. *, ** and *** denote statistical significance at the 10%, 5% and 1% level, respectively.

$HCI_h^{S,H}$ is constructed as a weighted average of each member's human capital, and the weight is determined by how many labor days the member allocates to work type S ($LaborDay_i^S$) divided by how many labor days the household allocates to work type S in total ($\sum_i LaborDay_i^S$). Thus, index $HCI_h^{S,H}$ measures the average human capital level of labor devoted to each type of work per household. According to this construction method, the average age for household agricultural labor is approximately 43 years, and their average education level is less than six years during our sample period.

However, the NFPS data set does not come without limitations. First, the information is not broken down at the land-parcel level. Second, the data do not provide direct measures of land quality. Third, the data do not include information on each land rental contract.

4.2. Calculating Total Factor Productivity (TFP)

This subsection explains the methods we adopt to calculate the agricultural TFP. We firstly follow the literature to calculate $TFP_{conventional}$ when only the quantity of labor is treated as labor inputs. We firstly calculate $TFP_{conventional}$ at the household-crop level. Next, we aggregate $TFP_{conventional}$ to the household level by aggregating across crops weighted by the revenue from each crop. Then, we control for measures of agricultural human capital at the household level when estimating the production function, and acquire an alternative measure, $TFP_{human\_capital\_control}$, which captures factors other than human capital that influence productivity.

4.2.1. Conventional TFP

We follow Chari et al. (2021) to construct a conventional measure of agricultural TFP. In this framework, we assume a Cobb-Douglas crop--specific production function, which is written in logarithm functional form as follows:

$$y_{icvt} = \alpha_c \log L_{icvt} + \beta_c \log N_{icvt} + \gamma_c \log K_{icvt} + \delta_c \log M_{icvt} + \varphi_{ic} + \varphi_{it} + \varphi_{cvt} + e_{icvt} \tag{1}$$

where y_{icvt} denotes log output (in the form of revenue or physical

Table 3
The effects of land titling on allocation of labor.

	(1)	(2)	(3)	(4)
	Farm Labor Days	Local Off-Farm Working Days	Migration Days	Migration Days (Ratio)
Post*Treated Villages	−0.181**	−0.019	0.145**	0.018*
	(0.088)	(0.094)	(0.072)	(0.009)
Household Fixed Effects	Yes	Yes	Yes	Yes
Province*Year Fixed Effects	Yes	Yes	Yes	Yes
Cluster of Standard Errors	County	County	County	County
Observations	99633	99633	99633	93349
Adjusted R-square	0.5689	0.5507	0.5815	0.6339
	(5)	(6)	(7)	
	Migration Extensive Margin	Migration Cost	Migration Income	
Post*Treated Villages	0.025**	0.305***	0.321**	
	(0.013)	(0.105)	(0.151)	
Household Fixed Effects	Yes	Yes	Yes	
Province*Year Fixed Effects	Yes	Yes	Yes	
Cluster of Standard Errors	County	County	County	
Observations	99633	99633	99633	
Adjusted R-square	0.557	0.607	0.589	

Notes: In this table, we show the effects of the land titling program on allocation of labor among agricultural work, local non-agricultural work, and migration work. "Farm Labor Days" refers to the amount of labor days spent on farming. "Local Off-Farm Working Days" refers to the amount of labor spent on local non-agricultural works. "Migration Days" refers to the amount of labor spent on migration non-agricultural works. All columns are estimated using the DID model specified as Equation (6). All labor days are measured in logarithm value. Robust standard errors clustered at the county level are shown in parentheses. *, ** and *** denote statistical significance at the 10%, 5% and 1% level, respectively.

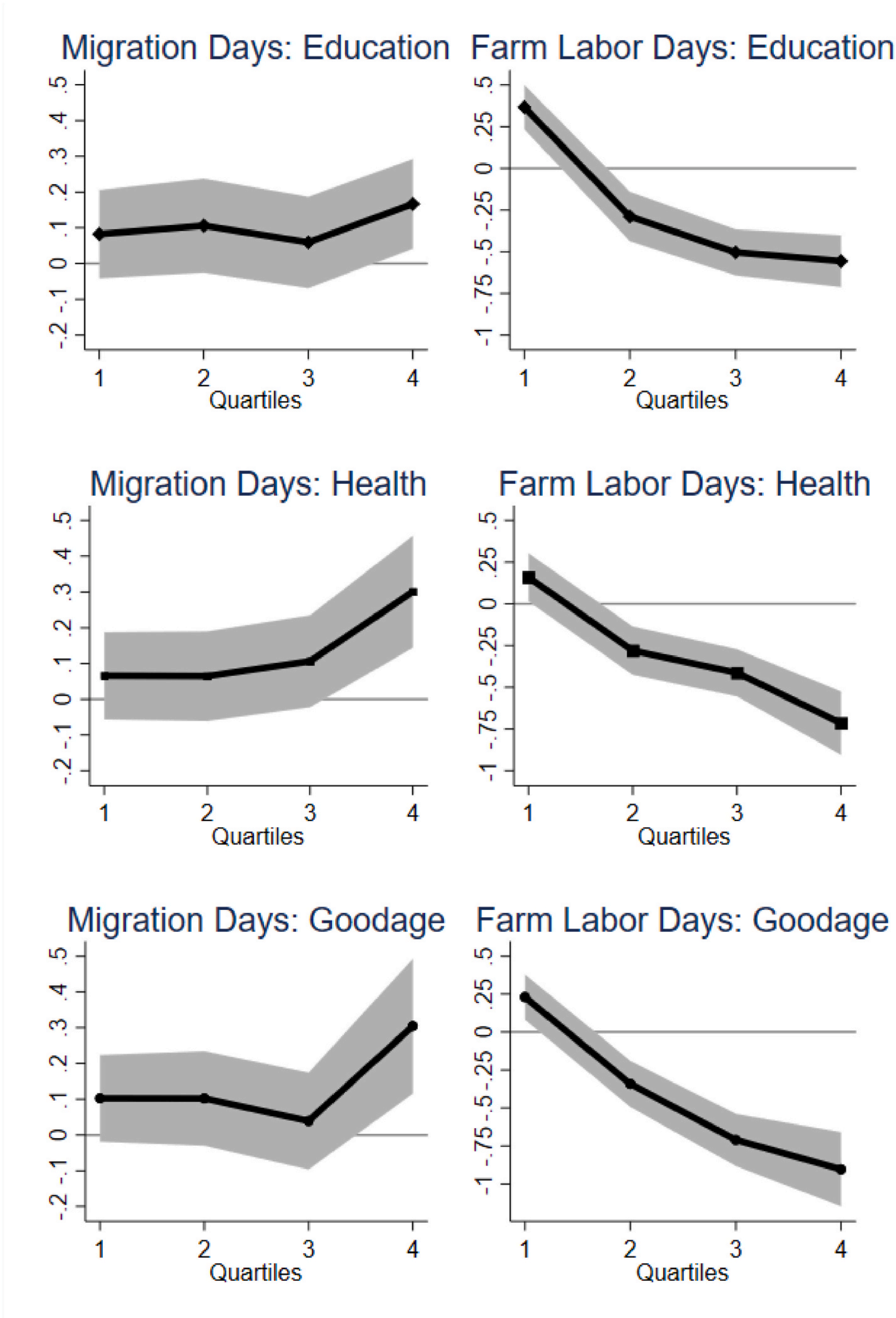

Fig. 3. The Effects of Land Titling on Migration by Agricultural Human Capital
Notes: These figures show the heterogenous effects of the land titling program on the allocation of labor by agricultural human capital before the land titling program. Coefficients are estimated using Equation (8). In the left column, we show the effects on migration days. In the right column, we show the effects on farm labor days. All labor days are measured in logarithm value. The horizontal axis denotes four quartile groups ranked from low to high. The vertical axis denotes the treatment effects for each quartile group. Human capital is measured by years of schooling, whether the labor is in good health, and whether the labor is in good working age. The figures report point estimates and 90% confidence intervals.

quantity[18]) of household i growing crop c in village v in year t; L_{icvt}, N_{icvt}, K_{icvt}, M_{icvt} denote land inputs (total cultivation area), labor inputs (total labor days), machinery costs and the aggregation of all other input costs, respectively. φ_{ic} , φ_{it} , φ_{cvt} refers to household-crop fixed effects, household-year fixed effects, and crop-village- year fixed effects. Household-crop level TFP_{icvt} is expressed in Equation (2) as the residual of the production function that cannot be explained by observable inputs:

$$TFP_{icvt,conventional} = y_{icvt} - \widehat{\alpha_c} log\ L_{icvt} - \widehat{\beta}_c log\ N_{icvt} - \widehat{\gamma}_c log\ K_{icvt} - \widehat{\delta}_c log\ M_{icvt} \quad (2)$$

The impact of human capital of agricultural labor on agricultural productivity is included as part of $TFP_{conventional}$.

A detailed description of the method used to estimate household-crop level TFP_{icvt} can be found in Appendix A1.

4.2.2. *Household level revenue-based TFP (TFP_{ivt})*

Next, we construct household-level revenue-based TFP by aggregating household-crop level TFP_{icvt} across crops cultivated by household i at time t.

[18] We use revenue based TFP as the baseline results. In case that the price levels of agricultural products can be influenced by the land titling program, we estimate the effects of the land titling program on quantity based TFP as robustness checks. The results reported in Table A7 shows that the land titling program significantly decreased conventional quantity based TFP, estimated using physical quantity as output without controlling for human capital.

$$TFP_{ivt,conventional} = \sum_{c} \omega_{icvt} TFP_{icvt,conventional}, \tag{3}$$

where the index TFP_{ivt} denotes household-level aggregate TFP of household i in village v at time t. TFP_{ivt} is calculated as the real revenue share weighted average of household-crop level TFP_{icvt}, where weight ω_{icvt} is determined by the real revenue from crop c divided by the real total revenue from all crops. With the detailed information on farm output by crops in physical terms, we need the real crop prices to calculate the real crop revenue. Following Adamopoulos et al. (2022a, b), we firstly compute the nominal crop prices at the village level, dividing the total revenue from sales by the total physical quantity of sales. Next, we discount the nominal prices in order to obtain the real value using the China Agricultural Product Price Producer Price Index.[19] We compute village-level average real prices for each crop between 2009 and 2018.

4.2.3. TFP after controlling for human capital

In order to clarify whether the changes in conventional TFP is driven by agricultural human capital or other factors, we control for human capital level of agricultural labor when estimating production function and get an alternative measure of TFP as follows.

We firstly regress household level conventional TFP , $TFP_{ivt,conventional}$, on household level agricultural human capital H_{it}, household fixed effects and province-year fixed effects.

$$TFP_{ivt,conventional} = \gamma H_{it} + \varphi_i + \varphi_{pt} + e_{icvt} \tag{4}$$

Then, we acquire the residual after controlling for human capital as:

$$TFP_{ivt,human\_capital\_control} = TFP_{ivt,conventional} - \widehat{\gamma} H_{it} \tag{5}$$

This process decomposes conventional TFP into household agricultural human capital and other factors that influence agricultural productivity at the household level. $TFP_{human\_capital\_control}$ is thus adopted to capture the impact of factors other than human capital on agricultural productivity.

5. Empirical strategy

We examine whether the land titling program affects agricultural productivity and explore its mechanisms. Our identification strategy employs the staggered implementation of China's land titling program across counties over time. The policy shock allows us to use a difference-in-differences (DID) model to identify the causal effects of secure land property rights on agricultural productivity and its underlying mechanisms. Using household-level panel data, we estimate the following equation for household i from county s in year t:

$$y_{ist} = \alpha + \beta Postreform_{st} + \gamma_i + \gamma_{pt} + \varepsilon_{ist} \tag{6}$$

where $PostReform_{st}$ is a dummy variable indicating treated counties after the completion of the titling program (including the completion year). $PostReform_{st} = 1$ if county s has completed the land titling program by time t; otherwise $PostReform_{st} = 0$. The regression controls for household and province-year fixed effects which are denoted by γ_i and γ_{pt}, respectively. The standard errors are clustered at the county level.

In order to test the parallel pre-trends between the treatment and control counties, we also estimate a specification that uses the leads and lags around the completion of the titling program:

$$y_{ist} = \alpha + \sum_{k=-4}^{3} \beta_k PostReform_{st,k} + \gamma_i + \gamma_{pt} + \varepsilon_{ist} \tag{7}$$

where $PostReform_{st,k}$ is a set of dummy variables that indicate the periods relative to the program completion year of county s. For example, $PostReform_{st,-3}$ refers to three years prior to the year of program completion in county s and $PostReform_{st,3}$ refers to three years after completion. The omitted category is $k = -1$. The sample in this analysis is restricted to an 8-year window around the completion year in each county. Equation (7) takes advantage of the panel nature of the data and allows us to test the identification assumption underlying the DID analysis, which is that the pre-trends of the outcome variable are parallel between the treatment and control counties before the implementation of the program.

Recent literature identifies that consistent estimation of the staggered DID design relies on the assumption that the treatment effects are constant across groups and over time (Borusyak et al., 2021; Sun and Abraham, 2021; Athey et al., 2018; Callaway and Sant'Anna, 2021; Goodman-Bacon, 2021; de Chaisemartin and D'Haultfoeuille, 2020). The OLS estimation of a staggered DID model might be biased if the land titling program's effects on agricultural production vary across counties or change over time. As additional robustness checks, we replicate the main empirical results adopting a set of methods proposed in the literature to check whether our results are sensitive to heterogenous treatment effects. Specifically, we adopt four methods from the literature that consistently estimate a staggered DID model allowing heterogeneous treatment effects across villages and over time: Borusyak et al. (2021), Callaway and Sant'Anna (2021), de Chaisemartin and d'Haultfoeuille (2020), and Sun and Abraham (2021). Table A4 shows that most of alternative estimates have the same sign and are similar in magnitude to the baseline OLS estimates.

6. Empirical results

In this section, we analyze the effects of the land titling program on agricultural productivity. First, we show that the land titling program reduces a household's agricultural productivity measured by revenue per area or conventional agricultural TFP. Then, we illustrate that the increase in migration and reallocation of human capital away from the agricultural sector are responsible for the decrease in agricultural productivity.

6.1. The effects of land titling on agricultural productivity

The results reported in Table 2 show that the land titling program reduces agricultural productivity in treated households. We estimate the DID model specified in Equation (6) and report the coefficient β in Table 2. In Columns (1) and (2), we use the logarithm function of agricultural revenue per area of land as the measure of productivity. In Columns (3) and (4), we use the logarithm function of conventional TFP calculated according to the methods discussed in Section 4.2.1 and Section 4.2.2 as the dependent variables. In Columns (1) and (3), we control for household fixed effects. In Columns (2) and (4), we control for village fixed effects to estimate productivity changes at the village level. We find that regardless of model specifications, the land titling program generates a negative and statistically significant effect on agricultural productivity. In terms of magnitude, the program reduces revenue per area by around 8 percent, and TFP by around 9 percent.

In Columns (5) and (6), we investigate whether agricultural human capital is the main driving force of the reduction in agricultural productivity. We generate an alternative measure of TFP ($TFP_{human\ \_capital\_control}$) by controlling for human capital of agricultural labor when estimating the production function (as discussed in Section 4.2.3). We find that the effects of the land titling program on $TFP_{human\_capital\_control}$ become statistically insignificant and much smaller in magnitude. This finding indicates that the drop in human capital of agricultural labor is one of the main driving forces of the reduction in conventional TFP. Factors other than human capital that influence productivity, which are captured by $TFP_{human\_capital\_control}$, are not statis-

[19] Data are obtained from the Agricultural Product Price Statistics Yearbooks.

tically significantly affected by the land titling program.

6.2. The effects of the land titling program on rural-to-urban migration and the relocation of human capital

The simple theoretical model proposed in Section 3 argues that more secure land property rights through delinking land ownership from land use can relax the constraint to migration, and promote the reallocation of human capital from the rural agricultural sector to the urban industrial sector. We test the hypotheses proposed in Section 3 by studying the impact of the land titling program on household migration decisions.

Table 3 tests the hypothesis that the land titling program will promote rural-to-urban migration **(H1)**. Specifically, we show the policy effects on the time allocation of rural households among agricultural work, local non-agricultural work and migration work. All models are estimated using a DID specification of Equation (6). Columns (1) to (4) show that rural households granted with land titles decrease the number of farming days by about 18 percent but increase rural-to-urban migration days by about 14 percent. The time allocated to local non-agricultural works is not significantly affected.[20] Additionally, the ratio of migration days to all labor days increases by about 1.8 percentage points. Furthermore, Columns (5) to (7) show a significant increase in the extensive margin of migration, cost of migration, and income from migration, thus indicating that migrant workers can explore more migration opportunities by paying a higher migration cost. For example, since the program causes the migrants to worry less about land property rights at home, they might choose to migrate further away in order to pursue better economic opportunities. Subsequently, both migration cost and income would increase, which is consistent with the empirical pattern that we observe in the data. Overall, the findings are consistent with the hypothesis that secure property rights through land titling will promote migration.

Second, we also hypothesize in the simple theoretical framework that households with higher agricultural human capital before the titling program will devote more time to migration after land titling, because the constraint due to insecure property rights is more binding for them **(H2)**. We empirically test this hypothesis in Fig. 3, which shows the estimation results using a triple DID model specified as Equation (8):

$$m_{ivst} = \alpha + \sum_{j=1}^{4} \delta_j (PostReform_{st}) \times \lambda_{iv}^{j} + \gamma_i + \gamma_{pt} + \varepsilon_{ivst}, \tag{8}$$

where the dependent variable m_{ivst} indicates the allocation of labor for household i from village v and county s in year t. λ_{iv}^{j} is an indicator for whether the agricultural labors' human capital of household i is in quartile j of the pre-reform human capital distribution within village v. The coefficients of the triple interaction terms δ_j indicate the heterogenous effects of the land titling program on each quartile group. As detailed in the data section, we measure human capital of household labor from three perspectives: education (schooling years), health status (whether the household member's health status is "Excellent", "Good" or "OK"), and good working age (whether each household member is between the ages of 18 and 65). The right column of Fig. 3 shows that the decrease in farming days is driven by households from the higher quartiles of the agricultural human capital distribution. At the same time, those households with the lowest human capital, increase their farming days. Contrastingly, the left column of Fig. 3 shows that the increase in migration days is mainly driven by households with higher agricultural human capital. These findings are generally consistent with our hypothesis.

Third, our theory predicts that land titling will eventually decrease human capital of agricultural labor, since household members with more human capital are more likely to migrate out **(H3)**. Table 4 tests this prediction by studying the policy effects on human capital of agricultural labor. Columns (1) and (2) show the policy effects on education, which is approximated by years of schooling and whether or not the household laborer has finished elementary school[21]. Columns (3) and (4) show the policy effects on health, which is measured by whether the health condition category of labor is good (if the household member's health status is reported as "Excellent", "Good", or "OK") or very healthy (if the household member's health status is recorded as "Excellent" or "Good"). Columns (5) and (6) show the policy effects on age, which is measured by whether the laborer is of good working age (if the household member is between the ages of 18 and 65) or of best working age (if the household member is between the ages of 18 and 60). Human capital of household agricultural labor is calculated by the weighted average of each individual labor's human capital following the methods discussed in Section 4.1. The policy effects on all measures of human capital are negative and statistically significant, which supports the prediction that land titling will decrease the human capital of agricultural labor.

Finally, we show that human capital of agricultural labor indeed positively correlates with agricultural productivity as suggested by a large body of literature that starts from the influential work by Foster and Rosenzweig (1995). Thus, the decrease in conventional TFP can be explained by the decrease in human capital. Table 5 shows the correlation between agricultural TFP (conventional, without controlling for human capital), migration, and the three measures of human capital: education (years of schooling), health (good health) and age (good working age). We regress conventional agriculture TFP and migration time on the three measures of human capital with the fixed effects controlled using a sample of households before the land titling program. Human capital is indeed found to strongly positively correlate with both conventional agricultural TFP and migration days. Both observations validate the underlying assumption of our model, which is that human capital increases both agricultural productivity and migration.[22]

6.3. Testing for the parallel pre-trends assumption and sensitivity to treatment heterogeneity

In Fig. 4 we show the tests for the parallel pre-trends assumption that underlies the DID design for our main outcome variables, including agricultural productivity (approximated by revenue per area and conventional TFP), migration, and human capital of agricultural labor. Specifically, we estimate Equation (7), and report the coefficients that capture the differences between the treatment and control groups at each year relative to the completion timing of the titling program. In addition to the baseline OLS estimates, we also show the dynamic estimates acquired from alternative methods that are robust to treatment heterogeneity in a staggered DID design (Callaway and Sant'Anna (2021); Sun and Abraham, 2021).

The results presented in Fig. 4 show that in most of the specifications,

[20] Bu and Liao (2022) find that the land titling program significantly increases employment in local non-agricultural businesses. The discrepancy could be the result of different employment measures. Bu and Liao (2022) measure employment by the number of employees in each sector using the following survey question: "How many people in your household were employed by local businesses in the survey year?" This paper adopts an arguably more accurate measure using the number of labor days employed locally in the non-agricultural sector for every individual member of every household.

[21] Finishing elementary school is about the median of the distribution of the human capital of agricultural labor.

[22] Other than agricultural productivity, human capital may also influence input costs and profits. In Appendix Table A3, we estimate whether the land titling program affects input costs and profits. We find negative but statistically insignificant effects.

Table 4
The effects of land titling on human capital of agricultural labor.

	(1)	(2)	(3)	(4)	(5)	(6)
	Years of Education	Education (Elementary)	Health (Good Health)	Health (Very Healthy)	Age (Good Age)	Age (Best Age)
Post*Treated Villages	−0.288**	−0.031**	−0.045**	−0.039**	−0.029*	−0.021*
	(0.127)	(0.014)	(0.019)	(0.018)	(0.015)	(0.0122)
Household Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Province*Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Cluster of Standard Errors	County	County	County	County	County	County
Observations	99309	99309	99309	99309	99309	99309
Adjusted R-square	0.522	0.619	0.405	0.480	0.548	0.608

Notes: In this table, we show the effects of the land titling program on human capital of agricultural labor. We measure human capital from three perspectives: education (Columns (1) and (2)), health (Columns (3) and (4)), and age (Columns (5) and (6)). Education is approximated by years of schooling and whether the household labor finished elementary school or not (elementary school is the sample median education level). Health is measured by whether the health condition category of labor is in good health (if the respondents' health status is "Excellent", "Good" or "OK") or very healthy (If the household member's health status is record as "Excellent" or "Good"). Age is measured by whether the labor is in good working age (18–65) or in the best working age (18–60). Robust standard errors clustered at the county level are shown in parentheses. *, ** and *** denote statistical significance at the 10%, 5% and 1% level, respectively.

Table 5
Agricultural TFP and human capital.

	(1)	(2)	(3)	(4)	(5)	(6)
	Agricultural TFP (Conventional)			Migration Days		
Education	0.064***			0.450***		
	(0.005)			(0.011)		
Good Health		0.512***			4.308***	
		(0.041)			(0.124)	
Good Age			0.381***			4.103***
			(0.032)			(0.128)
Household Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Province*Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Cluster of Standard Errors	County	County	County	County	County	County
Observations	75747	75747	75747	77023	77023	77023
Adjusted R-square	0.563	0.569	0.553	0.776	0.789	0.770

Notes: In this table we show the correlation between human capital, agricultural TFP (conventional without controlling for human capital) and migration days. In columns (1) to (3), we regress agricultural TFP on measures of human capital while controlling for household and province-by-year fixed effects. In columns (4) to (6), we regress migration days on measures of human capital. All models are estimated using a sample of households before the land titling reform. Robust standard errors clustered at the county level are shown in parentheses. *, ** and *** denote statistical significance at the 10%, 5% and 1% level, respectively.

the differences between the treatment and control groups do not exhibit different trends before the completion of land titling program.[23] Therefore, the parallel pre-trends assumption is satisfied in most of the cases.

In Table A4, we check whether our main estimation results are sensitive to biases induced by treatment heterogeneity in a staggered DID design. We adopt four methods from the literature that consistently estimate a staggered DID model allowing heterogeneous treatment effects across villages and over time: Borusyak et al. (2021), Callaway and Sant'Anna (2021), de Chaisemartin and D'Haultfeuille (2020), and Sun and Abraham (2021). Table A4 shows the estimates using these alternative methods and compare the results with the baseline OLS estimates. We find that for all major dependent variables, including conventional agricultural TFP, migration, and human capital of agricultural labor, most of alternative estimates have the same sign and are similar in magnitude to the baseline OLS estimates.[24] Therefore, we argue that our main results are not biased due to treatment heterogeneity in a staggered DID design.

6.4. *The effects of the land titling program on agricultural inputs*

This subsection explores how the land titling program affects the structure of agricultural inputs. First, we find that the land titling program does not significantly affect cultivated areas and the amount of hired labor input. Second, we find that the land titling program reduces spending on additional inputs such as fertilizer, pesticide, machinery, and agricultural mulch films. Furthermore, those households in the agricultural sector with reduced human capital spend less on inputs that may potentially improve long-term land fertility, such as organic

[23] The only potential concern is the coefficient on the −2 period when conventional TFP is the dependent variable. While none of the coefficients on the −4, −3, and −1 periods are statistically different from zero, the coefficient on the −2 period that is estimated using OLS is marginally significantly different from zero (90%). However, the adjusted coefficient following Callaway and Sant'Anna (2021) is not statistically different from zero. Thus, there is weak evidence to suggest deviation from parallel pre-trends at −2 period. We do not think the deviation is due to an incorrect timeline because the analyses on migration and agricultural human capital do not reveal a similar pattern at −2 period. Thus, we think it could be caused by productivity specific shocks at −2 period that are not completely controlled for in the OLS estimation model. We do not think the deviation is a threat to our major results for two reasons. First, the evidence is relatively weak (marginally significant for OLS in one pre-period). Second, the pattern is not observed for other variables that pin down the mechanisms.

[24] We follow the analytical framework proposed by de Chaisemartin and D'Haultfeuille (2020) to address the issue of negative weights. Our baseline estimate on conventional agricultural TFP is a weighted sum of 32,089 ATTs, in which 22.5 percent (7,207) receive a negative weight. To understand whether the presence of negative weight affects our baseline estimates, we check the robustness of our results by adopting the estimator DID_M as proposed by de Chaisemartin and D'Haultfeuille (2020). Table A4 shows that this method generates estimates that have the same sign as the baseline OLS estimates. In addition, the magnitude of coefficients is also similar to the baseline estimates, indicating that the baseline OLS estimates are not biased due to treatment heterogeneity across groups or over time.

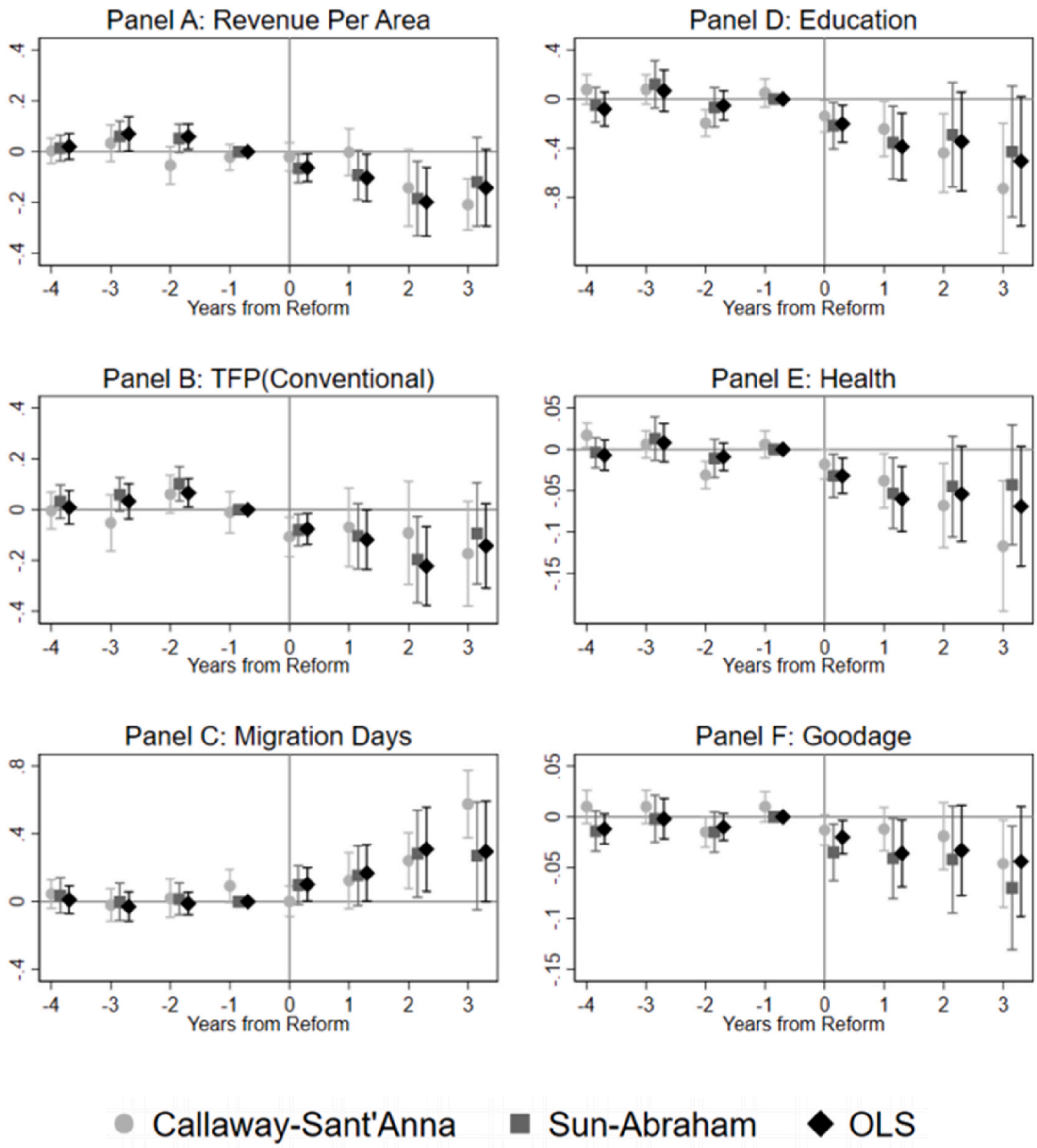

Fig. 4. The Effects of Land Titling on Agricultural Productivity, Migration, and Agricultural Human Capital (Test for Parallel Pre-trends)
Notes: These figures show the tests for the parallel pre-trends assumption that underlies the DID design for our main outcome variables, including agricultural productivity (approximated by revenue per area and conventional TFP), migration, and human capital of agricultural labor (measured by education, health, and age). Specifically, we estimate Equation (7), and report the coefficients that capture the differences between the treatment and control groups at each year relative to the timing of the titling program. In addition to the baseline OLS estimates, we also show the dynamic estimates we acquire from alternative methods that are robust to treatment heterogeneity in a staggered DID design (Callaway and Sant'Anna, 2021; Sun and Abraham, 2021). The figures report point estimates and 90% confidence intervals.

fertilizer and irrigation.

Table 6 presents the estimated DID coefficients on agricultural inputs. Column (1) shows that the land titling program does not significantly affect land input measured by total amount of cultivated area. This finding indicates that treated households do not change land input as a response to the increase in migration. Column (2) shows that the program does not affect hired labor input in order to compensate for agricultural labor losses due to migration; this indicates that total labor input should decrease since households devote less of their own time to farming (Table 3).

Column (3) shows that households receiving land titles reduce additional inputs such as fertilizer, pesticide, machinery, tools, and agricultural mulch films. Therefore, in this paper we argue that households with less human capital lack the necessary knowledge and skills to effectively use these additional inputs. Finally, Column (4) shows that households spend less on inputs that would enhance land fertility in the long term, such as organic fertilizer and irrigation. We speculate that households with less human capital are relatively short-sighted, and unable to fully perceive long-term gains in the future.[25]

[25] It is possible that households respond to the improvements in tenure security with long-term farm investments, such that the decrease in productivity is a short-run response. We use Equation (7) to estimate the dynamic effects of land titling on potentially long-term investments recorded in the data. The coefficients are reported in Table A6. We find that in the sample period (three years after titling) that we can track, the coefficients on additional inputs (fertilizer, pesticide, machinery, tools, agricultural films) and long-term investments (organic fertilizer and irrigation expenditure) after the land titling program are all negative, which thus provides no signs that households are increasing their long-term farm investments.

6.5. The effects of the land titling program on agricultural TFP by crop type

In Table 7, we explore the different effects of land titling by crop type.[26] Columns (1) and (2) show the policy effects on the conventional TFP of cash crops and staple crops separately.[27] We find that the negative effects on conventional agricultural TFP are mainly driven by the drop in the productivity of cash crops. Consequently, Column (3) shows at the household level that the share of land devoted to the cultivation of cash crops decreased accordingly. We hypothesize that this is due to a higher positive correlation between human capital and the TFP of cash crops, since the cultivation of cash crops may require more skills and knowledge. Columns (4) to (6) test our hypothesis by showing whether human capital improves the conventional TFP of cash crops more than that of staple crops. Specifically, we regress at the household-crop level conventional TFP on the measures of human capital and the interactions between human capital and a dummy variable indicating cash crops using a sample of households before the land titling program. For all three measures of human capital, namely education, health, and age, we find that the coefficients on the interaction terms are positive, indicating that the positive correlation between human capital and TFP is higher for cash crops than staple crops.

6.6. The effects of the land titling program on land holding and land rental by human capital

The outmigration of household members with higher human capital may indicate that agricultural land will become concentrated in households with lower agricultural human capital through land transfers. Such concentration of land may further aggravate the decrease in agricultural productivity.[28]

Fig. 5 firstly shows that households with lower agricultural human capital before the program tend to hold more land after the program. In the figures on the left column of Fig. 5, we use Equation (8) to estimate the changes in land holding before and after the land titling program by households' agricultural human capital before the program. Land holding measures the amount of agricultural land that a household actually cultivates each year, which includes land owned and rented-in by the household. We find that for all three measures of human capital, land held by households from the lowest quartile of the human capital distribution increase, while land held by other households decreases. This finding confirms the hypothesis that agricultural land is concentrated and cultivated by households with lower agricultural human capital as a result of migration.

Fig. 5 also shows that the changes in land holding by agricultural human capital are mainly driven by the changes in land rentals. In the figures on the right column of Fig. 5, we use Equation (8) to estimate the changes in the total amount of land households rented-in before and after the land titling program by households' agricultural human capital before the program. We find that households from the lowest quartile of the human capital distribution tend to rent in more land after the titling program. Thus, land rental activity is the main mechanism that drives the concentration of land into households with lower agricultural human capital.

Table 6
The effects of land titling on agricultural inputs.

	(1) Agricultural Area	(2) Hired Labor Days	(3) Additional Inputs (Fertilizer, Pesticide Machinery, Tools, Agricultural Films)	(4) Inputs Increasing long term productivity (Organic fertilizer Irrigation expenditure)
Post*Treated Villages	−0.022 (0.033)	−0.055 (0.040)	−0.076* (0.046)	−0.208* (0.109)
Household Fixed Effects	Yes	Yes	Yes	Yes
Province*Year Fixed Effects	Yes	Yes	Yes	Yes
Cluster of Standard Errors	County	County	County	County
Observations	99633	99633	99633	99633
Adjusted R-square	0.802	0.561	0.743	0.674

Notes: In this table we show the effects of the land titling program on a range of agricultural inputs. "Agricultural Area" refers to agricultural land inputs. "Hired Labor Days" refers to hired labor inputs. All inputs are total inputs measured in logarithm value. Robust standard errors clustered at the county level are shown in parentheses. *, ** and *** denote statistical significance at the 10%, 5% and 1% level, respectively.

6.7. Heterogenous effects of the land titling program

To further clarify the mechanisms, this subsection estimates the heterogenous effects of the land titling program on agricultural productivity (conventional TFP) by land tenure security and migration opportunity.

First, we argue that the land titling program affects agricultural productivity and migration through delinking land property rights from contingent use of the land. If tenure insecurity in the form of *"use-based" land property rights* is the underlying mechanism, we should observe a greater impact on villages with higher land tenure insecurity before implementation of the program. We adopt three measures to capture village-level land tenure insecurity before the program: the number of land-related legal disputes, land expropriation risk, and the amount of adjustable land held by the village. We assume that the probability of

[26] Staple crops include wheat, rice, corn, soybeans, and other grains; cash crops include cotton, oilseed, sugar, hemp, tobacco leaf, vegetables, and fruits.

[27] We conduct this analysis at the household-crop-year level.

[28] It is possible that households allocate all of their labor force into migration. Since these households quit from agricultural production, they are not included in the baseline sample that we apply to calculate agricultural productivity. If the households that quit from agricultural production rent out their land to others, our estimation at the household level may not fully capture the changes in overall productivity. To address this concern, we firstly conduct a robustness check by aggregating our data into the village level and calculating the effects of land titling on agricultural productivity at an aggregated village level. If land transfers are conducted mainly by households within the same village, the village level estimates will reflect the overall productivity effects that are not biased due to the sample attrition of households. This is because the household sample is a representative random sample of the village. Table A5 shows the effects of land titling on conventional agricultural TFP and human capital of agricultural labor estimated at the village level. We find that the signs and magnitudes of coefficients are very similar to the estimates we obtain from household level analysis. Second, Table A8 shows that the amount of land households rent out to farmers from outside the village is not significantly affected by land titling, which validates the previous assumption that land transfer within the village is the main mechanism that requires consideration. Third, households may rent land to collectives or firms rather than other households (Cheng et al., 2019). However, Table A8 shows that the land titling program did not induce households to rent more land to non-individual entities, such as agricultural collectives or firms. Finally, Table A8 also shows that sample attrition, measured by all households' labor allocated to migration (quit from agricultural production), is not significantly affected by the land titling program.

Table 7
The effects of land titling by crop types.

	(1) Conventional TFP (Cash-crops)	(2) Conventional TFP (Staple-crops)	(3) Cash Crop Ratio	(4) TFP (Conventional)	(5) TFP (Conventional)	(6) TFP (Conventional)
Post*Treated Villages	−0.123*	−0.026	−0.025**			
	(0.069)	(0.028)	(0.012)			
Education				0.066***		
				(0.013)		
Education*Cash Crop				0.042***		
				(0.016)		
Good Health					0.523***	
					(0.083)	
Good Health*Cash Crop					0.313**	
					(0.121)	
Good Age						0.491***
						(0.082)
Good Age*Cash Crop						0.338***
						(0.105)
Province*Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Crop Type Fixed Effects	Yes	Yes	No	Yes	Yes	Yes
Household Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Cluster of Standard Errors	County	County	County	County	County	County
Observations	84349	156189	98614	178440	178440	178440
Adjusted R-square	0.568	0.542	0.767	0.475	0.480	0.475

Notes: In this table, we show the effects of the land titling program by crop types. In Columns (1) and (2), we estimate the effects of land titling program on conventional TFP at the household-crop level separately for cash and staple crops. In Column (3), we use the ratio of land devoted to cash crops over all crops as the dependent variable and estimate the effects at the household level. In Columns (4), (5), and (6), we show the correlation between conventional TFP, human capital, and crop types by regressing TFP on human capital and the interaction between human capital and crop type. Columns (4), (5), and (6) are estimated at household-crop level using a sample of households before the land titling reform. Robust standard errors clustered at the county level are shown in parentheses. *, ** and *** denote statistical significance at the 10%, 5% and 1% level, respectively.

losing land tenure will be higher if there are more land-related disputes, a higher land expropriation risk, and more adjustable land.[29] In Panel A of Table 8, we firstly estimate the effects of land titling on agricultural TFP for those villages with low tenure security (below the median of the distribution, measured by more land-related disputes, higher land expropriation risk, and more adjustable land) and secondly, villages with high tenure security before the implementation of the program. We find that the estimation results are generally consistent with our hypothesis. The policy effects on agricultural TFP were only significantly negative if tenure security was low prior to the program. The results suggest that the land titling program has reduced agricultural TFP mainly through enhancing tenure security.

Second, we hypothesize that the land titling program reduces agricultural productivity through promoting rural-to-urban migration. If migration is the underlying mechanism, we should observe a greater impact when the rural households face higher migration return and opportunity. We adopt three measures to capture the variations in migration return and opportunity. First, we use farm size to capture return in the agricultural sector. If the return in the agricultural sector is high, households will be less likely to migrate out. Second, we construct a migration opportunity index to capture the distance from the village to potential migration destinations. The migration index is high if the village is close to the destinations. Third, we calculate the ratio of migrant wage over agricultural wage at the village level before the implementation of the program. If the ratio is high, the relative attractiveness to migrate will be higher. We split the sample at the median of the distribution of the three migration opportunity measures. Panel B of Table 8 shows that the negative effects of land titling on agricultural TFP are driven by those households with less land, villages that are closer to migration destinations, and villages with a higher migration to agricultural wage ratio. This finding implies that the policy effects are more salient when migration return and opportunity are higher, which is consistent with our argument that migration is the channel that drives the decline in agricultural TFP.

7. Conclusion

This paper examines the importance of land property rights for the allocation of human capital across agricultural and non-agricultural sectors in the context of a developing country. Leveraging China's county-by-county roll-out of the land titling program, our DID estimates indicate that farmers with higher human capital endowments are more likely to migrate out of the agriculture sector once land has been titled. Consequently, agricultural productivity decreases by approximately 8–9%. We show that this decrease is mainly caused by the "brain drain" in the agricultural sector induced by the land titling program.

Our findings contrast with existing evidence that land titling leads to higher agricultural productivity in many other countries. This may be due to the fact that the human capital reallocation mechanism in China dominates other underlying mechanisms that link titling with productivity, such as investments, land market frictions, or access to credit. Two features that are specific to China contribute to these observed different effects. First, there had been other reforms in China before the implementation of land titling that had attempted to address a range of insecure property rights problems, such as lack of *transaction rights*. Thus, land titling may play a limited role in correcting land misallocation within the agricultural sector, which is the main mechanism that drives the findings of many previous studies (e.g., Beg, 2022). Second, China's non-agricultural labor markets have expanded rapidly since 2000s, thus creating millions of job opportunities for potential migrants prior to the land titling program in 2014. Correspondingly, the financial returns from the agricultural sector stagnated over time, making migration a much more lucrative choice for agricultural laborers. Therefore, this is an instructive setting in which the reallocation of human capital has become the most significant policy consequence. It is noteworthy that our findings are not suggesting that untitled land is

[29] Land-related disputes increase when property rights are not clearly defined; land expropriation risk is proxied by the ratio of land expropriation income to the total income at the village level; the amount of adjustable land approximates the power of the village collectives to change the allocation of land.

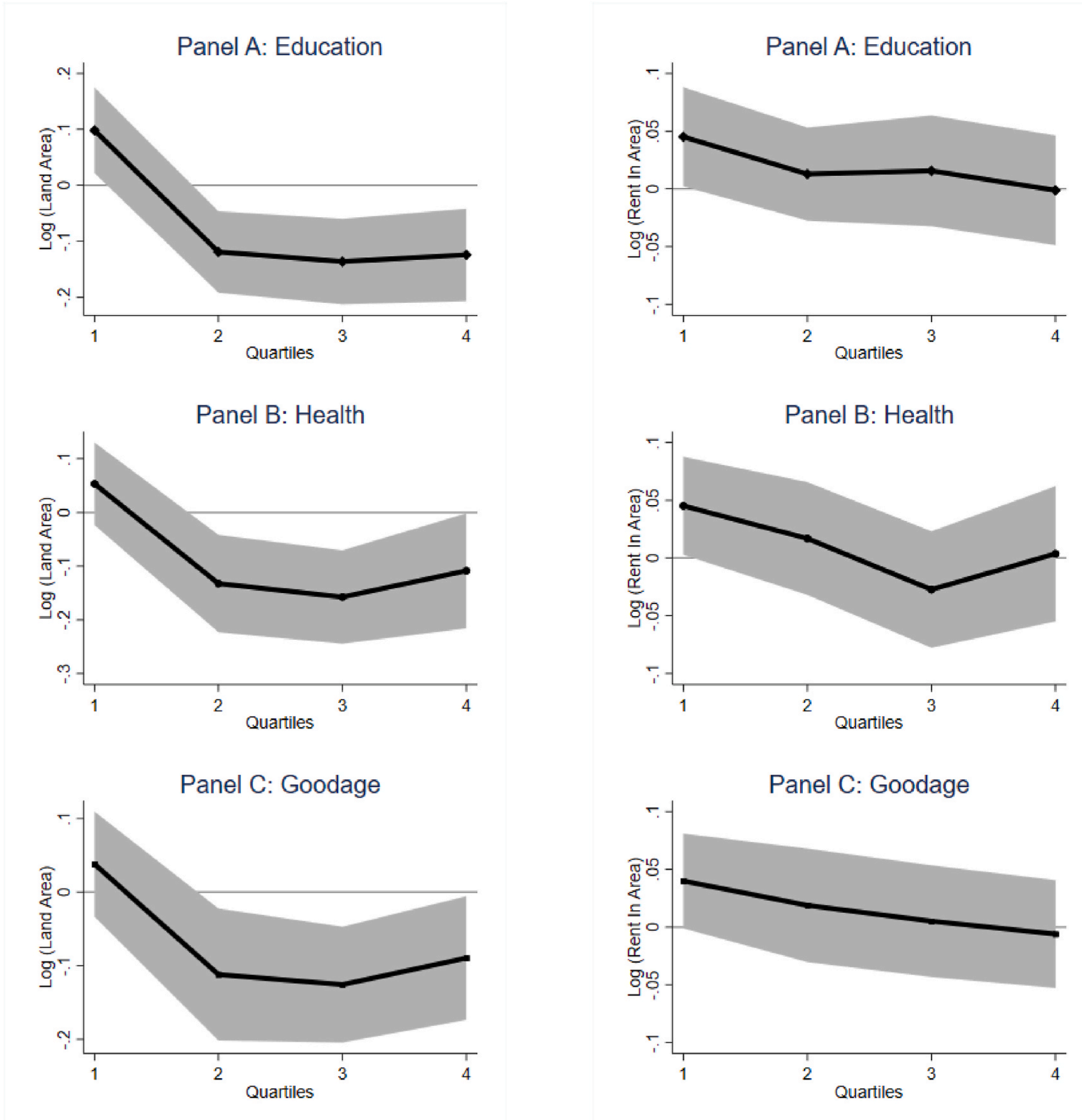

Fig. 5. The Effects of Land Titling on Land Holding and Land Rented-in by Agricultural Human Capital
Notes: These figures show the heterogenous effects of the land titling program on land holding and land rented-in by agricultural human capital. The horizontal axis denotes four quartile groups of agricultural human capital before the titling program ranked from low to high. Figures on the left column show the treatment effects on land holding for each quartile group. Figures on the right column show the treatment effects on the total amount of land households rented in for each quartile group. Human capital is measured by years of schooling, whether the labor is in good health, and whether the labor is in good working age. The figures report point estimates and 90% confidence intervals.

conducive to higher agricultural productivity. Indeed, untitled land status may be detrimental to agricultural productivity through multiple mechanisms. Additionally, our findings exclusively reflect the policy's consequences in the context of China and not in the context of other developing nations.

Our results give rise to two potential questions worth studying in the future. First, the decrease in agricultural productivity reflects the effects of an actual land titling policy that only frees a certain barrier of cross-sector human capital reallocation, it would be worthwhile to understand the optimal allocation of human capital across agricultural and non-agricultural sectors when the whole sets of institutional barriers are lifted. Second, the reallocation of human capital should improve overall economic efficiency, even though at the cost of reducing agricultural productivity. Therefore, a potential field worthy of exploration would be the quantification of the policy impact of land titling on the manufacturing sector and overall productivity.

Recent decades have seen governments from developing countries spend millions of dollars annually on land titling programs. The policy practice is based on the common belief that land titling is a necessary first-step policy to address low agricultural productivity, which is a common problem in many developing countries. However, our study suggests that the land titling program may not realize its policy objective when a fast-growing non-agricultural sector constantly attracts resources away from agriculture. Thus, we argue that the effects of land titling on agricultural productivity should be substantially different for each developing country due to their unique institutions, cultures, geographies, legal systems, and economic structures. Governments from developing countries should seriously consider the conditions and contexts when designing any land titling programs.

Declaration of competing interest

None.

Table 8
Heterogenous effects of land titling on agricultural productivity.

Dependent Variable: Agricultural TFP (Conventional)						
Panel A: By Tenure Security						
	Number of Disputes Per Area		Land Expropriation /Annual Income		Village Adjustable Land/Aggregate Land	
	(1)	(2)	(3)	(4)	(5)	(6)
	High (lower security)	Low (higher security)	High (lower security)	Low (higher security)	High (lower security)	Low (higher security)
Post*Treated Villages	−0.160**	−0.054	−0.149**	−0.008	−0.219**	−0.086
	(0.076)	(0.057)	(0.061)	(0.074)	(0.103)	(0.104)
Household Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Province*Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Cluster of Standard Errors	County	County	County	County	County	County
Observations	43777	49181	48388	49473	28331	28741
Adjusted R-square	0.606	0.605	0.548	0.663	0.627	0.572
Panel B: By Return to Land Relative to Return to Migration						
	Farmer Size		Migration Opportunity		Pre-policy Migration Wage/Agricultural wage	
	(7)	(8)	(9)	(10)	(11)	(12)
	High	Low	High	Low	High	Low
Post*Treated Villages	−0.0745	−0.140**	−0.147***	−0.060	−0.109**	−0.060
	(0.061)	(0.054)	(0.055)	(0.055)	(0.047)	(0.083)
Household Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Province*Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Cluster of Standard Errors	County	County	County	County	County	County
Observations	43379	44415	43625	44176	40342	48371
Adjusted R-square	0.648	0.581	0.624	0.616	0.682	0.589

Notes: In this table, we show the effects of the land titling program on agricultural productivity by pre-reform tenure security and migration return. Tenure security is approximated by the number of land-related legal disputes, land expropriation risk, and the amount of adjustable land held by the village. Migration return is approximated by farm size, distance from the village to potential migration destinations, and the ratio of migrant wage over agricultural wage. We split the sample at the median and estimate separately for the high and the low groups in pre-reform tenure security and migration return. We use conventional agricultural TFP as the dependent variables (without controlling for human capital). Robust standard errors clustered at the county level are shown in parentheses. *, ** and *** denote statistical significance at the 10%, 5% and 1% level, respectively.

Data availability

The authors do not have permission to share data.

Acknowledgements

The authors thank Shaohua Chen, Lucas Davis, Per Fredriksson, Shanjun Li, Giovanni Peri, Liugang sheng, Yu Sheng, Qinghua Zhao, and applied-micro brown bag seminar participants at the Institute for Economic and Social Research (IESR) at Jinan University and the Wang Yanan Institute for Studies in Economics (WISE) at Xiamen University for helpful comments, and Wanjuan Xu, Sirui Yu, and Xinyu Li for excellent research assistant. The authors also acknowledge generous financial support from the National Natural Science Foundation of China (NSFC) (No. 72103174; 72133004; 71903075; and 71903067), the NSFC's Fundamental Scientific Center Project (No. 71988101), and the 111 Project of China (No. B18026). Thanks as well to China Ministry of Agriculture Research Center of Rural Economy (RCRE) and the staff of the Fixed-Point Survey Office for data access. The usual disclaimers apply.

Appendix A1

The estimation of TFP relies on the consistent estimation of the parameters of the production function, which depends on how we assume unobserved terms, because the error term is likely to be correlated with input decisions (Marschak and Andrews, 1944). Following Chari et al. (2021), we assume that TFP can be decomposed according to Equation. (2) into (i) φ_{ic}: household-crop fixed effect, which captures the household's fixed ability to farm a given crop; (ii) φ_{it}: household-year fixed effect, which captures time-varying shocks to productivity that are common to all crops grown by the household, (iii) φ_{cvt}: crop-village-year fixed effect, which is a time-varying component that is common to all farmers in the village that are growing crop c (for example, weather shocks or pest infestations), and (iv) e_{icvt}: an idiosyncratic shock that is specific to the household and the crop in a given year.[30]

Thus, the TFP for household i growing crop c in village v at time t is estimated as follows:

$$Log\widehat{TFP}_{icvt} = \widehat{\varphi_{ic}} + \widehat{\varphi_{it}} + \widehat{\varphi_{cvt}} \tag{A1}$$

As households grow multiple crops in any given year, we can jointly estimate the regression specification (Equation (1)) for all crops (i.e., we estimate a single regression in which the coefficients of inputs are allowed to be crop-specific), while absorbing φ_{ic}, φ_{it} and φ_{cvt} by household-crop, household-year and village-crop-year fixed effects. The household-crop effect φ_{ic} absorbs all time-invariant productive characteristics such as gender; the household-year effect φ_{it} absorbs changes in farm composition, health shocks, rainfall shocks, etc.; the village-crop-year component additionally absorbs shocks such as pest infestations, which may be crop- and location-specific. Additionally, the idiosyncratic component of TFP, e_{icvt}, is unobserved by the farmer at the time that input decisions are made. The inclusion of these fixed effects addresses omitted variable bias arising from

[30] We use the method suggested by Bils et al. (2021), which assesses the degree of additive measurement error in the measures of distortions. We find that our panel fixed effect estimates of distortions significantly reduce measurement error.

the dependence of input choices on the farmer-observed component of TFP[31].

Appendix Table A1 presents the estimated (crop-specific) production function coefficients. This table allows elasticities to vary across crops when estimating coefficients. Alternatively, if we restrict elasticities such that they are equal across crops, the elasticity of output with respect to land is 0.51 on average across all crops, which is slightly larger than the estimates obtained from aggregate data that range from 0.35 to 0.47 (Chow, 1993; Cao and Birchenall, 2013; Chari et al., 2021). However, it should be noted that our estimates of elasticities exhibit substantial variation across crops.

Appendix Table A2 assesses the importance of selection due to entry or exit by estimating the production function using a balanced sample of farmer-crop combinations that span the period of 2009–2018. The production function coefficients are largely similar to those obtained with the unbalanced panel, indicating that selection driven by unobserved productivity shocks is not a serious problem.

Table A1
Production Function Coefficients (Unbalanced Panel)

	Land Area	Labor Days	Machinery Cost	Other Cost
Wheat	0.606***	0.113***	0.071***	0.120***
	(0.037)	(0.017)	(0.013)	(0.019)
Rice	0.650***	0.069***	0.057***	0.137***
	(0.043)	(0.020)	(0.014)	(0.028)
Corn	0.528***	0.122***	0.063***	0.222***
	(0.037)	(0.016)	(0.009)	(0.020)
Soybean	0.681***	0.135***	0.095***	0.034**
	(0.065)	(0.035)	(0.025)	(0.016)
Potato	0.366***	0.155***	0.176***	0.068**
	(0.063)	(0.039)	(0.030)	(0.026)
Other Grains	0.666***	0.130***	0.016	0.112***
	(0.068)	(0.047)	(0.025)	(0.038)
Cotton	0.646***	0.074	0.063	0.207***
	(0.109)	(0.061)	(0.064)	(0.056)
Oilseed	0.499***	0.177***	0.081***	0.157***
	(0.032)	(0.025)	(0.017)	(0.022)
Sugar	0.356*	0.118	0.047	0.631***
	(0.194)	(0.145)	(0.106)	(0.170)
Tobacco Leaf	0.270	0.257*	0.111	0.207
	(0.176)	(0.143)	(0.118)	(0.165)
Vegetables	0.248**	0.231***	0.200***	0.135***
	(0.114)	(0.053)	(0.046)	(0.037)
Other Cash	0.492***	0.204**	0.163***	0.132***
	(0.095)	(0.083)	(0.053)	(0.035)
Fruit	0.277**	0.260***	0.171***	0.263***
	(0.123)	(0.056)	(0.042)	(0.059)
Other Orchard	0.429***	0.264***	0.047	0.085***
	(0.166)	(0.094)	(0.050)	(0.031)
Total	0.445***	0.247***	0.119***	0.067***
	(0.017)	(0.018)	(0.003)	(0.004)
Total Observations	185989			

Notes: In this table we show the estimated production function coefficients following Equation (1). We estimate Equation (1) jointly for all crops. *, ** and *** denote statistical significance at the 10%, 5% and 1% level, respectively.

Table A2
Production Function Coefficients (Balanced Panel)

	Land Area	Labor Days	Machinery Cost	Other Cost
Wheat	0.615***	0.062***	0.032***	0.129***
	(0.038)	(0.006)	(0.005)	(0.020)
Rice	0.644***	0.039***	0.018***	0.149***
	(0.022)	(0.008)	(0.004)	(0.015)
Corn	0.612***	0.060***	0.021***	0.161***
	(0.018)	(0.005)	(0.003)	(0.001)
Soybean	0.640***	0.104***	0.027***	0.053***
	(0.022)	(0.011)	(0.006)	(0.007)
Potato	0.497***	0.091***	0.041***	0.068***
	(0.022)	(0.011)	(0.007)	(0.007)
Other Grains	0.693***	0.090***	0.016**	0.066***
	(0.029)	(0.014)	(0.008)	(0.014)
Cotton	0.6504***	0.019	0.044***	0.151***
	(0.0823)	(0.0241)	(0.0140)	(0.0573)
Oilseed	0.571***	0.091***	0.023***	0.105***
	(0.015)	(0.008)	(0.004)	(0.009)
Sugar	0.822***	−0.074	−0.007	0.457***
	(0.140)	(0.085)	(0.030)	(0.132)

(continued on next page)

[31] Note that the inclusion of farmer-year and village-crop-year fixed effects also absorbs any changes in the village-level average TFP arising from the land titling program; this enables us to consistently estimate the production function for the entire sample period.

Table A2 (*continued*)

	Land Area	Labor Days	Machinery Cost	Other Cost
Tobacco Leaf	0.518***	0.017	0.013	0.208***
	(0.100)	(0.030)	(0.015)	(0.075)
Vegetables	0.181	0.248***	0.031	0.118**
	(0.141)	(0.051)	(0.052)	(0.047)
Other Cash	0.192***	0.095***	0.073***	0.091***
	(0.030)	(0.007)	(0.006)	(0.005)
Fruit	0.324***	0.058***	0.020***	0.196***
	(0.041)	(0.010)	(0.007)	(0.017)
Other Orchard	0.162***	0.323***	0.0051	0.0926***
	(0.049)	(0.040)	(0.022)	(0.015)
Total	0.468***	0.217***	0.021***	0.044***
	(0.013)	(0.021)	(0.004)	(0.007)
Total Observations	144564			

Notes: In this table we show the estimated production function coefficients following Equation (1). We estimate Equation (1) jointly for all crops, using a balanced sample of household-crop combinations that span the period from 2009 to 2018. *, ** and *** denote statistical significance at the 10%, 5% and 1% level, respectively.

Table A3
The Effects of Land Titling on Input Costs and Profits

	(1)	(2)	(3)	(4)
	Cost per Area	Cost per Area	Profits per Area	Profits per Area
Post*Treated Villages	−0.100	−0.098	−0.043	−0.047
	(0.071)	(0.073)	(0.055)	(0.055)
Household Fixed Effects	Yes	No	Yes	No
Province*Year Fixed Effects	Yes	Yes	Yes	Yes
Village Fixed Effects	No	Yes	No	Yes
Cluster of Standard Errors	County	County	County	County
Observations	99633	99633	99633	99633
Adjusted R-square	0.589	0.428	0.207	0.072

Notes: In this table, we show the effects of the land titling program on agricultural input costs and profits. All models are estimated using Equation (6). In Columns (1) and (2), we use the logarithm function of total input costs per area as the dependent variables. In Columns (3) and (4) we use profits per area as the dependent variables. In Columns (1) and (3), we control for household fixed effects. In Columns (2) and (4), we control for village fixed effects. Robust standard errors clustered at the county level are shown in parentheses. *, ** and *** denote statistical significance at the 10%, 5% and 1% level, respectively.

Table A4
Estimating the Staggered DID design using Alternative Methods

	Point Estimate	Standard Error	Lower Bound 95% Confidence Interval	Upperbond 95% Confidence Interval
Panel A: Log Revenue per Area				
OLS	−0.076**	0.035	−0.176	−0.011
Borusyak, Jaravel, and Spiess	−0.134***	0.032	−0.197	−0.071
Callaway and Sant'Ana	−0.055	0.041	−0.136	0.026
de Chaisemartin and D'Haultfeuille	−0.051	0.077	−0.201	0.100
Sun and Abraham	−0.096**	0.044	−0.182	−0.010
Panel B: Log TFP (Conventional)				
OLS	−0.092**	0.040	−0.170	−0.014
Borusyak, Jaravel, and Spiess	−0.148**	0.040	−0.227	−0.070
Callaway and Sant'Ana	−0.098	0.071	−0.238	0.042
de Chaisemartin and D'Haultfeuille	−0.107**	0.048	−0.211	−0.002
Sun and Abraham	−0.095**	0.047	−0.187	−0.003
Panel C: Migration (Days)				
OLS	0.145**	0.072	0.004	0.286
Borusyak, Jaravel, and Spiess	0.188**	0.062	0.065	0.310
Callaway and Sant'Ana	0.139**	0.053	0.035	0.242
de Chaisemartin and D'Haultfeuille	0.114*	0.064	−0.012	0.241
Sun and Abraham	0.107	0.074	−0.038	0.252
Panel D: Years of Education				
OLS	−0.288**	0.127	−0.537	−0.039
Borusyak, Jaravel, and Spiess	−0.238**	0.102	−0.439	−0.038
Callaway and Sant'Ana	−0.289**	0.123	−0.529	−0.049
de Chaisemartin and D'Haultfeuille	−0.273**	0.126	−0.519	−0.026
Sun and Abraham	−0.262**	0.130	−0.519	−0.006
Panel E: Health (Good Health)				
OLS	−0.045**	0.019	−0.082	−0.008
Borusyak, Jaravel, and Spiess	−0.037**	0.014	−0.065	−0.010
Callaway and Sant'Ana	−0.043**	0.018	−0.079	−0.008
de Chaisemartin and D'Haultfeuille	−0.040**	0.018	−0.074	−0.005

(continued on next page)

Table A4 (*continued*)

	Point Estimate	Standard Error	Lower Bound 95% Confidence Interval	Upperbond 95% Confidence Interval
Sun and Abraham	−0.038**	0.019	−0.075	−0.001
Panel F: Age (Good Age)				
OLS	−0.029*	0.015	−0.054	0.004
Borusyak, Jaravel, and Spiess	−0.028**	0.014	−0.056	0.000
Callaway and Sant'Ana	−0.022**	0.011	−0.045	0.000
de Chaisemartin and D'Haultfeuille	−0.018	0.013	−0.043	0.008
Sun and Abraham	−0.035**	0.017	−0.069	−0.001

Notes: In this table, we estimate the effects of the land titling program on revenue per area, agricultural TFP (conventional), migration, and human capital of agricultural labor using different methods proposed in the literature to address the potential bias in a staggered DID design. The model specifications follow Equation (6) and are the same as Table 2. We report estimates from four methods respectively: Borusyak et al. (2021),Callaway and Sant'Anna (2021),de Chaisemartin and D'Haultfeuille (2020), and Sun and Abraham (2021). Most of the methods generate estimates similar to the baseline OLS estimates. Robust standard errors clustered at the county level are shown in parentheses. *, ** and *** denote statistical significance at the 10%, 5% and 1% level, respectively.

Table A5
The Effects of Land Titling on Agricultural TFP and Human Capital of Agricultural Labor at the Village Level

	(1)	(2)	(3)	(4)
	Log TFP (Conventional)	Years of Education	Health (Good Health)	Age (Good Age)
Post*Treated Villages	−0.093*	−0.323**	−0.042**	−0.028*
	(0.054)	(0.145)	(0.019)	(0.017)
Province*Year Fixed Effects	Yes	Yes	Yes	Yes
Village Fixed Effects	Yes	Yes	Yes	Yes
Cluster of Standard Errors	County	County	County	County
Observations	2093	2093	2093	2093
Adjusted R-square	0.670	0.780	0.773	0.814

Notes: In this table, we estimate the effects of the land titling program on agricultural TFP (conventional) and the human capital of agricultural labor at the village level. We calculate village average TFP by averaging household level TFP weighted by total agricultural revenue. We calculate village average human capital of agricultural labor by averaging household level human capital weighted by the amount of agricultural labor. Robust standard errors clustered at the county level are shown in parentheses. *, ** and *** denote statistical significance at the 10%, 5% and 1% level, respectively.

Table A6
The Effects of Land Titling on Long Term Investments Over Time

	(1)	(2)
	Additional Inputs (Fertilizer, Pesticide Machinery, Tools, Agricultural Films)	Inputs Increasing long term productivity (Organic fertilizer Irrigation expenditure)
Pre 4 years*Treated Villages	0.026	0.057*
	(0.100)	(0.031)
Pre 3 years *Treated Villages	0.088	0.048
	(0.122)	(0.032)
Pre 2 years *Treated Villages	0.024	0.019
	(0.104)	(0.024)
Policy year* Treated Villages	−0.166	−0.052
	(0.116)	(0.040)
Post 1 year*Treated Villages	−0.382**	−0.176**
	(0.194)	(0.082)
Post 2 years*Treated Villages	−0.805***	−0.217*
	(0.288)	(0.126)
Post 3 years*Treated Villages	−0.646*	−0.146
	(0.335)	(0.149)
Household Fixed Effects	Yes	Yes
Province*Year Fixed Effects	Yes	Yes
Cluster of Standard Errors	County	County
Observations	99633	99633
Adjusted R-square	0.667	0.727

Notes: In this table, we show the effects of the land titling program on long term investments over time. We provide additional results for the effects on long term investments reported in Columns (3) and (4) of Table 6. Specifically, we estimate the dynamic version of the DID model following Equation (7) and report coefficients for all time periods in this table. We find that the decrease in long term investments persisted over time, lasting for at least three time periods after the reform. Robust standard errors clustered at the county level are shown in parentheses. *, ** and *** denote statistical significance at the 10%, 5% and 1% level, respectively.

Table A7
The Effects of Land Titling on Quantity TFP (Conventional)

	(1)	(2)	(3)
	Quantity TFP	Quantity TFP	Quantity TFP
Post*Treated Villages	−0.043*	−0.047**	−0.047**
	(0.023)	(0.023)	(0.023)
Household Fixed Effects	Yes	No	No
Province*Year Fixed Effects	Yes	Yes	Yes
Crop Fixed Effects	Yes	No	No
Household*Crop Fixed Effects	No	Yes	No
Village*Crop Fixed Effects	No	No	Yes
Cluster of Standard Errors	County	County	County
Observations	240538	240538	240538
Adjusted R-square	0.633	0.839	0.754

Notes: In this table, we use Equation (6) to estimate the effects of the land titling program on quantity TFP at the household-crop level. The dependent variable is the logarithm function of physical output of household *i* growing crop c in village v in year t. Robust standard errors clustered at the county level are shown in parentheses. *, ** and *** denote statistical significance at the 10%, 5% and 1% level, respectively.

Table A8
The Effects of Land Titling on the Migration of all Labor Force and Land Rentals

	(1)	(2)	(3)	(4)
	All Labors Migrate Out	Land Rented Out of Village	Land Rented to Non-individual Entities (Collectives or Firms)	Hired Labor Days
Post*Treated Villages	0.002	−0.002	0.044	−0.055
	(0.006)	(0.006)	(0.028)	(0.040)
Household Fixed Effects	Yes	Yes	Yes	Yes
Province*Year Fixed Effects	Yes	Yes	Yes	Yes
Cluster of Standard Errors	County	County	County	County
Observations	130570	130570	130570	99633
Adjusted R-square	0.504	0.197	0.263	0.561

Notes: In this table, we show the effects of the land titling program on the potential of sample attrition due to all labor force migrating out of the home village. In Column (1), the dependent variable is a dummy variable taking the value 1 if all household labors are allocated to migration in year *t*. In Columns (2) and (3), we also evaluate whether the land titling program induce households to rent out their land to farmers from outside the village or to non-individual entities such as collectives or firms. We include non-farming households when estimating Columns (1), (2), and (3). Robust standard errors clustered at the county level are shown in parentheses. *, ** and *** denote statistical significance at the 10%, 5% and 1% level, respectively.

Table A9
Balance Test between Villages with Missing Titling Timing and Villages with Accurate Titling Timing

	(1)	(2)	(3)	(4)
	Villages with Missing Titling Timing	Villages with Accurate Titling Timing	Difference (1)–(2)	P value
Total Population	1898.532	2043.228	−144.696	0.297
Land Area per Capita	9.017	7.645	1.372	0.214
Arable Land per Capita	1.961	2.181	−0.220	0.298
Share of Non-agricultural Income	0.504	0.485	0.018	0.392
Income from Farming per Capita	72.927	58.041	14.886	0.620
Share of Labor with Education Level higher than Elementary School	0.265	0.277	−0.012	0.280
Share of Labor with Education Level higher than Middle School	0.696	0.686	0.010	0.664
Share of Migrants out of Home Province	0.129	0.127	0.003	0.829
Share of Migrants out of Home County within Home Province	0.092	0.109	−0.017	0.039

Notes: In this table, we conduct a balance test at the village level using information from village surveys, and compare those villages for which we cannot find information on the timing of land titling with other villages. The village level characteristics include variables that describe the total population of the village, the situation of land holding of the village, the development of non-agriculture sector in the village, the level of human capital of labor, and the pattern of out-migration. We report the mean of village level characteristics before the land titling program in Columns (1) and (2). Column (3) shows the difference between the two groups of villages. Column (4) shows the p-value of the difference. Notice that the summary statistics reflect the average characteristics of villages. Therefore, they are not necessarily consistent with the summary statistics of the main analytical sample, which reflect the characteristics of farming households. *, ** and *** denote statistical significance at the 10%, 5% and 1% level, respectively.

Appendix A10

Can the contracted land be reclaimed during the land contracting period[32]?

[32] The case can be found at: https://www.court.gov.cn/zixun-xiangqing-362801.html#~:text=%E6%B0%91%E6%B3%95%E5%85%B8%E7%AC%AC%E4%B8%89%E7%99%BE%E8%BF%9B%E5%9F%8E%E8%90%.

Case Details: Mr. Cai and his wife were farmers in *Shang Cai* village and contracted 15 mu of farmland in the village. Mr. Cai worked off-farm in a factory outside the village, but still within the county. Later, Mr. Cai's wife and child all worked and lived in the county and only occasionally returned to *Shang Cai* village. As they were working off-farm outside the village, the committee of village collectives decided to take back their 15 mu of farmland. Mr Cai's family argued that their land rights were guaranteed and protected by their land certificate/titles and therefore, the village collectives had no authority to take back the land they contracted. After futile attempts at negotiations, they filed a lawsuit to the county-level people's court, claiming that the village's decision to reclaim the land was unlawful.

The court ruled that contracted land serves as an "informal social insurance" for farmers. Farmers who have obtained contracted land and been granted with land titles should not lose their property rights when they work in the city; the village collectives have no rights to take back farmers' land during the contracted period, regardless of what changes occur to the farmers such as changes in permanent address, nature of work, hukou reallocation, and so on. In this case, the village collectives must return the 15 mu of farmland to them.

References

Adamopoulos, Tasso, Restuccia, Diego, 2014. The size distribution of farms and international productivity differences[J]. Am. Econ. Rev. 104 (6), 1667–1697.

Adamopoulos, Tasso, Brandt, Loren, Chen, Chaoran, Restuccia, Diego, Wei, Xiaoyun, 2022a. Land Security and Mobility frictions[R]. National Bureau of Economic Research. No. w29666.

Adamopoulos, Tasso, Brandt, Loren, Leight, Jessica, Restuccia, Diego, 2022b. Misallocation, selection, and productivity: a quantitative analysis with panel data from China[J]. Econometrica 90 (3), 1261–1282.

Aryal, Jeetendra P., Stein, T., 2011. Holden. Caste Discrimination, Land Reforms and Land Market Performance in Nepal[R]. Centre for Land Tenure Studies Working Paper.

Athey, Susan, Imbens, Guido W., Wager, Stefan, 2018. Approximate residual balancing: debiased inference of average treatment effects in high dimensions[J]. J. Roy. Stat. Soc. B 80 (4), 597–623.

Banerjee, Abhijit V., Gertler, Paul J., Ghatak, Maitreesh, 2002. Empowerment and efficiency: tenancy reform in West Bengal[J]. J. Polit. Econ. 110 (2), 239–280.

Banerjee, Abhijit, Iyer, Lakshmi, 2005. History, institutions, and economic performance: the legacy of colonial land tenure systems in India[J]. Am. Econ. Rev. 95 (4), 1190–1213.

Beg, Sabrin, 2022. Digitization and development: property rights security, and land and labor markets[J]. J. Eur. Econ. Assoc. 20 (1), 395–429.

Benjamin, Dwayne, Brandt, Loren, Giles, John, 2005. The evolution of income inequality in rural China. Econ. Dev. Cult. Change 53 (4), 769–824.

Besley, Timothy, 1995. Property rights and investment incentives: theory and evidence from Ghana[J]. J. Polit. Econ. 103 (5), 903–937.

Besley, Timothy, Ghatak, Maitreesh, 2010. Property Rights and Economic development [M]//Handbook of Development Economics, vol. 5. Elsevier, pp. 4525–4595.

Besley, Timothy, Leight, Jessica, Pande, Rohini, Rao, Vijayendra, 2016. Long-run impacts of land regulation: evidence from tenancy reform in India[J]. J. Dev. Econ. 118, 72–87.

Bils, Mark, Klenow, Peter J., Ruane, Cian, 2021. Misallocation or mismeasurement? [j]. J. Monetary Econ. 124, S39–S56.

Borusyak, Kirill, Jaravel, Xavier, Spiess, Jann, 2021. Revisiting Event Study Designs: Robust and Efficient Estimation [R]. arXiv preprint arXiv:2108.12419.

Brandt, Loren, Huang, Jikun, Guo, Li, Scott, Rozelle, 2002. Land rights in rural China: facts, fictions and issues[J]. China J. (47), 67–97.

Bu, Di, Liao, Yin, 2022. Land property rights and rural enterprise growth: evidence from land titling reform in China[J]. J. Dev. Econ. 157, 102853.

Callaway, Brantly, Sant'Anna, Pedro HC., 2021. Difference-in-differences with multiple time periods[J]. J. Econom. 225 (2), 200–230.

Cao, Kang Hua, Birchenall, Javier A., 2013. Agricultural productivity, structural change, and economic growth in post-reform China[J]. J. Dev. Econ. 104, 165–180.

Carter, Michael R., Yang, Yao, 2002. Local versus global separability in agricultural household models: the factor price equalization effect of land transfer rights[J]. Am. J. Agric. Econ. 84 (3), 702–715.

Carter, Michael R., Pedro, Olinto, 2003. Getting institutions "right" for whom? Credit constraints and the impact of property rights on the quantity and composition of investment[J]. Am. J. Agric. Econ. 85 (1), 173–186.

Caselli, Francesco, 2005. Accounting for cross-country income differences[J]. Handb. Econ. Growth 1, 679–741.

Chankrajang, Thanyaporn, 2015. Partial land rights and agricultural outcomes: evidence from Thailand[J]. Land Econ. 91 (1), 126–148.

Chari, Amalavoyal, Liu, Elaine M., Wang, Shing-Yi, Wang, Yongxiang, 2021. Property rights, land misallocation, and agricultural efficiency in China[J]. Rev. Econ. Stud. 88 (4), 1831–1862.

Chen, Chaoran, Restuccia, Diego, Santaeulàlia-Llopis, Raül, 2022. The effects of land markets on resource allocation and agricultural productivity[J]. Rev. Econ. Dynam. 45, 41–54.

Chen, Xi, Zhang, Xiaobo, 2009. The Distribution of Income and Well-Being in Rural China: a Survey of Panel Data Sets, Studies and New Directions.

Cheng, Wenli, Xu, Yuyun, Zhou, Nan, He, Zaizhong, Zhang, Longyao, 2019. How did land titling affect China's rural land rental market? Size, composition and efficiency [J]. Land Use Pol. 82, 609–619.

Chow, Gregory C., 1993. "Capital formation and economic growth in China [J]. Q. J. Econ. 108 (3), 809–842.

de Brauw, Alan, Mueller, Valerie, 2012. Do limitations in land rights transferability influence mobility rates in Ethiopia?[J]. J. Afr. Econ. 21 (4), 548–579.

de Chaisemartin, Clément, d'Haultfoeuille, Xavier, 2020. Two-way fixed effects estimators with heterogeneous treatment effects[J]. Am. Econ. Rev. 110 (9), 2964–2996.

de Janvry, Alain, Fafchamps, Marcel, Sadoulet, Elisabeth, 1991. Peasant household behaviour with missing markets: some paradoxes explained[J]. Econ. J. 101 (409), 1400–1417.

de Janvry, Alain, Emerick, Kyle, Gonzalez-Navarro, Marco, Sadoulet, Elisabeth, 2015. Delinking land rights from land use: certification and migration in Mexico[J]. Am. Econ. Rev. 105 (10), 3125–3149.

Deininger, Klaus, Jin, Songqing, 2005. The potential of land rental markets in the process of economic development: evidence from China[J]. J. Dev. Econ. 78 (1), 241–270.

Deininger, Klaus, Jin, Songqing, 2006. Tenure security and land-related investment: evidence from Ethiopia[J]. Eur. Econ. Rev. 50 (5), 1245–1277.

De La Rupelle, Maëlys, Deng, Quheng, Shi, Li, Vendryes, Thomas, 2009. In: Land rights insecurity and temporary migration in rural China[R]. halshs-00575041.

Deininger, Klaus, Daniel, Ayalew Ali, Tekie, Alemu, 2010. Land rental markets: transaction costs and tenure insecurity in rural Ethiopia[M]. In: The Emergence of Land Markets in Africa. Routledge.

Deininger, Klaus, Goyal, Aparajita, 2012. Going digital: credit effects of land registry computerization in India[J]. J. Dev. Econ. 99 (2), 236–243.

Deininger, Klaus, Jin, Songqing, Liu, Shouying, Xia, Fang, 2020. Property rights reform to support China's rural-urban integration: household-level evidence from the Chengdu experiment[J]. Aust. J. Agric. Resour. Econ. 64 (1), 30–54.

Deng, Dacai, 2014. Property rights development and rural governance: determinants and patterns-an examination of four villages in Guangdong, Hunan [J], 01 Zhongzhou Journal 205, 40–44 (Chinese).

Ding, Chengri, 2003. Land policy reform in China: assessment and prospects[J]. Land Use Pol. 20 (2), 109–120.

Do, Quy-Toan, Iyer, Lakshmi, 2008. Land titling and rural transition in Vietnam[J]. Econ. Dev. Cult. Change 56 (3), 531–579.

Feng, Lei, Ye, Jianping, Jiang, Yan, Lang, Yu, Roy, 2013. Farmers' attitudes in the changing rural land adjustment system in China: an empirical analysis based on a survey in 17 provinces from 1999 to 2010[J]. Manag. World (7), 44–58 (Chinese).

Field, Erica, Torero, Maximo, 2006. Do Property Titles Increase Credit Access Among the Urban Poor? Evidence from a Nationwide Titling program[R]. Working paper, Department of Economics, Harvard University, Cambridge, MA.

Foster, Andrew D., Rosenzweig, Mark R., 1995. Learning by doing and learning from others: human capital and technical change in agriculture[J]. J. Polit. Econ. 103 (6), 1176–1209.

Foster, Andrew D., Rosenzweig, Mark R., 2022. Are there too many farms in the world? Labor market transaction costs, machine capacities, and optimal farm size[J]. J. Polit. Econ. 130 (3), 636–680.

Galiani, Sebastian, Schargrodsky, Ernesto, 2010. Property rights for the poor: effects of land titling[J]. J. Publ. Econ. 94 (9–10), 700–729.

Gao, Xuwen, Shi, Xinjie, Fang, Shile, 2021. Property rights and misallocation: evidence from land certification in China[J]. World Dev. 147, 105632.

Giles, John, Ren, Mu, 2018. Village political economy, land tenure insecurity, and the rural to urban migration decision: evidence from China[J]. Am. J. Agric. Econ. 100 (2), 521–544.

Goldstein, Markus, Udry, Christopher, 2008. The profits of power: land rights and agricultural investment in Ghana[J]. J. Polit. Econ. 116 (6), 981–1022.

Gollin, Douglas, Parente, Stephen, Rogerson, Richard, 2002. The role of agriculture in development. Am. Econ. Rev. 92 (2), 160–164.

Goodman-Bacon, 2021. Andrew. Difference-in-differences with variation in treatment timing[J]. J. Econom. 225 (2), 254–277.

Gottlieb, Charles, Jan, Grobovšek, 2019. Communal land and agricultural productivity [J]. J. Dev. Econ. 138, 135–152.

Guo, Xiaolin, 2001. Land expropriation and rural conflicts in China[J]. China Q. 166, 422–439.

Ho, Peter, 2001. Who owns China's land? Policies, property rights and deliberate institutional ambiguity[J]. China Q. 166, 394–421.

Ho, Peter, 2005. Institutions in Transition: Land Ownership, Property Rights, and Social Conflict in China[M]. Oxford University Press.

Holden, Stein T., Deininger, Klaus, Ghebru, Hosaena, 2011. Tenure insecurity, gender, low-cost land certification and land rental market participation in Ethiopia. J. Dev. Stud. 47 (1), 31–47.

Jacoby, Hanan G., Guo, Li, Scott, Rozelle, 2002. Hazards of expropriation: tenure insecurity and investment in rural China[J]. Am. Econ. Rev. 92 (5), 1420–1447.

Ji, Yueqing, Yang, Zongyao, Fang, Chenliang, Wang, Yanan, 2021. From expectation to implementation: how does land titling affect farmers' decision to transfer their land out? [J]. China Rural Economy (07), 24-43 (Chinese).
Jin, Songqing, Deininger, Klaus, 2009. Land rental markets in the process of rural structural transformation: productivity and equity impacts from China[J]. J. Comp. Econ. 37 (4), 629–646.
Kung, James Kai-sing, 2000. Common property rights and land reallocations in rural China: evidence from a village survey[J]. World Dev. 28 (4), 701–719.
Kung, James Kai-sing, 2002. Off-farm labor markets and the emergence of land rental markets in rural China[J]. J. Comp. Econ. 30 (2), 395–414.
Li, Guo, Scott, Rozelle, Brandt, Loren, 1998. Tenure, land rights, and farmer investment incentives in China[J]. Agricultural economics 19 (1–2), 63–71.
Li, Lixing, 2012. Land titling in China: Chengdu experiment and its consequences[J]. China Econ. J. 5 (1), 47–64.
Li, Ping, 2003. Rural land tenure reforms in China: issues, regulations and prospects for additional reform[J]. Land Reform, Land Settl. Coop. 11 (3), 59–72.
Lichtenberg, Erik, Ding, Chengri, 2008. Assessing farmland protection policy in China[J]. Land Use Pol. 25 (1), 59–68.
Liu, Shouying, Carter, Michael R., Yang, Yao, 1998. Dimensions and diversity of property rights in rural China: dilemmas on the road to further reform[J]. World Dev. 26 (10), 1789–1806.
Liu, Xiaoyu, Zhang, Linxiu, 2008. Analysis of the relationship between the stability of rural land property rights and labor transfer[J]. China Rural Economy 278, 29–39, 02.
López, Ramón, Romano, Claudia, 2000. Rural poverty in Honduras: asset distribution and liquidity constraints[M]. In: Rural Poverty in Latin America. Palgrave Macmillan, London, pp. 227–243.
Lunduka, Rodney, Stein T, Holden, Ragnar, Øygard, 2009. Land rental market participation and tenure security in Malawi. In: The Emergence of Land Markets in Africa: Impacts on Poverty, Equity and Efficiency, pp. 112–130.
Macours, Karen, de Janvry, Alain, Sadoulet, Elisabeth, 2010. Insecurity of property rights and social matching in the tenancy market[J]. Eur. Econ. Rev. 54 (7), 880–899.
Marschak, Jacob, Andrews, William H., 1944. Random simultaneous equations and the theory of production[J]. Econometrica. J. Econom. Soc. 143–205.
Olson, Mancur, 1990. Agricultural exploitation and subsidization: there is an explanation [J]. Choices 5, 316-2016-7378.
Pan, Qian, Zhong, TaiYang, Jin, XiaoBin, Zhou, YinKang, 2013. Impact of land tenure security on farm household land use change: a case study of Changshu City, Fengxian District, Jiangdu City and Funan County[J]. Journal of China Agricultural University 18 (5), 173–180 (Chinese).
Prosterman, Roy, Zhu, Keliang, Ye, Jianping, Riedinger, Jeffrey, Li, Ping, Yadav, Vandana, 2009. Secure Land Rights as a Foundation for Broad-Based Rural Development in China[J], vol. 18. NBR Special Report.
Restuccia, Diego, Yang, Dennis Tao, Zhu, Xiaodong, 2008. Agriculture and aggregate productivity: a quantitative cross-country analysis[J]. J. Monetary Econ. 55 (2), 234–250.
Rozelle, Scott, Guo, Li, 1998. Village leaders and land-rights formation in China[J]. Am. Econ. Rev. 88 (2), 433–438.
Sha, Wenbiao, 2023. The political impacts of land expropriation in China[J]. J. Dev. Econ. 160, 102985.
Song, Wei, Pijanowski, Bryan C., 2014. The effects of China's cultivated land balance program on potential land productivity at a national scale[J]. Appl. Geogr. 46, 158–170.
Sun, Liyang, Abraham, Sarah, 2021. Estimating dynamic treatment effects in event studies with heterogeneous treatment effects[J]. J. Econom. 225 (2), 175–199.
Wang, Yahui, Li, Xiubin, Li, Wei, Tan, Minghong, 2018. Land titling program and farmland rental market participation in China: evidence from pilot provinces[J]. Land Use Pol. 74, 281–290.
Zhang, Lijing, Hong, Mingyong, Guo, Xiaolin, Qian, Wenrong, 2022. How does land rental affect agricultural labor productivity? An empirical study in rural China[J]. Land 11 (5), 653.
Zhang, Longyao, Cheng, Wenli, Cheng, Enjiang, Wu, Bi, 2020. Does land titling improve credit access? Quasi-experimental evidence from rural China. Appl. Econ. 52 (2), 227–241.
Zhao, 2020. Xiaoxue. Land and labor allocation under communal tenure: theory and evidence from China[J]. J. Dev. Econ. 147, 102526.
Zhao, 1999. Yaohui. Leaving the countryside: rural-to-urban migration decisions in China[J]. Am. Econ. Rev. 89 (2), 281–286.
Zheng, Zhihao, Gao, Yang, 2017. The central "no land transfer" policy: farmers' attitudes and village land adjustment decisions: a survey of farmers in Heilongjiang, Anhui, Shandong, Sichuan, and Shanxi provinces[J]. China Rural Observation (4), 72–86 (Chinese).
Zhu, Jieming, 1999. Local growth coalition: the context and implications of China's gradualist urban land reforms[J]. Int. J. Urban Reg. Res. 23 (3), 534–548.